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# **Spatial Stratification of Urban Neighbourhoods and Their Influence on Health Outcomes**

Thesis presented by

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# Declaration

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property.

A handwritten signature in black ink, consisting of a stylized 'H' followed by a large loop and a horizontal line.

Signature: \_\_\_\_\_

Date: 24/10/2025

# Dedication

To my family, friends (Deo and Dingani), and supervisors (Jean and Ger),

thank you for your constant support, guidance, and belief in me throughout this journey.

A heartfelt thanks to Ger's family,

who welcomed me with warmth and made me feel at home during my time in Ireland.

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Finally, to all my friends and family, thank you for standing by me every step of the way. I could not have done it without you.

**Asanteni sana!!....**



*“In Dar es Salaam, a single neighbourhood can tell many stories, where high-rise apartments and informal dwellings stand side by side, and even two homes sharing a wall may face vastly different exposures to disease. These contrasting fabrics are not just architectural contrasts, but spatial expressions of inequality that shape who stays healthy, and who falls sick.”*

*Ibrahim Msuya, PhD Thesis (2025).*



# Abstract

This thesis investigates the spatial and socio-environmental determinants of non-communicable diseases in Dar es Salaam, Tanzania, with a focus on respiratory and cardiovascular health outcomes. Through a series of three interlinked studies, it explores how urban spatial inequalities intersect with environmental risks to shape health disparities in a rapidly urbanizing African context. The first chapter establishes a foundation by examining how neighbourhoods can be more meaningfully stratified to reflect socio-economic realities. It contrasts a participatory, locally informed classification method with a statistical approach using latent profile analysis (LPA) on census data. This chapter demonstrates the value of nuanced neighbourhood typologies in capturing the lived experience of inequality and sets the stage for spatially sensitive health analyses. Building on this foundation, the second chapter investigates the spatial prevalence of chronic respiratory diseases using household survey data and environmental indicators such as the Topographical Wetness Index. It highlights the role of urban hydrology proximity to stagnant water and flood-prone areas as a key environmental determinant of respiratory health, particularly in vulnerable communities. The third chapter turns to cardiovascular health, examining how satellite-derived measures of urban greenness (NDVI) and surface temperature (LST) relate to hypertension across socio-economic strata. It reveals that environmental exposures like heat and limited greenery disproportionately affect urban residents, contributing to higher disease prevalence. Together, these chapters provide an integrated understanding of how spatial, socio-economic and environmental factors combine to shape urban health outcomes, offering insights for more equitable and context-specific urban planning and public health interventions.

# Research Chapters Summaries

## Chapter 2

The first study lays the groundwork by critically examining how urban neighbourhoods in Dar es Salaam can be stratified in meaningful ways to reflect socio-economic realities. Recognizing the limitations of administrative boundaries and aggregate data, this chapter evaluates two contrasting approaches to neighbourhood classification: a subjective, participatory method involving local knowledge of income-based differentiation and an objective, data-driven approach using latent profile analysis (LPA) on census-derived deprivation indicators. By comparing these methods, the study interrogates how well formal datasets capture the lived experience of inequality and whether participatory approaches can enhance the granularity and relevance of neighbourhood-level health analyses. This chapter underscores the importance of neighbourhood stratification not only as a methodological tool, but also as a conceptual foundation for understanding urban spatial heterogeneity and its implications for health outcomes.

## Chapter 3

The second study builds on the previous neighbourhood stratification analysis, by examining the spatial distribution of chronic respiratory diseases in the urban landscape and how these are shaped by both environmental and household-level factors. Utilizing data from a household survey alongside an environmental proxy specifically, the Topographical Wetness Index (TWI) as an indicator of waterlogging, it investigates the spatial prevalence of respiratory conditions. Particular attention is given to urban hydrological features in ground truthing, such as proximity to stagnant water bodies and flood-prone areas, as potential environmental determinants of respiratory health. This chapter explains the intersection between spatially

embedded environmental risks and socio-economic vulnerabilities in influencing respiratory health outcomes. By integrating spatial analysis with household-level data, the study offers a contextually grounded perspective on how environmental stressors disproportionately impact health regardless of income in Dar es Salaam.

## **Chapter 4**

The third study also builds upon the first chapter and links to cardiovascular health, exploring how variations in urban greenness and thermal conditions relate to the prevalence of hypertension across neighbourhoods with different income strata. Using satellite-derived indicators such as Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), the study quantifies environmental exposures that are often overlooked in conventional public health analyses. It examines whether access to urban green spaces and exposure to urban heat islands correlate with higher rates of hypertension and how these patterns differ across socio-economically stratified areas. This analysis deepens our understanding of environmental determinants of non-communicable diseases in rapidly urbanizing African cities and reinforces the importance of integrating environmental justice considerations into urban health planning and policy.

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# 1 CHAPTER ONE

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## General Introduction

## 1.1 General introduction

Urbanization is a defining force of the 21st century, profoundly influencing where and how people live, work and critically navigate their health (WHO, 2022). Cities concentrate economic opportunity and innovation, yet they also magnify inequalities that shape health disparities (Sennett, 2018). In low- and middle-income countries (LMICs), where urban growth is most rapid, unequal access to infrastructure, healthcare and healthy environments creates stark divides in health outcomes (Ezeh et al., 2017). These disparities are not inevitable, they reflect systemic failures in urban governance, resource distribution and the social determinants of health (Marmot, 2020). Understanding how urban environments constrain or enable health-related choices is essential to addressing these inequities and fostering healthier cities (Galea & Vlahov, 2005).

This chapter establishes the foundation for analysing the interplay between urban spatial structures and public health, examining how inequalities are systematically produced, perpetuated and lived within cities. It begins by framing the global urbanization context and the emergence of intra-urban health disparities, drawing attention to the unequal health risks and outcomes that arise from spatial segregation and uneven urban development. The discussion then focuses on the processes through which cities evolve and become stratified, particularly through historical legacies, governance choices, land markets and infrastructural investments. These dynamics create differentiated urban environments that shape daily exposures and vulnerabilities.

By situating Dar es Salaam within this global and regional landscape, the chapter highlights why it serves as a critical site for examining urban health inequality. It proceeds to review existing data gaps in mapping intra-urban diversity, introduces the conceptual framework

guiding this research and outlines the study's objectives, methodology, structure and contributions.

## **1.2 The evolution of cities and the production of inequality**

Cities have long served as centres of economic concentration and political power, their development deeply influenced by colonial legacies, industrial capitalism and globalization (King, 2015; Robinson, 2006). The urban landscapes we see today have not naturally evolved but are shaped by deliberate political-economic decisions that embed social hierarchies within the built environment. Foundational urban theory highlights how zoning laws, housing policies and transportation investments have historically favoured affluent neighbourhoods while marginalizing poorer populations into hazardous and underserved peripheries (Harvey, 2012; Logan & Molotch, 2007; Marcuse, 2013). This process is captured by Graham and Marvin's (2002) concept of "splintering urbanism," where high-quality infrastructure and services are concentrated in privileged areas, leaving informal settlements disconnected from essential amenities.

The spatial inequalities embedded in urban form have profound health consequences. Studies across diverse contexts reveal that marginalized urban populations, whether in redlined neighbourhoods in the United States (Krieger, 2021), South African townships (Coovadia et al., 2009), Nairobi Kibera-slums (Gallaher et al., 2013), or Brazilian favelas (Riley et al., 2007), suffer disproportionately from respiratory illnesses, mental health disorders, infectious and non-infectious diseases. This "architecture of inequality" (Sassen, 2014) manifests in clear environmental health disparities, such as informal settlements experiencing two to three times higher exposure to fine particulate matter (PM<sub>2.5</sub>) compared to formal neighbourhoods (Baue, 2023), having 50% less access to green spaces (Shuvo et al., 2020) and facing travel times to tertiary hospitals that are four to five times longer (Sverdlik, 2011).

In African cities, these dynamics are particularly acute due to rapid informal urbanization. Estimates suggest that 60 - 80% of urban growth in Africa occurs through informal settlement expansion, often in environmentally vulnerable locations such as floodplains or industrial zones, as documented in Nairobi's Mathare Valley (Sverdlik et al., 2025) and Lagos' Makoko community (Ajibade, 2017). The state's role is paradoxical, neglecting these settlements while intermittently demolishing them, giving rise to what Bayat (2000) terms "quiet encroachment," where residents gradually build urban systems outside formal governance frameworks (Huchzermeyer, 2011).

The production of urban health inequalities operates through several intertwined mechanisms. Institutional path dependence means that colonial-era health infrastructure remains concentrated in former European quarters, as seen in Dar es Salaam (Brennan et al., 2007). The financialization of urban space, driven by global capital flows, creates speculative real estate markets that displace health services and vulnerable populations, exemplified by Accra's expanding peripheries (Grant, 2009). Moreover, climate change interacts with urban form to exacerbate health risks, with urban heat island effects increasing mortality in dense informal settlements (Yu et al., 2022).

Understanding these historical and institutional dimensions is critical for explaining why apparently neutral urban planning decisions continue to reproduce health disparities decades after independence (Myers, 2011). Contemporary challenges, including climate change and digital divides, further compound these embedded inequalities, demanding integrated approaches that address both legacy spatial injustices and emerging urban pressures (Masucci et al., 2021).

### **1.3 Global urbanization and health inequality**

The 21st century has witnessed an unprecedented demographic shift toward urban living, marking what scholars describe as the "urban age" (Brenner & Schmid, 2015). Currently, 56% of the world's population - over 4.4 billion people - reside in urban areas, with projections indicating this will rise to 68% (6.7 billion) by 2050 (Chen et al., 2022). This urban expansion is occurring disproportionately in low- and middle-income countries (LMICs), where cities are growing at three times the rate of high-income nations (Ragazzo, 2021). Africa and Asia alone are expected to account for 90% of global urban population growth in coming decades, placing extraordinary pressure on infrastructure, housing and public health systems in rapidly expanding cities like Lagos, Dhaka and Kinshasa (UN-Habitat, 2020). The accelerated growth of urban areas creates a dual dynamic for public health, simultaneously offering potential benefits while introducing significant risks. While cities theoretically offer better access to healthcare services through economies of scale (Galea & Vlahov, 2005). The reality in many LMICs reveals stark health inequalities between different urban populations. The World Health Organization (2016) estimates that urban slum dwellers experience mortality rates two to three times higher than their non-slum urban counterparts, with particularly pronounced disparities in maternal health, infectious diseases and child malnutrition.

These urban health disparities stem from multiple interconnected factors. Spatial segregation frequently concentrates poverty in hazardous environments, as approximately one billion slum dwellers worldwide are disproportionately located in floodplains, industrial zones and other high-risk areas (Ezeh et al., 2017). Environmental risks compound these challenges, with air pollution levels in low-income urban neighbourhoods typically 30% higher than in affluent areas, contributing to the seven million premature deaths attributed to air pollution annually (Ragazzo, 2021). Health systems in rapidly urbanizing LMICs often struggle to keep pace with population growth, evidenced by critical healthcare worker shortages - sub-Saharan Africa has

just 0.2 doctors per 1,000 people compared to 3.3 in Europe (Murray, 2022). Financial barriers further exacerbate inequities, with poor urban residents in some contexts spending over half their household income on emergency medical care (Knaul, 2012). Social determinants of health create additional layers of inequality, as urban income disparities correlate strongly with life expectancy gaps that can exceed 20 years between a city's richest and poorest districts (Kawachi & Kennedy, 1997).

These challenges have gained recognition in global policy frameworks, particularly through the Sustainable Development Goals emphasis on health (SDG 3) and sustainable cities (SDG 11) (SDGs, 2015). However, implementation remains uneven across regions. While some Latin American cities like Curitiba and Medellín have demonstrated success in reducing urban health inequalities through integrated planning approaches, most LMICs continue to struggle with fragmented governance systems that fail to adequately coordinate housing, transportation and health policies (Rydin et al., 2012; UN-Habitat, 2020). This global landscape of urban health inequality underscores the urgent need for context-specific research and interventions that address the systemic roots of disparities while acknowledging cities' potential as engines of health equity and sustainable development.

#### **1.4 Environmental determinants of health in urban areas**

The urban environment plays a crucial role in shaping population health outcomes, with significant variations across different neighbourhoods and socioeconomic groups. A growing body of evidence demonstrates that environmental factors in cities account for nearly 25% of the global burden of disease (Shaffer et al., 2019). These determinants interact with social, economic and political factors to create distinct health landscapes within urban areas, often reinforcing existing inequalities. The complex interaction between built environments, natural



systems and human health has become a critical focus of urban planning and public health research in recent decades.

Urban heat islands (UHIs) represent one of the most significant environmental health threats in cities, with temperature differentials of up to 10°C compared to surrounding rural areas (Heisler & Brazel, 2010). The health impacts are particularly severe in low-income neighbourhoods where housing quality is poor, green space is limited and residents often lack access to air conditioning. A study in New York City found that heat-related mortality rates were three times higher in the poorest neighbourhoods compared to wealthier areas (Madrigano et al., 2015). These disparities are exacerbated by the urban morphology, areas with high building density, dark surfaces and minimal vegetation retain more heat (Lin et al., 2023).

Moreover, flood risks in urban areas have increased significantly due to climate change and inadequate infrastructure. Research in Mumbai showed that informal settlements located in flood-prone areas experience 40% higher rates of waterborne diseases during monsoon seasons (Patwardhan, 2023). The health consequences extend beyond immediate injuries and drownings to include long-term mental health impacts, with flood-affected communities showing elevated rates of PTSD and depression (Fernandez et al., 2015).

Furthermore, urban air pollution remains a major public health challenge, responsible for an estimated 4.2 million premature deaths annually worldwide (WHO, 2023). The spatial distribution of air pollution is highly unequal, with marginalized communities often bearing the highest exposures. A landmark study in the United States found that Black Americans are exposed to 56% more pollution than they generate, while white Americans experience 17% less pollution than they generate (Tessum et al., 2019). This environmental injustice persists globally, with low-income urban dwellers more likely to live near major roads, industrial facilities and other pollution sources.

The health impacts of poor air quality are particularly severe for vulnerable populations. Children in highly polluted urban areas show reduced lung function development (Gauderman et al., 2015), while long-term exposure contributes to cardiovascular disease, lung cancer and neurodegenerative disorders (Landrigan et al., 2018). Emerging research also suggests that air pollution may increase vulnerability to respiratory infections like COVID-19 (Wu et al., 2020).

Additionally, urban green spaces provide numerous health benefits, including reduced stress, improved mental health and enhanced social cohesion. A longitudinal study in England found that people living near green spaces had significantly lower mortality rates, even after adjusting for socioeconomic status (Mitchell & Popham, 2008). The mental health benefits are particularly significant, with access to green space associated with lower rates of depression and anxiety (Bratman et al., 2019). However, the distribution of urban green space is often highly unequal. Research in Barcelona showed that wealthy neighbourhoods had 18 times more green space per capita than poorer areas (Baró et al., 2019).

Equally important, housing quality also plays a crucial role in urban health. Poor ventilation and dampness in substandard housing contribute to respiratory diseases like asthma (Krieger & Higgins, 2002). In many cities, the lack of affordable housing forces low-income families into overcrowded or substandard living conditions, exacerbating health risks (Rolnik, 2020).

Addressing environmental health disparities requires comprehensive, equity-focused urban policies. Successful interventions have included heat mitigation strategies like cool roofs and urban forestry programs (Santamouris, 2014), low-emission zones to reduce air pollution (Holman et al., 2015), participatory upgrading of informal settlements (Parikh et al., 2020) and equitable green space distribution policies (Wolch et al., 2014). The concept of "healthy cities" promoted by WHO emphasizes the need for intersectoral collaboration to address environmental health determinants (De Leeuw & Simos, 2017). While future urban

development must prioritize health equity through inclusive planning processes and targeted investments in disadvantaged neighbourhoods, there is also a need to understand the underlying causes of health inequities in cities.

### **1.5 Global turn toward spatially explicit health research**

In response to growing awareness of urban health inequalities, scholars and practitioners have begun emphasizing spatially explicit research approaches. Geographic Information Systems (GIS), remote sensing and fine-grained epidemiological surveys are increasingly used to map and analyse intra-urban variations in health outcomes, service provision and exposure to environmental risks (Corburn, 2015; Galea et al., 2019). This shift marks a departure from earlier city-level averages and embraces a more nuanced perspective, one that views the city as a mosaic of interconnected but unequal places. These approaches are particularly valuable in cities of the Global South, where conventional datasets are limited and heterogeneity is profound. This thesis builds on this spatial turn by applying it to Dar es Salaam, demonstrating how hyper-local environmental and social dynamics shape urban health disparities in ways that demand targeted and equitable urban interventions.

### **1.6 Urban inequality and health in Dar es salaam**

Urbanization is one of the most significant global trends of the 21st century, with more than half of the world's population now residing in urban areas (Kundu & Pandey, 2020; UN-Habitat, 2020). This rapid urban growth has brought about profound changes in the social, economic and environmental landscapes of cities, particularly in low and middle-income countries (LMICs) (United-Nations, 2016). Cities in these regions typically face challenges that include inadequate infrastructure, overcrowding and socio-economic disparities, which can have far-reaching implications for public health. Among these challenges, urban health inequalities occurring within city neighbourhoods, characterized by granular hetero-

geographical differences in income, deprivation, environmental exposure and access to essential resources, has emerged as a critical determinant of health (Roux, 2016; Sclar et al., 2005; Vlahov & Galea, 2002). Understanding how these spatial-environmental inequalities shape health outcomes is essential for designing targeted interventions and policies aimed at advancing urban health equity in these contexts.

Dar es Salaam, the largest city in Tanzania and one of the fastest-growing urban centres in sub-Saharan Africa, exemplifies all these common place urban health inequality issues (Mberu et al., 2016; Todd et al., 2019). As the city continues to urbanize rapidly, it presents a complex mosaic of neighbourhoods, varying from affluent, well-serviced areas to sprawling informal settlements with limited access to basic services and heightened exposure to environmental risks (Gallaher et al., 2013; Msuya et al., 2025; Shaffer et al., 2019). These include poor air and water pollution, limited access to green spaces and vulnerability to climate-related hazards such as flooding. Such hetero-geographical and environmental disparities reflect broader challenges to achieving equitable health outcomes and sustainable urban development. Addressing them requires spatially nuanced, fine-grained analyses that are grounded in local realities and lived experiences, that can inform inclusive urban planning and medical services also key health service delivery practices aligned with often overlooked urban dynamics (Kibuchi et al., 2024; Ntegwa et al., 2023).

While the city's well documented fine scale diversity (Dumedah et al., 2024; Tirado-Ballestas et al., 2025) makes it an ideal setting to examine how spatial stratification across neighbourhoods shapes health outcomes, this area of investigation remains underexplored. There is still a critical gap in systematic research investigating how neighbourhood-level socio-economic and environmental conditions contribute to persistent health disparities in cities like Dar es Salaam, limiting evidence-based policy interventions (Konkor, 2023).

This thesis seeks to address this gap by exploring the spatial stratification and internal heterogeneities of urban neighbourhoods in Dar es Salaam and their influences on health outcomes, over and above household level characteristics. The research in this thesis is composed of three interrelated studies, each employing distinct methodologies to examine different dimensions of urban health. The first study evaluates a subjective participatory approach to stratifying neighbourhoods by income and compares it with an objective, data-driven method using latent profile analysis of deprivation based on national census data (Msuya et al., 2025). The second study investigates the prevalence and spatial distribution of chronic respiratory diseases, focusing on the influence of hydrology and household characteristics upon risk. The third study explores the relationship between green vegetation, thermal conditions and hypertension prevalence across neighbourhoods with diverse income levels. Together, these studies provide a comprehensive understanding of how spatial inequalities shape health outcomes in Dar es Salaam.

### **1.7 The data deficit in understanding urban neighbourhood diversity**

The fine-scale spatial stratification of urban neighbourhoods is a critical, yet understudied subject linked to determinant of health outcomes, particularly in low and middle-income countries (LMICs) (Abascal et al., 2022; Chandola, 2012). While there is a growing body of literature on urban health disparities, much of this research has relied on broad, city-level comparisons (Freitas et al., 2020; Galea & Vlahov, 2005). In contrast analyses at the neighbourhood level and even finer scales, particularly in rapidly urbanizing cities like Dar es Salaam, remain scarce (Thomson et al., 2019). This gap is particularly concerning because neighbourhoods represent the immediate environments in which people live, work and interact with the city as a whole. All of which significantly shapes health behaviours, access to resources and exposure to environmental risks, all of which play a crucial role in determining

health outcomes (Roux, 2016). Addressing this gap is essential for understanding the nuances of urban health inequities and designing effective, localized interventions (Friel et al., 2011).

For example, in Dar es Salaam, the lack of granular data on neighbourhood-level socio-economic and environmental exposures has hindered efforts to fully understand and address health disparities (Msuya et al., 2025). Although census data in Tanzania is collected at a relatively fine spatial resolution, using enumeration areas (EAs) that often disregard administrative street boundaries and break the city into smaller, more detailed units, publicly available data is typically aggregated at the district or regional level. Moreover, these relatively large geographic units often lack theoretical bases for stratification especially as the nuances creating spatial heterogeneities sometimes need more than data to be fully observed and interpreted (Guo et al., 2022; Wang et al., 2024). As a result, many existing studies rely on broad categorizations at quite coarse scales, which can obscure important intra-urban variations, patterns of spatial segregation and localized socio-environmental differences that are critical to explaining and improving urban health (Guo et al., 2022; Thomson et al., 2019).

Moreover, the rapid pace of urbanization in Dar es Salaam means that traditional methods of neighbourhood classification may not capture the dynamic and fluid heterogeneous nature of urban spaces. This thesis addresses these challenges by employing innovative methodologies, including participatory mapping, as well as statistical and geospatial analyses of diseases prevalence, to provide a more nuanced understanding of inter and intra neighbourhood heterogeneities and their health implications.

## **1.8 Linking space, environment and health**

Urban environments are complex socio-ecological systems where spatial, environmental and socio-economic processes interact to shape individual and population-level health outcomes (Kearns et al., 2007; McPhearson et al., 2022). Understanding the mechanisms by which

neighbourhood stratification influences health requires a conceptual framework that captures these intersections across multiple scales. This study therefore adopts an integrated framework (Figure 1.1) that draws from urban health geography, environmental epidemiology and socioeconomic determinants of health, placing spatial heterogeneity at the centre of health disparities in rapidly urbanizing contexts of Dar es Salaam. Particularly, it draws on the conceptual distinction between contextual and compositional influences on health (Diez Roux, 2001), recognising that neighbourhood effects stem both from the characteristics of the physical and social environments and from those of the individuals residing within them. Contextual factors encompass aspects such as environmental quality, social cohesion, and infrastructure provision, whereas compositional factors refer to the aggregate socioeconomic and demographic profiles of residents (Macintyre et al., 2002). Understanding health disparities in urban areas therefore requires examining how these interacting dimensions shape spatial variations in exposure and vulnerability particularly within rapidly transforming urban settings where neighbourhoods differ markedly in both environmental conditions and population characteristics (Macintyre & Ellaway, 2003; Pickett & Pearl, 2001).

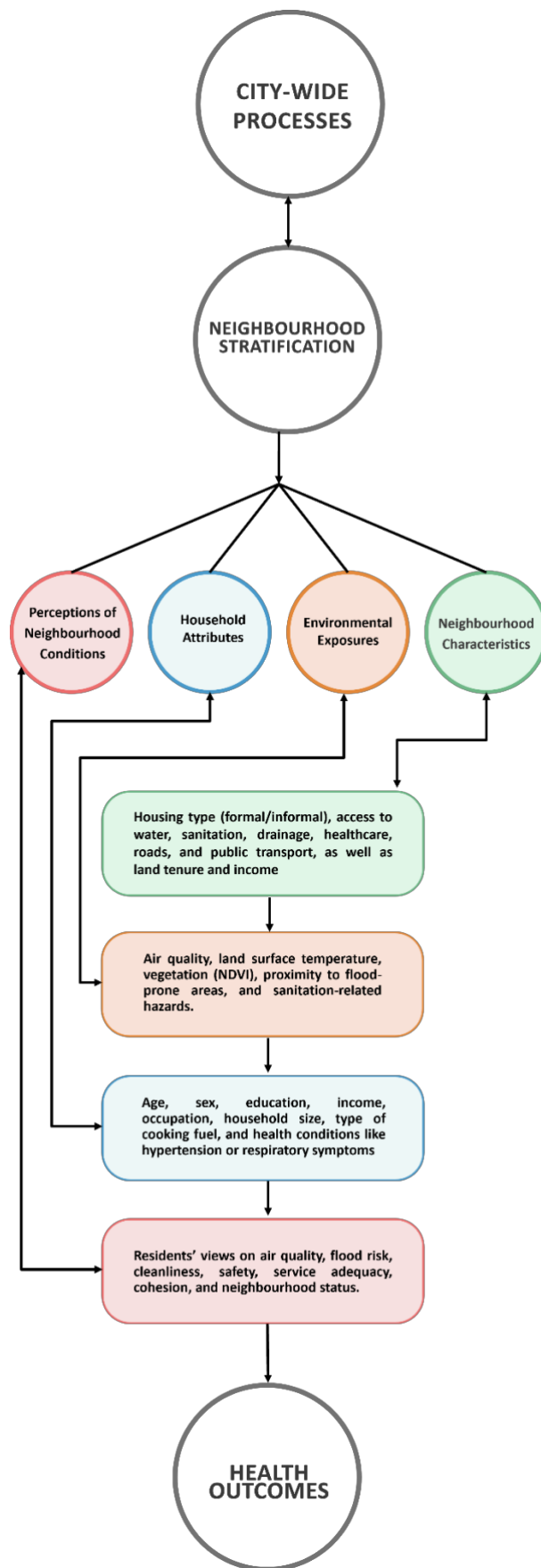


Figure 1.1: Study conceptual framework



At its core, the framework posits that neighbourhoods are not merely passive backdrops to health but active determinants of it (Benninger et al., 2021). The physical and social characteristics of these neighbourhoods, including environmental quality, access to infrastructure and services, social cohesion and economic opportunity, interact with individual and household-level attributes to shape health risks and outcomes (Levira & Todd, 2017; Oh et al., 2023). In rapidly changing urban landscapes, the dynamism of neighbourhood boundaries and resource distribution complicates these relationships further. Urban areas, particularly informal settlements, may lack clearly defined limits, evolve rapidly due to migration and land-use change (Zhang et al., 2020) and reflect entrenched socio-spatial inequalities that conventional datasets often fail to capture.

Environmental exposures, such as air pollution, heat stress, flooding and green space availability often vary dramatically significantly across individual neighbourhoods. These highly granular variations are closely tied to urban morphology, land-use patterns and infrastructure investment, all of which correlate strongly with income levels and historical patterns of urban development (Brennan, 2007). For instance, wealthier areas may enjoy more tree cover and better drainage systems, while low-income settlements are more likely to experience heat islands, poor sanitation and greater vulnerability to waterborne and airborne diseases (Shaffer et al., 2019). These environmental disparities, when mapped spatially, provide a crucial lens to assess health vulnerability in ways that simultaneously drill down below the neighbourhood scale but nevertheless transcend individual behaviours or genetic predispositions.

Additionally, the framework acknowledges that perceptions of neighbourhood conditions such as safety, social cohesion or resource adequacy can influence health behaviours, stress levels and decision-making processes. Hence, participatory methods that incorporate resident perspectives are vital to complement quantitative assessments (Salter et al., 2010). The

inclusion of both subjective and objective data sources in this research therefore enables a more holistic understanding of how neighbourhood stratification operates and is experienced in everyday life (Msuya et al., 2025).

Finally, the framework recognizes the multi-level nature of urban health disparities. It bridges household characteristics, neighbourhood environments and city-wide processes such as policy planning, land governance and service delivery. This nested approach is critical for identifying leverage points where targeted interventions of infrastructural, environmental or social nature can have the most impact. By structuring the research in this thesis around this conceptual foundation, the study was able to not only document the subtle spatial health disparities in Dar es Salaam but also explain *why* and *how* they persist.

## **1.9 Goal and objectives of the thesis**

The overall goal of this thesis is to examine the spatial heterogeneity of urban neighbourhoods in Dar es Salaam and its influence on health outcomes. The specific scientific objectives are listed as follows:

1. Evaluate a subjective participatory approach to stratifying neighbourhoods by income and compare it with an objective, statistical method using latent profile analysis (LPA) of deprivation using large amounts of detailed on national census data.
2. Investigate the prevalence and spatial distribution of chronic respiratory diseases across Dar es Salaam, with a focus on the roles of hydrology and household characteristics.
3. Explore the relationship between green vegetation land cover, thermal conditions and hypertension prevalence across diverse neighbourhoods spanning all income strata in Dar es Salaam.

By addressing these specific objectives, the thesis seeks to provide a comprehensive understanding of how neighbourhood-level socio-economic and environmental factors contribute to health disparities in Dar es Salaam. Each of these specific objectives is reflected in a distinct thesis chapter in which it is addressed with a corresponding specific study.

### **1.10 General methodological approach and scope**

To investigate the spatial determinants of health disparities in Dar es Salaam, this thesis adopts a mixed-methods approach grounded in spatial analysis, epidemiology and participatory research. The use of both quantitative and qualitative techniques enables a comprehensive understanding of how neighbourhood-level factors influence health outcomes across the urban landscape.

The research is structured around three interlinked studies, each addressing a specific dimension of urban spatial stratification and health. The first study develops a neighbourhood classification framework using both subjective (resident-informed) and objective (census-derived) methods. This comparison not only tests the reliability of participatory mapping approach but also offers insights into how residents perceive socio-economic divides within their neighbourhoods over and above the characteristics of individual households. Latent profile analysis (LPA) is used to statistically identify discrete strata of deprivation using census data.

The second study focuses on chronic respiratory disease prevalence and determinant of its demographic and spatial distribution using household-level health survey data, environmental indicators and topographical determinants of hydrological status and spatial regression models. This study was designed to identify environmental health linkages that are often masked in more generalized health studies focusing only on household level social and behaviour factors.

The third study investigates the relationship between green vegetation land cover, urban heat exposure (based on estimated land surface temperature) and hypertension rates across a variety of different neighbourhood clusters encompassing the full range of socioeconomic strata. It employs geospatial overlays of satellite derived Normalized Difference Vegetation Index (NDVI) and fine temperature data estimates in combination with household level health status data to examine how urban microclimates affect non-communicable disease outcomes.

Each study draws on multiple data sources, including:

- Tanzania's National Bureau of Statistics census data (<https://www.nbs.go.tz/statistics/topic/census-2012> )
- High-resolution remote sensing imagery (Landsat and MODIS <https://earthexplorer.usgs.gov/> )
- Household survey datasets (1533 households across 15 neighbourhoods) collected under the GCRF Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods (SHLC) (2021–2022) to analyse socio-economic, health and environmental challenges in urban communities, aligned with UN Sustainable Development Goals 3, 4 and 11. ([10.5255/UKDA-SN-855998](https://doi.org/10.5255/UKDA-SN-855998))
- Participatory mapping exercises conducted in Dar es Salaam (Msuya et al., 2025)

The scope of the research is limited to Dar es Salaam but emphasizes variability within the city rather than comparing it to other urban centres. By focusing on the fine scale level rather than coarser sub-ward, neighbourhood or census enumeration area (EA) units, this thesis highlights intra-urban disparities that are often overlooked in national health planning and reporting.

This methodological design is intentionally interdisciplinary and exploratory. It is guided by the principle that health outcomes are not only biomedical events but also spatial and social processes. The triangulation of data types and methods enhances both the validity and relevance

of findings to urban health planning, particularly in contexts where conventional data may be limited or outdated.

### 1.11 Structure of the thesis

The thesis is structured as follows:

- **Chapter 1** established the foundation by outlining the urban health inequality challenges, identifying the research gaps surrounding spatial heterogeneities of risk and data limitations and grounding the study within relevant theoretical perspectives that link urban form, environment and health.
- **Chapter 2** presents the first study, which evaluates a subjective participatory approach to stratifying neighbourhoods by income and compares it with an objective latent profile analysis of deprivation based on national census data.
- **Chapter 3** presents the second study, which investigates the prevalence and spatial distribution of chronic respiratory diseases in Dar es Salaam, with a focus on the role of hydrology and household characteristics.
- **Chapter 4** presents the third study, which explores the relationship between green vegetation cover, thermal conditions and hypertension prevalence across diverse income neighbourhoods in Dar es Salaam. This chapter demonstrates the role of the urban microclimate in shaping health outcomes in Dar es Salaam's diverse spatial fabric.
- **Chapter 5** synthesizes the combined insights from the three empirical studies, drawing connections between spatial stratification of neighbourhoods, environmental exposures and health inequities. It reflects on the implications for urban planning and health

service policy and practice while addressing the study's methodological limitations and proposing directions for future research in rapidly urbanizing cities.

### **1.12 Contribution to knowledge**

This thesis advances the field of urban health by developing fine-scale, context-sensitive methods for capturing spatial inequality in a city where traditional data boundaries obscure intra neighbourhood lived realities. It bridges methodological gaps by combining participatory insight with statistical assessment and introduces spatially explicit analysis of underexamined health-environment relationships in a low-income urban context. By grounding empirical evidence in locally relevant frameworks, the research offers actionable knowledge for rethinking how neighbourhood-level disparities are measured, interpreted and addressed in urban planning and health interventions.

### **1.13 Ethical considerations**

The research was conducted in accordance with ethical guidelines for research involving human subjects in Tanzania. Ethical clearance for the studies reported in this thesis, all of which were components of the Sustainable Cities project at the Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara Health Institute (IHI/IRB/NO: 26-2018) and the Medical Research Coordination Committee of the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954).

### **1.14 Summary and research framework**

This chapter has established the conceptual and contextual foundations of the thesis, framing the investigation into how spatial inequalities influence health outcomes in Dar es Salaam. It has highlighted the need for fine-scale, context-aware analysis in urban health research, particularly in rapidly expanding cities of the Global South where conventional data and frameworks often fall short. By combining participatory insights with geospatial and statistical

methods, the research sets the stage for improved multidimensional exploration of neighbourhood-level disparities in the future. The chapters that follow present three interconnected empirical studies that deepen our understanding of the spatial dynamics of urban health and offer new directions for evidence-based urban planning policy and practice.

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## **2 CHAPTER TWO**

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**Stratifying urban neighbourhoods by income:  
Comparison of a subjective participatory approach  
and an objective statistical analysis of deprivation  
indicators in Dar es Salaam, Tanzania**

# Preface

**Title:** Stratifying urban neighbourhoods by income: Comparison of a subjective participatory approach and an objective statistical analysis of deprivation indicators in Dar es Salaam, Tanzania

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# Abstract

**Background** Studying geographic heterogeneities in urban neighbourhoods normally informs targeted interventions. Participatory stratification approaches (PSAs) are popular for their affordability and practicality, despite subjectivity in these studies. While objective methods like latent profile analysis (LPA) require rich data and advanced capacities, often lacking in low and middle-income countries. This study assessed a PSA to stratify neighbourhoods across the Tanzania city of Dar es Salaam in terms of income, by comparing it with a complementary LPA using national census data from 2012 to stratify them in terms of deprivation.

**Methods** A consultative community-based workshop was used for the PSA, while 15 selected deprivation indicators from the census data were used to profile them using LPA. While the PSA allocated neighbourhoods to five income strata, six clear deprivation strata could be distinguished by LPA.

**Results** A strong positive correlation was observed between the stratum identified by the LPA and that obtained through the PSA ( $\rho = 0.739$ ,  $p < 0.0001$ ). Furthermore, paired comparison of the two sets of correlation coefficients between each deprivation indicator and the stratum assigned by each stratification approach revealed no difference ( $V = 33$ ,  $p\text{-value} = 0.1354$ ), confirming that the two approaches yielded very similar patterns of stratification. Also, the two approaches yielded broadly comparable cartographic pictures of the city, depicting similar spatial distribution of wealth and poverty.

**Conclusions** Overall, this evidence indicates that subjective community knowledge and lived experience may be invaluable for understanding built environment and for mapping out pockets of poverty and affluence at fine scales with minimum resources.

## 2.1 Introduction

More than half of the world's population now lives in towns and cities (United-Nations, 2016). While Africa and eastern and southern Asia have been urbanized most rapidly, the pace of urbanization in these regions is expected to slow over the coming decade (UN-Habitat, 2020). Meanwhile, limited government investment in urban planning has contributed to more extensive and overcrowded informal settlements, where approximately 47% of the world's 4.3 billion urban dwellers live (UN-Habitat, 2020). In Tanzania, for instance, it has been estimated that more than 75% of settlements have been informally developed (Magina et al., 2020). Indeed, Dar es Salaam is the largest city in Tanzania, where >75% of the population live in informal settlements with highly heterogeneous wealth distribution (Rasmussen, 2013). Several historical studies on the early development of what is now the old city centre of Dar es Salaam have rationalized the distribution of settlement patterns in terms of colonial planning processes, which were heavily influenced by residential segregation policies. During the colonial era, the city was planned in a way that segregated people by race and income, with affluent neighbourhoods located near the city centre and along the Indian Ocean (Europeans and Indians) and the less affluent near and around the city centre (black Africans, referred to in that era as natives) (Brennan & Burton, 2007). The evident pattern in the city demonstrates that a significant portion of its development has unfolded through informal processes (Msuya et al., 2021). Informal settlements tend to be situated either within formal areas or near them, aligning with the contextual reality of the city's historical evolution. This historical development trajectory has contributed to an uneven distribution of neighbourhood attributes in terms of income and affluence, a disparity that persists today. However, despite the inclination to attribute these disparities solely to colonial influences, a more thorough investigation challenges this prevailing narrative. Contrary to the common assumption that the current state of Dar es Salaam, beyond the old city, is a direct result of colonial planning (Brennan, 2007),

in fact, it emerged from limited planning, especially during the city's rapid expansion from the 1970's onward (Brennan & Burton, 2007)

While both formal and informal settlements co-exist side-by-side in cities, they exhibit varying neighbourhood characteristics. Urban neighbourhoods constantly evolve at very fine scales, resulting in a myriad of spatial, sociodemographic, economic and cultural diversities coexisting within relatively small, but nevertheless, very heterogeneous geographic areas. This vibrant evolutionary process is particularly dynamic in unplanned, informal settlements, catalyzing different types of disparities, such as health inequality, social division, exclusion, segregation, which are typically assessed in terms of income inequality or socioeconomic deprivation, (Odoi et al., 2005). Despite the conceptual differences in how income and deprivation are used to assess the two-sided coin of poverty and wealth (Box 2.1), either may be just as readily applied to surveying the distribution of inequalities across urban areas.

**Box 2.1: Summary of the conceptual and methodological distinctions between *income inequality* and *socioeconomic deprivation*.**

**Income inequality:** The concept of *income inequality* specifically targets the unequal allocation of income among individuals or households within a given population. Surveyed indices of income inequality express the disparity between the earnings of the wealthiest and the poorest members of society in semi-quantitative terms, often employing statistical summary measures, such as the Gini coefficient or income quintiles (Charles et al., 2022).

**Socioeconomic deprivation:** On the other hand, *socioeconomic deprivation* refers to disadvantages that a person or group face in an inequitable manner (Trinidad et al., 2022). Such disadvantages can be linked to geographic factors, such as living in a certain neighbourhood or community, or other factors like housing and built environment quality. These disadvantages can take various forms, such as limited access to job opportunities, education, healthcare and other basic needs. Essentially, it describes the relative absence of power that certain individuals or groups have over their economic



and social circumstances (Drukker & Os, 2003). This can perpetuate a cycle of poverty, marginalization and exclusion, leading to increased social inequality and decreased opportunities for upward mobility (Lamniso et al., 2019). Semi-quantitative measures of socioeconomic deprivation often involve use multidimensional indices to account for these diverse factors affecting well-being (Charles et al., 2022).

For the first time within the context of internationally agreed development goals, the 2030 Agenda aims to reduce inequality based on income (UN, 2020b). While efforts are being made to bridge the gap between rich and poor (Apel, 2020; Cingano, 2014), there is still insufficient investment in methodologies for socioeconomic profiling of urban neighbourhoods (2020). In response to that methodological need, this study set out to evaluate a subjective participatory stratification approach (PSA) to classifying neighbourhoods across the Tanzanian city of Dar es Salaam in terms of income, by comparing it with an objective latent profile analysis (LPA) of deprivation based on national census data (Box 2.2).

**Box 2.2: Summary of the relevant evidence base and methodological considerations that informed the formulation of the study design.**

**Participatory Stratification Approaches (PSA):** Participatory stratification approaches involve active, collaborative engagement and involvement of participants who are residents of the study area in question (Emmel, 2008; Koti, 2010). These participants may sometimes be influential or authoritative stakeholders, in the research investigation or decision-making process. PSA can be used to understand socioeconomic, geographical inequalities and the hierarchical arrangement of social groups within a given society or system and is especially useful where socio-economic classes are distributed very unevenly among people within a population (Cornwall & Jewkes, 1995; Israel et al., 2005), forcing people with comparable socio-economic characteristics to reside in similar spatial localities (UN, 2020a). However, it is essential to recognise the subjective nature of PSA, which can

be influenced by relative income assessments within the social circles or communities of individual participants, drawing from lived experiences and personal knowledge (Diener & Suh, 1997a, 1997b; Wish, 1986). Nonetheless, such subjective impressions of individual members within a community can yield qualitative insights that complement objective quantitative measurements, thus enriching an understanding of the broader economic landscape within cities (Jungman, 2013; Muñoz, 2014).

**Latent Profile Analysis (LPA):** A more objective way to understand such socioeconomic strata within in urban spatial and administrative subunits, is through statistical analysis of more structured empirical data from surveys of the major drivers and consequences of such heterogeneities. Specifically, LPA is a statistical method used to identify unobserved subgroups, or latent class or profiles within a sample of observed entities, based on similar patterns observed variables (Oberski et al., 2013). LPA has been sometimes referred to as an advanced model-based clustering approach, due to its ability to use different fit statistics to select the best profile, class, or cluster. Over the last decade, LPA has become more widely applied as an alternative to previously existing methods for identifying clusters (e.g. K-means clustering, Hierarchical clustering, Fuzzy C-means clustering and Partitioning Around Medoids), due its flexibility in model criterion selection, such as variance and covariance estimation and the objectivity of its best fit model selection procedures (Ding, 2022; Mathew & Doorenbos, 2022; Rosenberg et al., 2019; Schmidt et al., 2021). LPA of detailed data from the 2012 national Population and Housing Census (PHC) for Tanzania was therefore adopted as the gold standard objective statistical methodology, with which the PSA was compared and contrasted as a means to assess the advantages and disadvantages of the latter relative to the former.

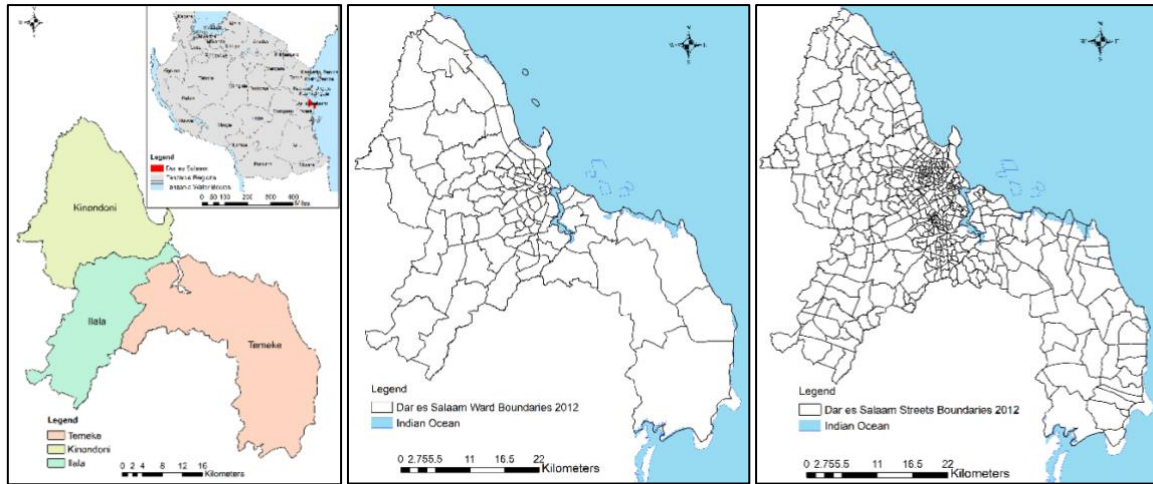
## **2.2 Methods**

### **2.2.1 Ethics statement**

This research was conducted as part of Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods, supported by funding from UK Research and Innovation (UKRI) through the Economic and Social Research Council (ESRC) under the UK Government's Global Challenges Research Fund (GCRF) with project reference (ES/P011020/1). Ethical clearance for the study, a component of the Sustainable Cities project at Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara Health Institute (IHI/IRB/NO: 26-2018) and the Medical Research Coordinating Committee at the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954). Verbal consent, in accordance with the approved protocols, was obtained from all human participants.

### **2.2.2 Geographical context and study data**

Dar es Salaam is the largest city in Tanzania, located on the Indian Ocean coast (Figure 2.1). The city had a population of approximately 4.4 million in 2012 but currently has approximately 5.4 million inhabitants, distributed across an administrative area that has remained constant at 1,590 km<sup>2</sup> (URT & NBS, 2022). It is also the port in Tanzania, contributing substantially to the national economy and served as a government administrative centre before *de facto* relocation to the official capital, Dodoma, was practically implemented in 2016 (Todd et al., 2019).



**Figure 2.1: National and regional setting of Dar es Salaam city with district's boundaries in 2012 (A), wards boundaries (B) and neighbourhood boundaries, the finest administrative scale which could be accessed and used in the study (C).**

The study reported herein used Tanzania's 2012 Population and Housing Census (PHC) data from the National Bureau of Statistics of Tanzania (NBS) to generate variables which were considered likely to represent deprivation in the study context (S1 Table). The data is presented via administrative units, starting from regions down to districts, wards (*kata*) and neighbourhoods (*mitaa*, literally translated as *streets* but actually means a larger, formalized administrative area with defined boundaries, rather than just a road and structures built along it). The data from PHC primarily consisted of socio-demographic information such as gender, age, disability, marital status, citizenship, place of residence, education status, migration patterns, economic activities, fertility rates, general mortality rates and enrolment in social security programs. Other data include household with members who are living in diaspora, food and cash crops cultivation and information about asset ownership and housing conditions. The current study used data aggregated at the neighbourhood level (Figure 2.1C), the finest scale freely available to the public upon request for research purposes to derive deprivation indicators based relevant variables in the PHC (S1 Table). The dataset included 452 neighbourhoods from three districts that comprised Dar es Salaam at the time (Figure 2.1A)

Neighbourhoods in Dar es Salaam city are unevenly distributed, with Kinondoni District having the highest number of neighbourhoods, while Ilala has the lowest number of neighbourhoods (Table 2.1). In terms of population, Kinondoni also has the highest share of residents living in this district, while Ilala is the least. However, from a historical perspective, Ilala stands as the most well-established district, comprising neighbourhoods with a rich legacy that dates back over a century. On the other hand, most parts of Temeke were relatively new and were experiencing rapid growth and development at the time.

Table 2.1: Population and neighbourhoods across districts in Dar es Salaam

| District     | No.<br>Neighbourhoods | %<br>Neighbourhoods | Population       | %<br>Population | Area<br>(sq.<br>km) | Population<br>Density<br>(people/area sq.<br>km) |
|--------------|-----------------------|---------------------|------------------|-----------------|---------------------|--------------------------------------------------|
| Kinondoni    | 171                   | 37.83               | 1,775,049        | 40.67           | 512.71              | 3462.07                                          |
| Ilala        | 101                   | 22.35               | 1,220,611        | 27.97           | 389.63              | 3132.72                                          |
| Temeke       | 180                   | 39.82               | 1,368,881        | 31.36           | 728.65              | 1878.64                                          |
| <b>Total</b> | <b>452</b>            | <b>100.00</b>       | <b>4,364,541</b> | <b>100.00</b>   |                     |                                                  |

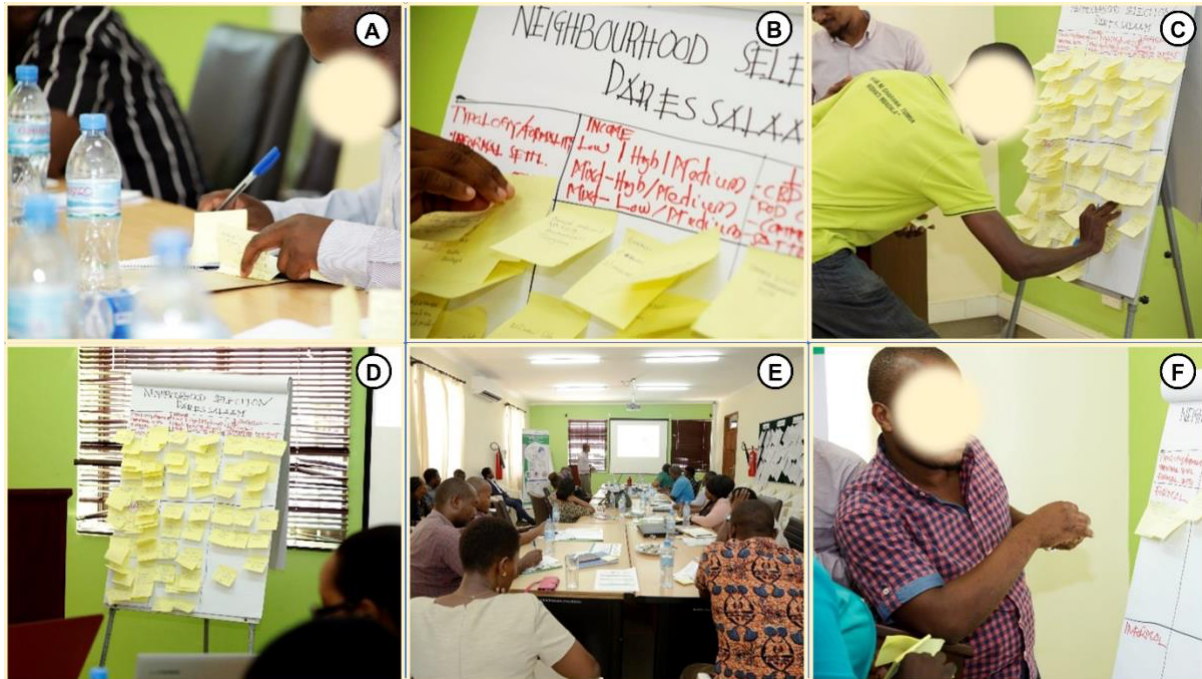
### 2.2.3 Study design

Based on considerations of the relevant methodological literature (Box 2.1 and 2.2), the current study sought to assess a subjective participatory stratification approach (PSA) to classifying neighbourhoods in terms of income level by comparing it with an objective statistical approach using latent profile analysis (LPA), to stratify neighbourhoods in terms of deprivation based on socioeconomic data from the 2012 PHC in the Tanzania city of Dar es Salaam. While the income which is referred by the PSA is inherently subjective and based on the lived experiences and knowledge of the city's residents, the LPA of deprivation strata in quantitative terms is a more objective socioeconomic metric derived from formal ways of living standards, conditions and education at the neighbourhood level (Dirksen et al., 2022).

### ***2.2.3.1 Participatory stratification approach (PSA)***

The PSA involved active participation of community members and professionals in the stratification of Dar es Salaam neighbourhoods into different income strata. This one-day workshop, carried out on Friday, 22<sup>nd</sup> March 2019, from 09:00 AM to 17:00 PM at Ifakara Health Institute offices in Mikocheni, Dar es Salaam, involved 50 people, specifically five residents from each district recommended by the neighbourhood leaders, two town planners from each district, three community development officers from each district (Table 2.1), five practicing town planners from the private sector, two urban and regional planning lecturers from Ardhi University and 13 Ifakara Health Institute scientists working in urban projects in Dar es Salaam. Participants in the PSA were selected using purposive sampling to ensure representation from diverse neighbourhoods and stakeholder groups across the study area. Selection criteria included local residency, familiarity with neighbourhood dynamics, and involvement in community development or planning initiatives, but also length in term of how long they lived in the neighbourhood or Dar es Salaam city. To minimise selection bias, recruitment was undertaken through collaboration with ward leaders and local organisations, ensuring inclusion of both male and female participants from varying socioeconomic backgrounds. The task started by collectively agreeing on the number of income strata to which the city's neighbourhoods should be assigned. Then, each of the 452 neighbourhoods were assigned to a respective stratum by each individual participant, following which a consensus was established through group discussion to collectively agree on the stratum it was finally assigned to (Figure 2.1). During participatory sessions, differing perspectives and interpretations of spatial boundaries were openly discussed, and consensus was reached through facilitated group dialogue and triangulation with existing spatial data. Although the task fundamentally relied on the participants knowledge and lived experience of the city, some

other complementary sources of information, such as satellite images, were also used to facilitate the process of informed debate and consensus building.



**Figure 2.1: Images showing participants and activities conducted during the participatory neighbourhood stratification workshop.** Panel A and B show individual participants independently assigning neighbourhoods to one of five different income strata and sharing their assignment using sticky pad notes. Panels C and D show how the assignments of individual participants were collated and compared as basis for group discussion, by assembling such sticky notes on a flip chart. Panels E and F illustrate how the investigators then facilitated collective consensus building among the participants, based on group discussions to compare and contrast their different neighbourhood assignments to specific strata and then reach final agreement for each neighbourhood.

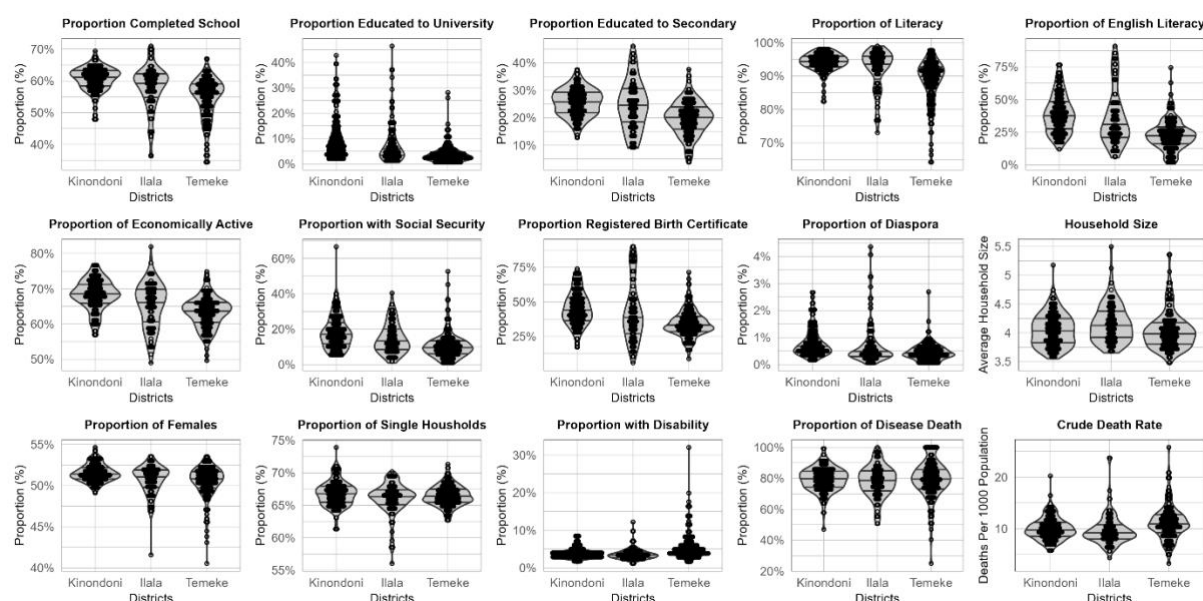
### **2.2.3.2 Latent profile analysis (LPA)**

Deprivation profiles were identified as unobserved variables (latent profiles), which were distinguished based on the observed values for relevant socioeconomic variables in the

neighbourhood-level PHC data. The first step of the LPA was the identification of the most appropriate recorded variables. Based on the data and context, 15 variables in the PHC data that were intuitively to expected to be closely associated with deprivation were identified. These included education indicators such as; *proportion completed any school level*, *proportion educated to university level*, *proportion educated to secondary level*, literacy and language proficiency; *proportion of literate*, *proportion of English literacy*, economic factors; *proportion of potentially economically active individuals*, *proportion enrolled in social security*, *proportion household with members in diaspora*, social and legal indicators; *proportion with registered birth certificate*, demographic factors; *average household size*, *proportion of female*, *proportion of single head households* and health and mortality statistics; *proportion with disability*, *proportion of death caused by diseases* and *crude death rate*. Different indicators from the census data were used to derive these variables (S1 Table) for participating respondents or households, aggregated at neighbourhood level. To provide a standardised way to compare different quantities while allowing for more accurate and meaningful comparisons between variables in predicting outcomes or estimate probabilities, almost all variables were transformed into proportions, except for household size and crude death rate which were presented in their actual metrics units.

Descriptive statistics of the selected variables can be found in figure 2.3, which shows prior expected general distribution of income and poverty across three study districts at the time, which are consistent with the actual existing situation in the city.





**Figure 2.3: Violin and dot plot showing the descriptive statistics of 15 potential indicators of deprivation derived from the 2012 national census data, distributed across three study districts at the time.** Horizontal lines within the violin plots represent the first, second and third quartiles, or the 25%, 50% (median) and 75% quantiles. The units for most of these variables are proportions of participating respondents or households, aggregated at neighbourhood level, the only two exceptions being household size and crude death rate.

Using the selected 15 variables from the neighbourhoods, LPA was used to profile neighbourhoods into statistically distinct strata.

Depending on the nature of data, different six LPA models structures can be used which range from simple to complex, determined by how variance and covariance are treated and whether relationships between variables are considered, thus affecting model parsimony and complexity (Rosenberg et al., 2018). In model selection process, Pearson's rank correlation test was employed to quantify the level of correlation to inform optional specification of model assumption and maximize model performance. In addition, the correlations between variables can help with the interpretation of the resulting latent profiles, as such, if two variables exhibit high level of correlation it can suggest that these two variables may be driving the occurrence of profile and provide insights into the nature of the profile. Broadly speaking, a correlation coefficient  $\rho \geq \pm 0.4$  and  $p \text{ value} \leq 0.05$  was considered as an indication of strong correlation (Gogtay & Thatte, 2017). The Pearson's rank correlation analysis revealed that a significant correlation existed among ten out of the fifteen variables ( $p \leq 0.05$ ), (S2 Figure and S3 Figure). Hence, from the six tidyLPA models structures proposed by Rosenberg *et al.* (Rosenberg et al., 2019), model structure six with varying variances and covariances was selected. It is the most complex model, so while it allows for the estimation of variances and covariances across profiles without constraints, potentially providing a deeper understanding of the relationships between the variables, it is also less parsimonious.

The LPA modelling was performed using R version 4.2.0 and RStudio version 2023.03.0+386 with the *tidyLPA* package. *tidyLPA* acts as an interface to the *mclust* package and provides the functionalities to estimate the commonly specified models used in the analysis, with different parameters depending on model complexity according to the structural forms developed by (Rosenberg et al., 2018). Seven criteria were used for best fit model selection: Log-Likelihood (LogLik), Akaike Information Criterion (AIC), Difference in AIC values ( $\Delta\text{AIC}$ ), Consistent

Akaike Information Criterion (AIC), Kullback-Leibler Information Criterion (KIC), Sample-Size Adjusted Bayesian Information Criterion (SABIC) and Entropy (Average Uncertainty or Randomness in Latent Class Assignments). Across the existing LPA literature, it has been widely reported that selection of the best fit model with the most informative number of distinct profiles remains a challenging task (Tein et al., 2013). Correspondingly, to validate the model optimization based on the fit statistics, an analytic hierarchy process (AHP), as proposed by (Akogul & Erisoglu, 2017) which helps in determining the correct number of profiles in a model based clustering was used.

Two approaches were used to interpret and assign meaning to each profile from the selected best fit model in relation to deprivation. Firstly, the distribution of the variables was plotted against every profile in a dot and violin plot. Secondly, using z-score or scaled mean of each variable on each profile. While median centre data around the second quartiles or 50% quantiles, z score means centre data around zero because the scaling involves standardizing each observed variable to have mean of zero and standard deviation of one ( $\mu = 0, \sigma = 1$ ), (DeVore, 2017). In the context of LPA, scaled means are often reported as part of the model output along with other fit statistics. Often, scaled means may have negative value due to scaling even though latent variable has only positive values, however, this does not necessarily indicate that the underlying construct is negative (Little et al., 2006). This helps in comparing the relative positions of the means across variables with different scales or variances, as well as for interpreting the magnitude and direction of the differences between the means of different profiles.

In LPA, after numbering profiles by ranking them according to their order of score, it is always a task to the investigators to interpret and assign their intuitive meaning (Ferguson et al., 2020). The ranked deprivation profiles were then each interpreted and assigned to named ranked deprivation stratum. The LPA deprivation strata were then compared to the results from the

PSA using a non-parametric statistical correlation test (Spearman's rank correlation test), to assess the strength and direction of the relationship between the ranked strata from the two approaches. Further analyses were performed to cross validate the PSA income strata by plotting values using violin and dot plot for the same PHC variables used in broken down by PSA stratum. To test statistical significance difference between the two approaches, a Wilcoxon signed-rank test, was applied using to compare the correlation coefficient of the Spearman's correlation ( $\rho$ ) obtained by PSA and LPA.

Additionally, using the ranked results from the two approaches, neighbourhood income and deprivation strata from PSA and LPA, respectively, were mapped using ArcGIS Pro 3.1.2, to understand and compare stratification of the city neighbourhoods by the two approaches in terms of comparative spatial distribution. In spatial comparative analysis, ground truthing evidence of the existing conditions in the selected neighbourhoods, specifically, housing density and quality of buildings, using in situ ground photographs and satellite images, were used to provide further descriptive insights into the meaning of the results.

## 2.3 Results

### 2.3.1 Latent profile identification

The best fit profile model identified by LPA of the census data was with 6-profiles: The goodness of fit consistently decreased as the number of profiles modelled increased, while entropy increased with a 98% classification quality reached for this final optimal 6-profile model that was the last one to converge Table 2.2. These model optimization results were confirmed using the AHP approach (Akogul & Erisoglu, 2017), which also indicated that the model with 6 profiles was optimal based on the fit statistics in Table 2.2. The results, therefore, suggested that six clear deprivation strata could be identified based on census data, as compared to the five income strata obtained from the participatory stratification approach.

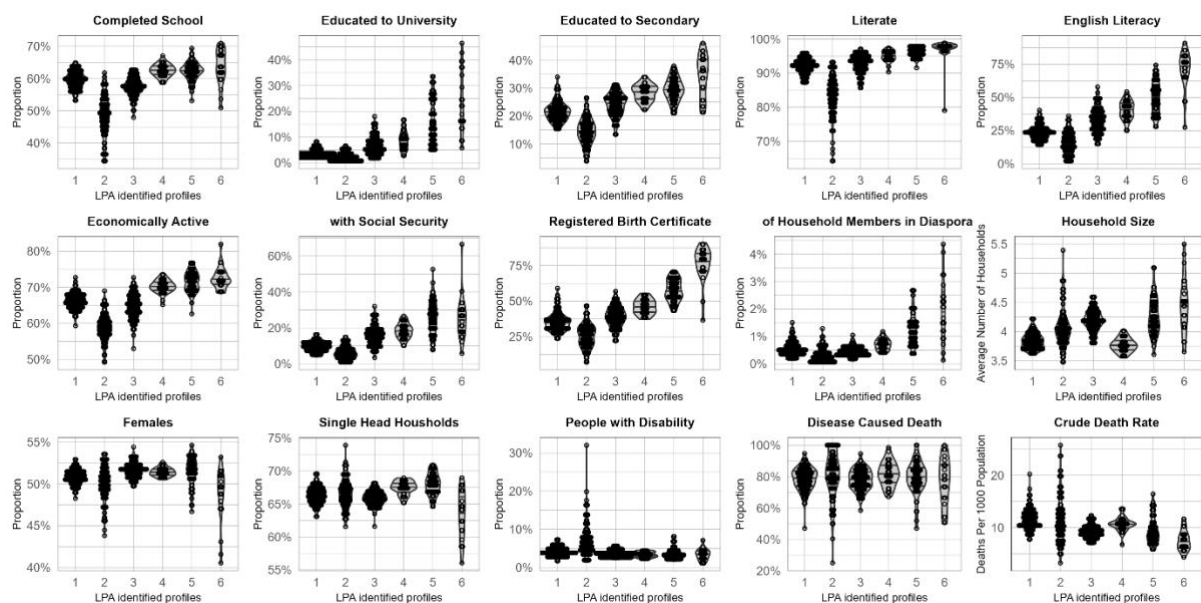
Table 2.2: Comparison of model fit statistics from different models with different numbers of profiles using the tidyLPA complex model structure 6 with varying variance and covariance (Rosenberg et al., 2019), which were then evaluated using an Analytic Hierarchy Process (AHP) (Akogul & Erisoglu, 2017) in the selection of the best fit model.

| No. Profile in a Model | LogLik       | AIC         | ΔAIC       | CLC         | KIC         | SABIC       | Entropy     |
|------------------------|--------------|-------------|------------|-------------|-------------|-------------|-------------|
| 1                      | -6128        | 12527       | N/A        | 12259       | 12665       | 12654       | 1           |
| 2                      | -4738        | 10017       | 2510       | 9477        | 10291       | 10272       | 0.96        |
| 3                      | -4486        | 9786        | 231        | 8974        | 10196       | 10169       | 0.95        |
| 4                      | -3945        | 8977        | 809        | 7893        | 9523        | 9487        | 0.97        |
| 5                      | -3677        | 8712        | 265        | 7356        | 9394        | 9350        | 0.98        |
| <b>6</b>               | <b>-3435</b> | <b>8500</b> | <b>212</b> | <b>6872</b> | <b>9318</b> | <b>9267</b> | <b>0.98</b> |

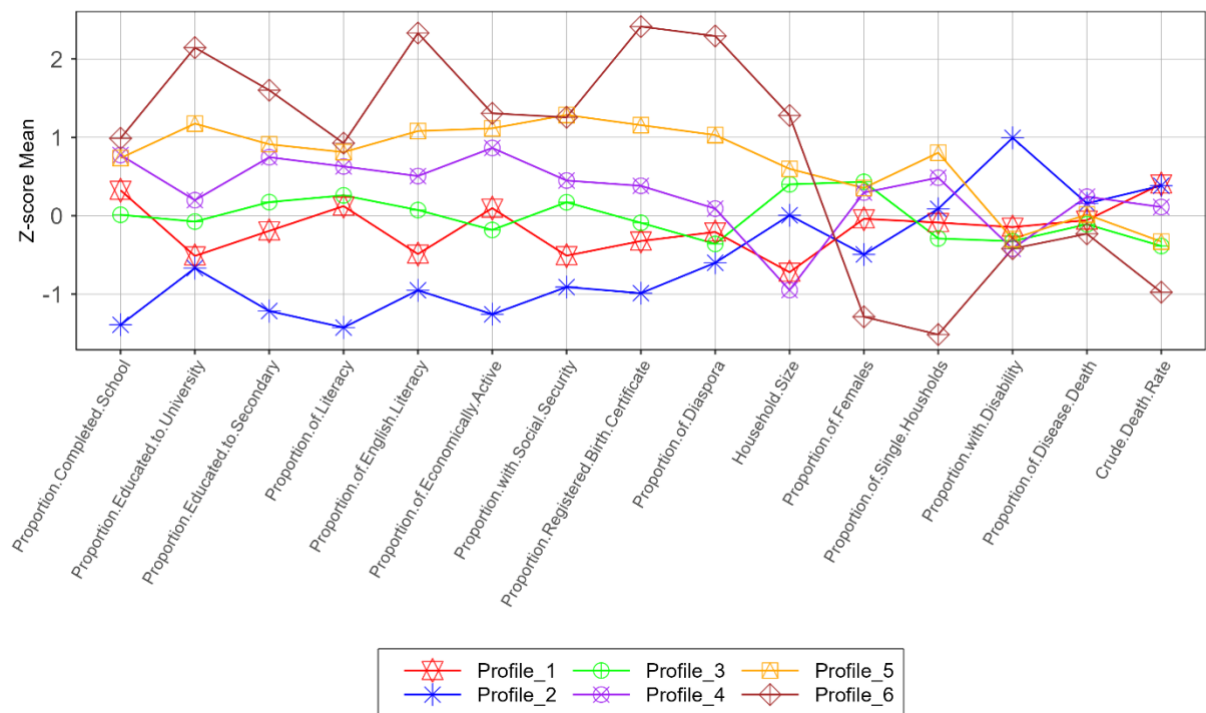
#### 2.3.1.1 Interpreting the underlying meaning of identified latent profiles.

From the dot and violin plots in Figure 2.4, the value distributions of the most important individual indicators of deprivation show that ranking the numbered LPA profiles based on these same variables, yields an order of 2, 1, 3, 4, 5 and 6 for the profile numbers assigned by the LPA best fit model (Table 2.2). Correspondingly, these were respectively assigned the

following stratum names; *Highly Deprived*, *Deprived*, *Moderately Deprived*, *Moderately Affluent*, *Affluent* and *Highly Affluent* (Table 2.3). To further examine and query these profile assignments based on variable value distributions, a calculated scaled mean for each variable was used (Figure 2.5), consistent with other LPA studies that assigned interpreted profile meanings (Mathew & Doorenbos, 2022; Pastor et al., 2007; Voisin et al., 2018; Yalçın et al., 2021). These scaled means for each variable within each stratum confirmed the same apparent profile order (Table 2.3) for most variables, as ranked from the most deprived to the most affluent (Figure 2.5)



**Figure 2.4: Violin and dot plot showing the distribution of values for 15 potential indicators of deprivation recorded by the 2012 national census, broken down across the six profiles distinguished by LPA analysis (Table 2.2).** Horizontal lines within the violin plot represent the first, second and third quartiles, or the 25%, 50% (median), 75% quantiles. The units for most of these variables are proportions of participating respondents or households, aggregated at neighbourhood level, the only two exceptions being household size and crude death rate.



**Figure 2.5: Line and dot plot illustrating the distribution of calculated z-score means for each contributing variable for each profile identified by latent profile analysis (LPA) and subsequently attributed to a named stratum of deprivation (Table 2.3). Means were scaled by standardizing observed variables (z-scores) within each latent profile and expressing them in standard deviation units instead of the original metric. Scaling transforms the latent variable to have mean of zero and standard deviation of one ( $\mu = 0, \sigma = 1$ ). Negative means do not imply negative values of the actual metric, but rather reflecting normalization around zero by the scaling process.**

Based on the above interpretation of the LPA identified profiles, six assigned deprivation strata could be resolved from the census data (Table 2.3). On the other hand, however, the results from participatory stratification approach revealed five income classes (Table 2.4) with *low-income stratum* accounting for a remarkably low percentage of neighbourhoods while the *medium income stratum* had the highest.

**Table 2.3: Latent profile analysis (LPA) assigned profiles numbers with investigator assigned ranked deprivation stratum names.** Based on interpretation of Figure 2.4 and Figure 2.5 with the number and proportion of neighbourhoods attributed to each stratum.

| <b>Profile Number</b> | <b>Assigned Profile Name</b>       | <b>No. of Neighbourhoods (n)</b> | <b>%</b> |
|-----------------------|------------------------------------|----------------------------------|----------|
| 2                     | Highly Deprived Neighbourhoods     | 98                               | 22       |
| 1                     | Deprived Neighbourhoods            | 117                              | 26       |
| 3                     | Moderately Deprived Neighbourhoods | 115                              | 25       |
| 4                     | Moderately Affluent Neighbourhoods | 33                               | 7        |
| 5                     | Affluent Neighbourhoods            | 66                               | 15       |
| 6                     | Highly Affluent Neighbourhoods     | 23                               | 5        |

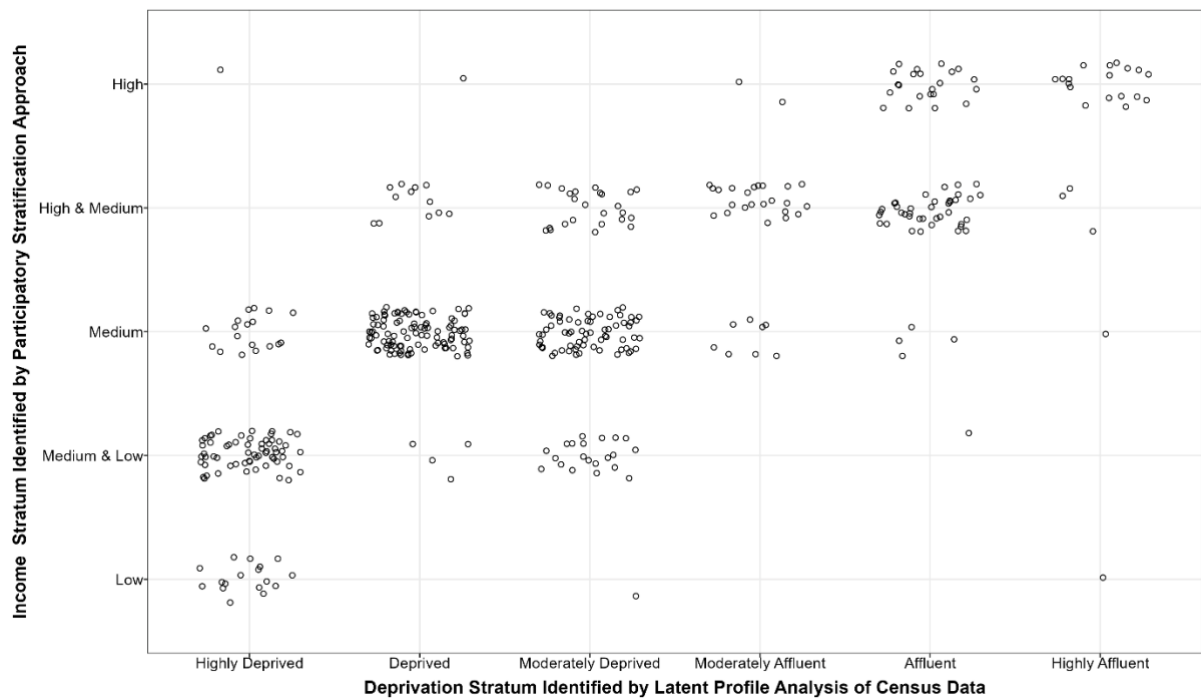
**Table 2.1: Neighbourhood income classes obtained from participatory stratification approach (PSA), with the number and proportion of neighbourhoods attributed to each stratum.**

| <b>Class Number</b> | <b>Assigned Classes Name</b> | <b>No. of Neighbourhoods (n)</b> | <b>%</b> |
|---------------------|------------------------------|----------------------------------|----------|
| 5                   | Low Income                   | 19                               | 4        |
| 4                   | Mixed Low and Medium Income  | 88                               | 19       |
| 3                   | medium income                | 199                              | 44       |
| 2                   | Mixed Medium and High        | 102                              | 23       |
| 1                   | High Income                  | 44                               | 10       |

### 2.3.2 Comparison of PSA with LPA of the census data

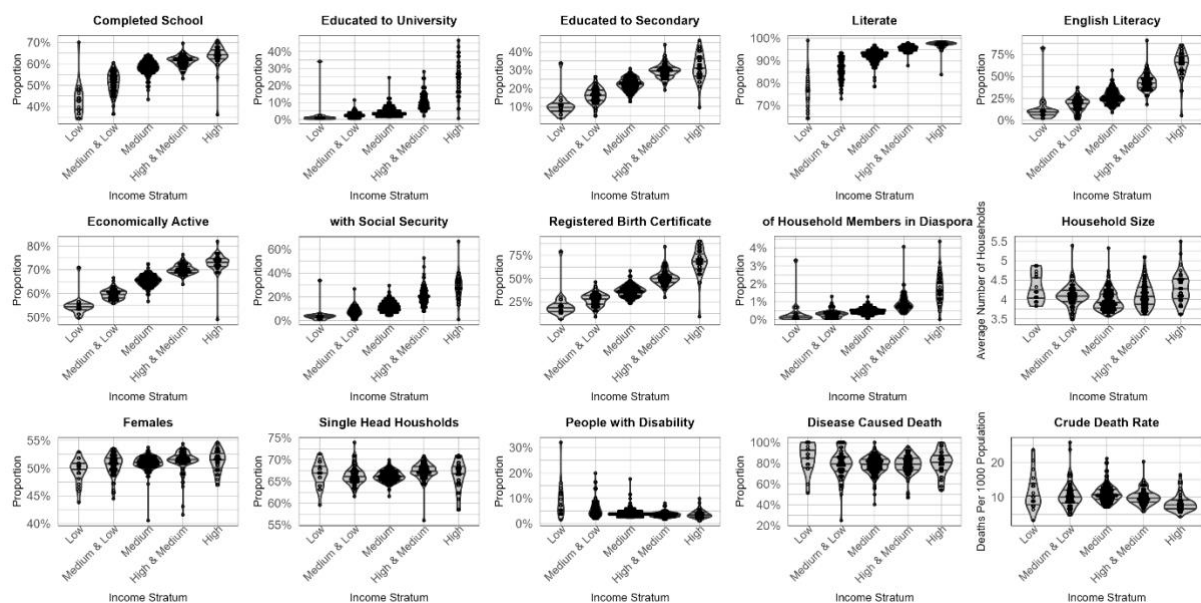
The results of the spearman rank correlation test shows that there is a strong positive correlation ( $\rho = 0.739$ ,  $S = 4015865$ ,  $p < 0.001$ ) between the stratum identified by the LPA of census data and the results of the PSA (Figure 2.6).





**Figure 2.6: Jitter plot showing the relationship between the neighbourhood classification obtained through the participatory stratification approach (PSA) and through statistical latent profile analysis (LPA) stratification based on national census data.**

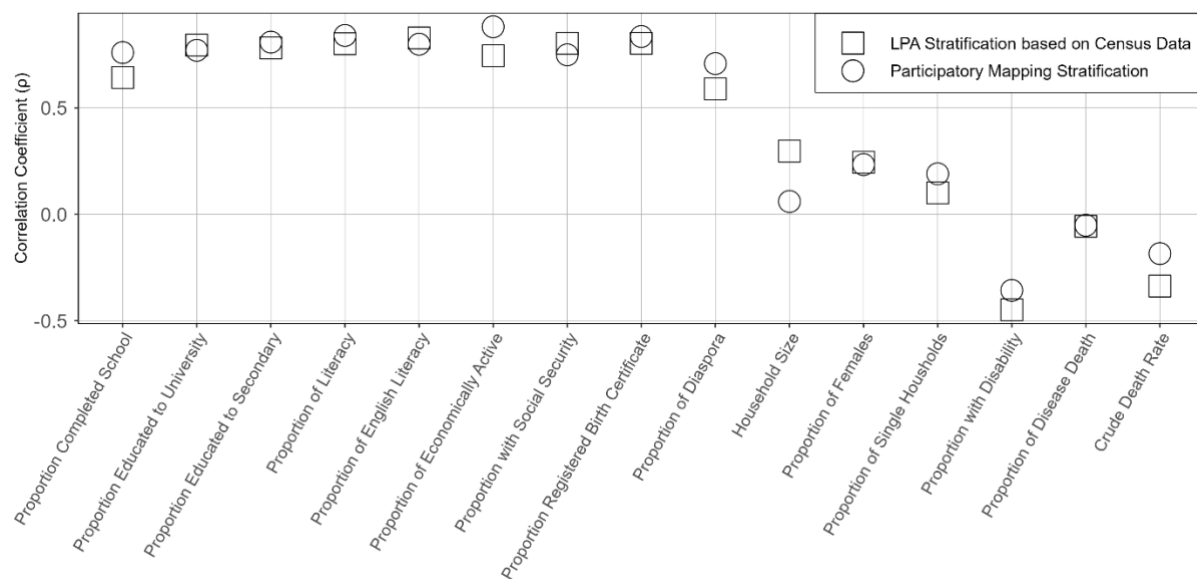
The same variables used to stratify the neighbourhoods by LPA yielded distribution of values that were just as consistent with their income stratum as determined by the PSA (Figure 2.7) as they were with their deprivation stratum as determined by the LPA (Figure 2.4 and Figure 2.7).



**Figure 2.7: Violin and dot plot showing the distribution of values for 15 potential indicators of deprivation recorded by the 2012 national census, broken down across the five income strata obtained from the participatory stratification approach (PSA).**

Horizontal lines within the violin plot represent the first, second and third quartiles, or the 25%, 50% (median) and 75% quantiles. The units for most of these variables are proportions of participating respondents' households aggregated at neighbourhood level, the only two exceptions being household size and crude death rate.

Further analysis of Spearman's rank correlation tests between each variable from the census data and stratum rank as determined by each of the two different stratification approaches can be seen in Figure 2.8. A Wilcoxon signed-rank test to compare these two sets of correlation coefficients in a paired manner revealed no difference between the two approaches ( $V = 33$ ,  $p\text{-value} = 0.1354$ ), indicating that the two approaches yielded very similar patterns of stratification.

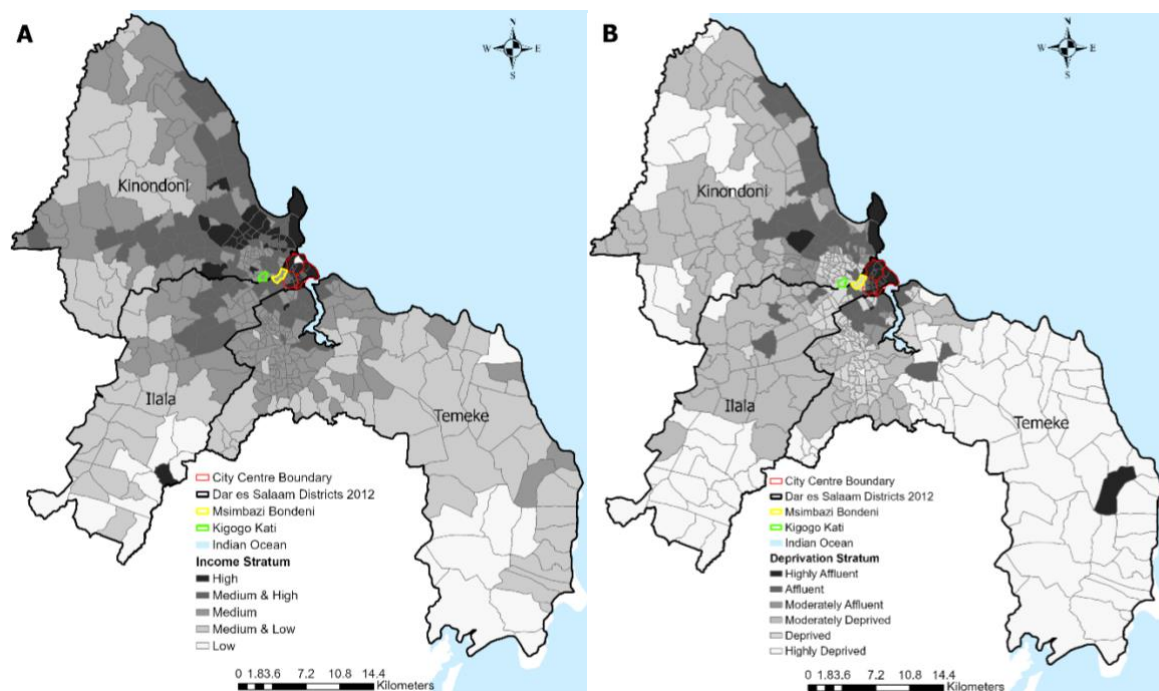


**Fig 2.8: Dot plot showing the results of the Spearman's rank correlation test of the census variables with each of the two stratification approaches, namely the participatory stratification approach (PSA) and the latent profile analysis (LPA), with vertical axis showing correlation coefficient ( $\rho$ ) of each variable with the stratum ranking for each stratification method.**

Overall, the two stratification approaches yielded relatively similar cartographic pictures of wealth and poverty distribution across the city (Figure 2.9). High income, highly affluent neighbourhoods are mainly located in or around the city centre and along the coast to the north, while low income, deprived neighbourhoods are generally distributed along the outskirts of the city. The distribution pattern of the medium income stratum, as determined by PSA,

corresponds well with the moderately deprived and moderately affluent strata identified by LPA. Focusing on the city centre and areas immediately around it, the results reveal patches of low income and deprived neighbourhoods located near high income and highly affluent neighbourhoods, forming a pocket of poverty running from central Ilala into Temeke District. However, in the western direction this pocket of deprived, medium income neighbourhoods is enclosed by moderately deprived, mixed medium and high-income neighbourhoods.

The overall distribution, on the other hand, shows that most of the neighbourhoods classified by PSA as medium income in Figure 2.9A, such as Msimbazi Bondeni and Kigogo Kati, have been classified as deprived neighbourhoods by LPA in Figure 2.9B. Many of these neighbourhoods are found in the same pocket of deprived neighbourhoods described above that cuts across all three districts but mostly sits in northern Temeke.



**Figure 2.9: The spatial distribution of income and deprivation strata across Dar es Salaam city neighbourhoods.** Panel A: Income strata obtained from the participatory stratification approach (PSA) (Table 2.4). Panel B: deprivation strata generated from a statistical latent profile analysis (LPA) (Table 2.3) of population census data.

Looking at the heterogeneous settlement patterns of these neighbourhoods sheds light on how they were classified differently by the two different methods (Figure 2.10 and Fig 2.11). For example, the varying density and quality of the buildings in Kigogo Kati illustrated in Figure 2.10 shows that, while participants in the PSA stratification process considered the mixed housing qualities and density that are clearly visible in panel A to be a reasonable basis for classifying it as medium income, LPA averaged out the diversity existing at fine scale within the neighbourhood and consequently classified it simply as being deprived.

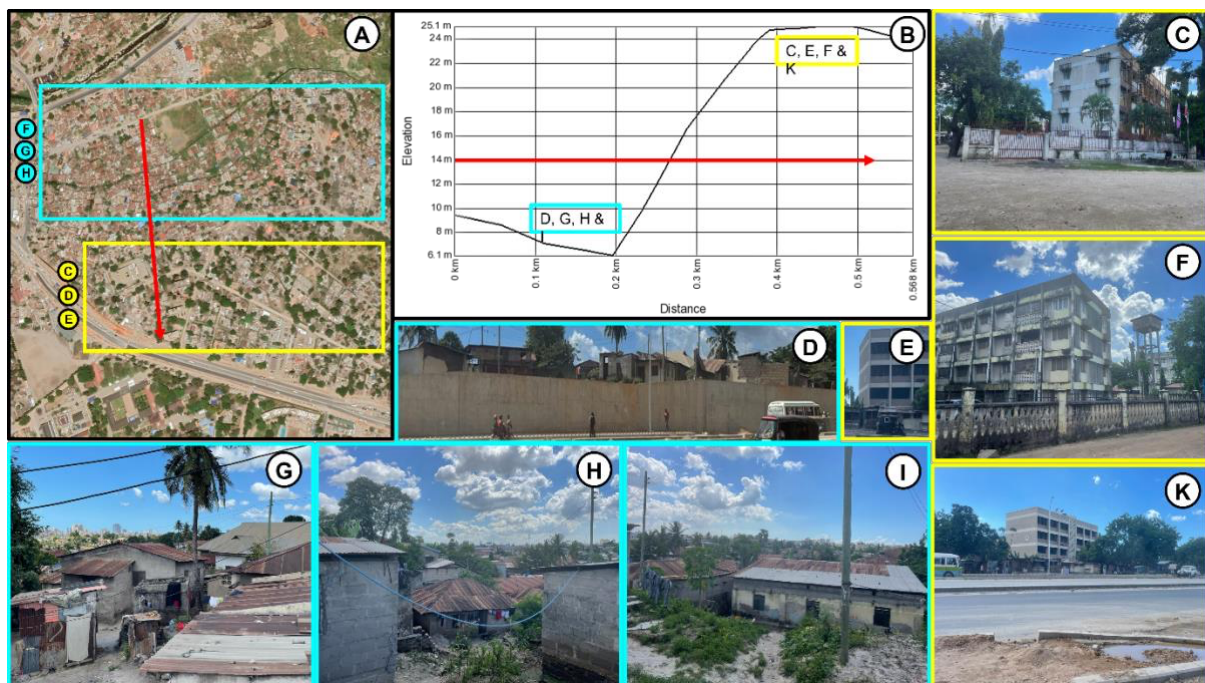


**Figure 2.10: Satellite and building images from the Kigogo Kati neighbourhood showing fine-scale variations in housing density and building quality within the neighbourhood.**

Kigogo Kati was classified as medium income by participatory stratification approach (PSA) (Figure 2.9A), but as deprived by statistical latent profile analysis (LPA) of national census data (Figure 2.9B). As mapped out in panel A, blocks of high-quality buildings (yellow bordered panels, B, C, F, K, M, N and P), are contrasted with blocks with generally poor-quality housing (blue bordered panels D, E, G, H, I, J and L) in the same neighbourhood.



Additionally, while the example in Figure 2.10 outlines the spatial distribution of different building qualities within the same neighbourhood, similar variability is clearly noticeable within some other neighbourhoods. For example, Figure 2.11 illustrates part of the Msimbazi Bondeni neighbourhood, where two housing blocks with obviously different building qualities are found in the same neighbourhood, which has been classified as medium income by PSA but deprived by LPA. Moreover, these two blocks with obviously different mean housing density and quality lie at opposite sides of a steep topographic incline (Figure 2.11A and B), with the denser informal settlements with generally smaller, poor quality housing being found in the flood-prone valley to the north of it, while the carefully constructed apartment blocks and planned housing developments (Figure 2.11 D and E) were all found approximately 20 meters uphill to the south. Indeed, as one walks southward along the transect depicted in Figure 2.11A and B, from the valley up the hill onward along a relatively flat plateau, a clearly noticeable shift is observed in building quality with elevation (Fig 2.11, panel D and E).



**Figure 2.11: Satellite and building images from the Msimbazi Bondeni neighbourhood, showing fine scale variation in housing density and building quality within the**

**neighbourhood.** Msimbazi Bondeni was classified as medium income by participatory stratification approach (PSA) (Figure 2.9A) but as deprived by statistical latent profile analysis (LPA) of national census data (Figure 2.9B). As mapped out in Panel A, blocks of high-quality buildings (yellow bordered panels, C, E, F and K) uphill and to the south of a steep topographic gradient (Panel B) are contrasted with downhill blocks to the south where high-density settlements have generally poor-quality housing (blue bordered panels D, G, H and I). Panels A and B illustrate how building quality changes with elevation, with the vertical axis in panel B projecting elevation above sea level, while the horizontal axis represents the distance southward along the red vector in panel A.

Although there are some differences between the two approaches in the distribution patterns of income and deprivation across neighbourhoods, with very few being classified as purely low income by PSA (Table 2.4), the geographic distribution of poverty displayed by the two approaches (Table 2.3 and Table 2.4) nevertheless follow a similar pattern (Figure 2.9).

## **2.4 Discussion**

This study contributes to a growing area of research demonstrating similarities and differences in the results obtained through quite different methodological approaches to neighbourhood stratification. The use of LPA has provided valuable insights into the classification of neighbourhoods, particularly in the assessment of deprivation profiles. The results demonstrate LPA's ability to identify statistically distinct discrete neighbourhood deprivation profiles using socioeconomic data, while highlighting its limitation in missing out the complex realities existing at a finer spatial scale within neighbourhoods. This, however, is just one facet of the broader challenge posed by profiling deprivation using aggregated data at the level of the neighbourhoods in which people live, especially in diversified cities like Dar es Salaam. Furthermore, through cross-validation of the two approaches, both statistically and spatially,

the results of the PSA yielded very similar patterns of heterogeneity as the LPA, in terms of the distributions of variable values and neighbourhood classifications, respectively. Furthermore, PSA proved capable of elucidating several hidden factors relying on perceived and lived understanding of poverty, which were easily missed by LPA (Figure 2.10 & Figure 2.11). Akin to many participatory approaches (Cook, 2018; Emmel, 2008; Israel et al., 2005; Lung-Amam & Dawkins, 2020; Meenar, 2017; Vaughn & Jacquez, 2020; Wallerstein, 2020) relying on the subjective perspectives of contributing participants, the PSA developed in this study, proved to be cost-effective and user-friendly. In contrast, while statistical analyses of formally collected data, such as the LPA approach described herein, have the advantage of being objective, they are also time-consuming, data-intensive and require advanced analytical skills.

Nevertheless, the subjectivity of participatory approaches has been confirmed by the numbers of neighbourhoods attributed to each income stratum. While PSA classified only 4% of the city's neighbourhoods as typically low-income (Table 2.4), LPA classified 22% as highly deprived neighbourhoods (Table 2.3) On the other hand, PSA classified 44% of the city's neighbourhoods as medium income, indicating a bias away from extreme classification assignments. The surprisingly low frequency with which neighbourhoods were classified as low income by PSA participants implies the subjectivity of the approach, as even some small pockets of better housing in a neighbourhood known to be generally very poor often prompted participants to classify it as medium income.

Furthermore, these PSA results seem incompatible with those of previous studies indicating widespread that large African cities accommodate large deprived populations (Kuffer, 2020; Thomson et al., 2020).

Additionally, the observation that PSA classified some of the neighbourhoods as medium income while LPA classified them as deprived, requires consideration of the fundamentally



different strengths and weakness of these two complementary approaches. A possible explanation for this apparent bias of PSA towards moderate stratum assignment may well lie in the diversity existing at fine scales within neighbourhoods. Such fine-scale heterogeneities can easily be missed by the objective statistical approaches but captured and perhaps subjectively over-represented, by the qualitative understanding of the city obtained through the lived experiences of the PSA participants, wherein even very small differences in housing quality and infrastructures within neighbourhoods were considered in the stratification. For example, the small blocks of high-quality, low-density housing that are highlighted in yellow bordered panels in Figure 2.10 and 2.11 resulted in these neighbourhoods being classified as medium income, despite being well known as poor neighbourhoods (Figure 2.10 and Figure 2.11). Also, the confirmatory stage of the consensus building process in the PSA workshop, resulted in participants providing supplementary justification for their initial income stratum assignment, taking into consideration additional factors that varied across coarser scales than income *per se*, such as physical accessibility, closeness to the valley, road condition, roof age and building density. These intuitive considerations and ability of the PSA to accommodate them in a flexible manner, differentiates the fine-scale lens of PSA from the coarser analysis of the LPA, which unavoidably blurs such heterogeneities within neighbourhoods.

Such mixed contexts at fine scales might also help explain some of the more puzzling outliers in Figure 2.6, because the nuanced, intuitive and holistic basis of the PSA could result in it being subjectively influenced by the most obvious features and characteristics of a neighbourhood in a disproportionate manner, whereas the LPA relies on an objective representation of the area as a whole. Nevertheless, the two approaches yielded statistically equivalent results, even though an intuitive conceptual rationale was used in selecting the quantitative deprivation indicators used for LPA, while qualitative participants knowledge were used in PSA. Hence, the two alternative approach can be applied to complement each other and

in different scenarios with different application requirements for stratifying neighbourhoods (Weller et al., 2020).

Results from PSA exercises were instrumental in grounding the subsequent analytical stages of this study. The spatial narratives and locally defined neighbourhood boundaries generated through community engagement provided an interpretive framework that complemented the statistical clustering of urban typologies which were later linked to health outcomes. In particular, the participatory insights offered nuanced understandings of social cohesion, perceived poverty and environmental risks that were not fully captured through quantitative indicators alone. Reflecting on these contributions, the study suggests that even in contexts where qualitative engagement may not be feasible due to resource constraints, the principles derived from participatory mapping such as recognising community perceptions of space and lived spatial hierarchies, can inform the construction of urban typologies.

This study contributes to the growing area of research by demonstrating methodological similarity and differences existing in neighbourhood stratification. It complements the existing literature on economic inequality and urban segregation (Babere & Chingwele, 2018; Musterd, 2020; Smiley, 2007, 2013; Todd et al., 2019; Vaughan & Arbaci, 2011; Villaça, 2011), which relies for the most part on statistical analysis of empirical data. Furthermore, it suggests that this more subjective participatory approach, which exploits community knowledge of the location, lived experiences and local expertise, could be used in the future without any such data-intensive statistical approaches to validate it. Overall, this study provides clear evidence that cost-effective PSA methodologies could have a variety of practical applications, such as services planning and local tailoring of urban interventions.

While this research reassuringly presents neighbourhood-level income and deprivation profiles, respectively assessed through a subjective PSA and an objective LPA of formal socioeconomic data, some important study limitations are worth mentioning. For example, the certainty of the findings may be somewhat limited by the fact that, at the time of this study, there were no more recent census data available than those from the 2012 PHC, so the results obtained with the two methods cannot be considered exactly contemporaneous. Similarly, the retrospective *post hoc* examination of heterogeneities within neighbourhoods (Figure 2.10 and Figure 2.11) relies on images of contemporary Dar es Salaam, which has obviously changed somewhat since the time that the PSA was conducted and the PHC data used for LPA were collected.

Moreover, the absence of data relating to variables like employment, household incomes, neighbourhood incomes, property ownership and living conditions (including housing, water and electricity) restricted our ability to establish a conclusive relationship between income and living standards on one hand and deprivation on the other. These factors are traditionally utilized as indicators for assessing deprivation across various geographical and poverty dimensions. Consequently, future studies should explore alternative poverty indicators and incorporate updated data when accessible.

Additionally, the study used area-based data aggregated at neighbourhood level, which was the finest administrative scale made available to the investigators, so the stark heterogeneities that clearly exist within individual neighbourhoods (Figure 2.10 and Figure 2.11), are obviously blurred around the neighbourhood average income by the LPA and cause underrepresentation of the lowest income neighbourhoods by PSA (Figure 2.6). Correspondingly, further research is needed to similarly compare subjective PSAs with objective statistical stratification based on formal survey data at finer scales, which in the context of Dar es Salaam, for example, could relate to ten cell unit housing clusters. Other avenues for future research can also include studies

on how the built environment influences income and deprivation and how the physical geography of the landscapes those human settlements are built upon affects patterns of income, access to services, health and wellbeing among residents.

While the empirical focus of this study is on Dar es Salaam, the methodological and conceptual understandings derived from the PSA have broader applicability to other rapidly urbanising cities in sub-Saharan Africa and similar contexts globally. The structural patterns of neighbourhood stratification, the influence of informal settlement dynamics, and the role of local knowledge in shaping spatial typologies are not unique to Dar es Salaam. Many urban centres in the Global South face comparable challenges of data scarcity, uneven infrastructure, and socio-spatial inequality. Therefore, the methodological framework employed in this research, particularly the integration of participatory mapping and statistical profiling can inform analyses in other metropolitan regions seeking to understand intra-urban disparities. Nonetheless, the generalisability of specific findings should be considered with caution, as local governance, historical trajectories, and socio-economic configurations may differ across cities.

## **2.5 Conclusion**

The purpose of this study was to evaluate a PSA to stratifying neighbourhoods across the Tanzanian city of Dar es Salaam in terms of income, by comparing with LPA of deprivation based on national census data. The findings revealed the potential of both LPA and PSA methods and set a precedent for their further application as complementary approaches to neighbourhood classification. With reference to PSA, this study highlights ample room for advancing our understanding of the complex relationships between poverty, location and socio-spatial dynamics in urban settings. To achieve a more comprehensive perspective, we recommend moving beyond reliance on relatively coarse geographic units for aggregating large-scale datasets. Instead, we propose adopting a finer-grained approach that can capture

previously overlooked social, economic, physical and environmental factors at the very fine scales they can vary across. Overall, such methodologies may be valuable, not only for policy makers, but also for urban planning practitioners and researchers who seek a deeper understanding of the diverse dynamics occurring within towns and cities across various scales. These findings confirm that subjective PSA methodologies offer more affordable and practical alternatives to conventional objective statistical analyses of formal survey data, with which to obtain detailed geographic information to inform decision-making and planning in towns and cities all across low and middle-income countries.

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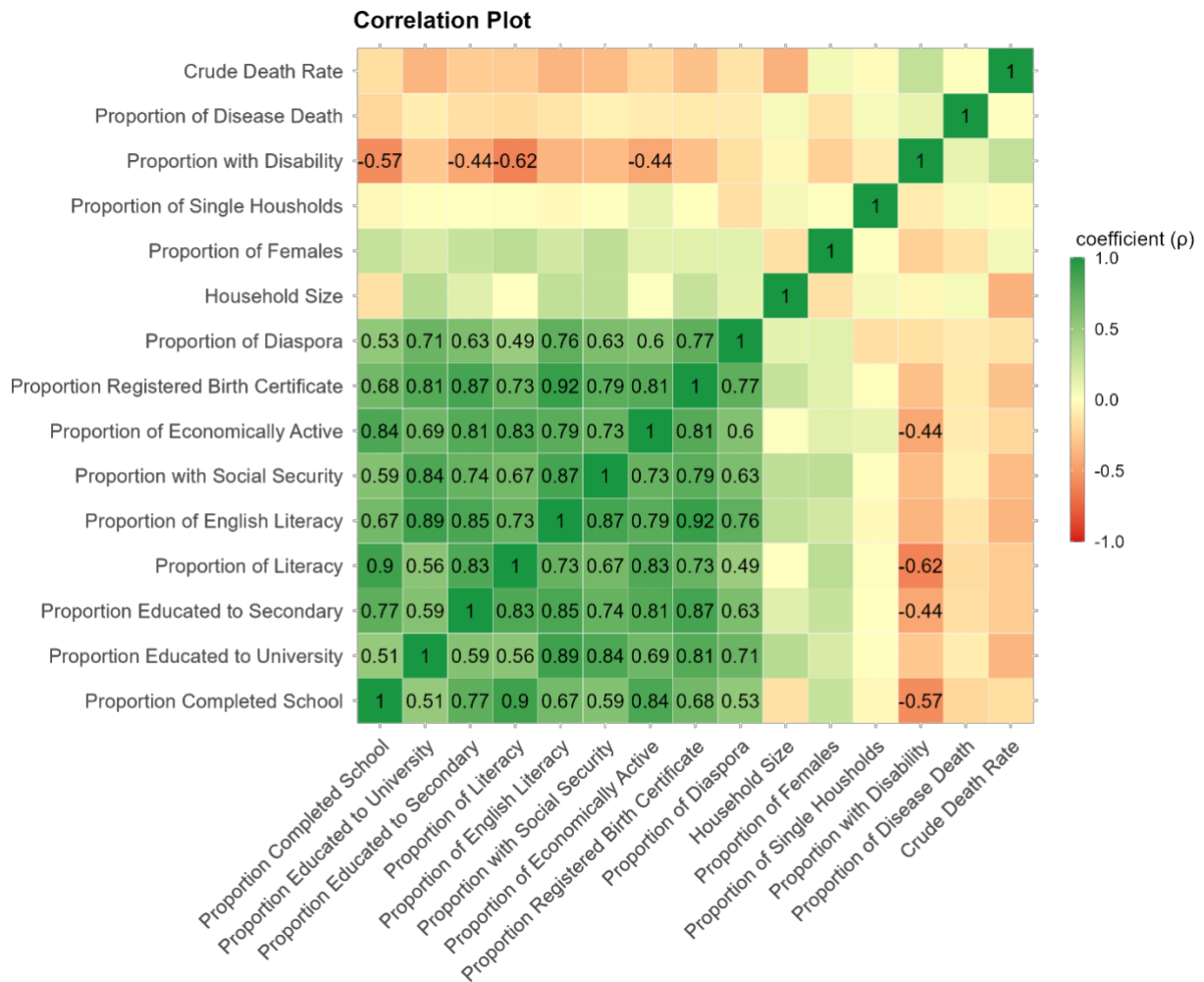
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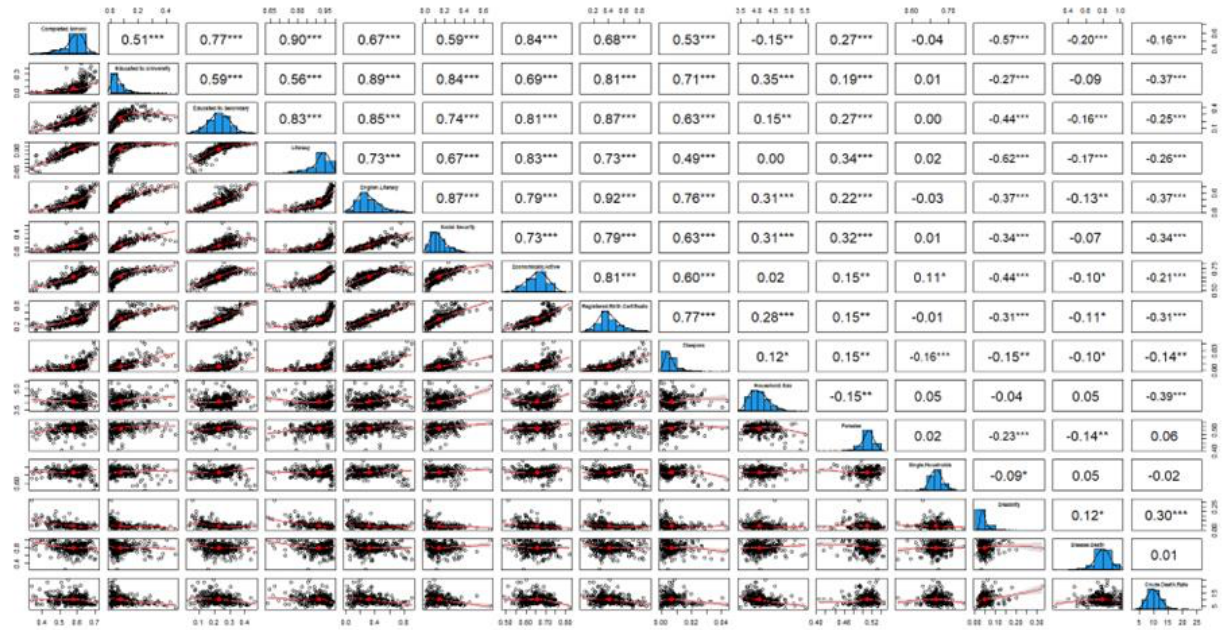
# Supplementary materials

**S1 Table: Equation used to derive census data and transform selected variables into proportion for each sample neighbourhood.**

| Category                          | Variable                                      | Equation                                                                                                                                                          |
|-----------------------------------|-----------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Education                         | Proportion completed any school level         | $= \left( \frac{CompleSch}{(CompleSch + AttendingSch + PartlyAttended + NeverAttended)} \right)$                                                                  |
|                                   | Proportion educated to university level       | $= \left( \frac{UniversityOther}{(NurseryEdu + Primary\{1,8\} + TrainingAfterPri + PreFormOne + Secondary\{1,6\} + TrainingAfterSec + UniversityOther)} \right)$  |
|                                   | Proportion educated to secondary level        | $= \left( \frac{Secondary\{1,6\}}{(NurseryEdu + Primary\{1,8\} + TrainingAfterPri + PreFormOne + Secondary\{1,6\} + TrainingAfterSec + UniversityOther)} \right)$ |
| Literacy and language proficiency | Proportion of literacy                        | $= \left( \frac{(Total\ Population - Illiterate)}{Total\ Population\ total} \right)$                                                                              |
|                                   | Proportion of English literacy                | $= \left( \frac{(English + SwahiliEnglish)}{(Swahili + English + SwahiliEnglish + Othelanguage)} \right)$                                                         |
| Economic factors                  | Proportion of economically active individuals | $= \left( \frac{Nage\{15,64\}}{Nage\{0,80 + \}} \right)$                                                                                                          |
|                                   | Proportion with social security               | $= \left( \frac{socialsec}{(socialsec + nosocialsec)} \right)$                                                                                                    |
| Social and legal indicators       | Proportion registered birth certificate       | $= \left( \frac{BirthCertificate}{(BirthCertificate + BirthNotification + noCertNot + bircernotknow)} \right)$                                                    |
| Economic factors                  | Proportion household members in diaspora      | $= \left( \frac{Diaspora}{Total\ Population} \right)$                                                                                                             |
| Demographic factors               | Average household size                        | $= \left( \frac{Total\ Population}{Total\ Household\ Heads} \right)$                                                                                              |
|                                   | Proportion of female in a neighbourhood       | $= \left( \frac{Females}{Total\ Population} \right)$                                                                                                              |
|                                   | Proportion of single head households          | $= \left( \frac{(NeverMarried + Divorced + Separated\& + Widowed)}{(NeverMarried + Married + LivingTogether\& + Divorced + Separated + Widowed)} \right)$         |
| Health and mortality statistics   | Proportion with disability                    | $= \left( \frac{(Albino + Seeing + Hearing + Walking + Remembering + SelfCare + otherDisability)}{Total\ Population} \right)$                                     |
|                                   | Proportion of death caused by diseases        | $= \left( \frac{Total\ Disease\ Death}{Total\ Death} \right)$                                                                                                     |
|                                   | Crude death rate                              | $= \left( 1000 * \left( \frac{Total\ Death}{Total\ Population} \right) \right)$                                                                                   |



**S2 Figure: Pearson correlation plot with correlation coefficients and p-values, showing numerical correlation coefficient labels only for pairs which are strongly correlated ( $\rho \geq \pm 0.4$ ) and statistically significant ( $p \leq 0.05$ ) while insignificant variables are unlabelled.**



**S3 Figure: Pairwise scatter plots of all the variables as well as histograms, locally smoothed regressions and Pairwise Pearson's correlation test matrix with correlation coefficients ( $\rho$ ) and p values (\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ). The x axis in each scatter plot represents the column variable, the y axis the row variable. The units for most of these variables are proportions of participating respondents or households, aggregated at neighbourhood level, the only two exceptions being household size and crude death rate.**

### **3 CHAPTER THREE**

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**Prevalence and spatial distribution of chronic respiratory diseases driven by hydrology and household characteristics in Dar es Salaam city, United Republic of Tanzania: a cross-sectional study.**

# Preface

**Title:** Prevalence and spatial distribution of chronic respiratory diseases driven by hydrology and household characteristics in Dar es Salaam city, United Republic of Tanzania: a cross-sectional study

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**Journal:** The Lancet Planetary Health

**Publication Status:** In Submission

**Key words:** *Chronic Respiratory Diseases (CRDs); Hydrology; Household Characteristics; Dar es Salaam; Spatial Distribution; Prevalence; Cross-Sectional Study; Tanzania; Environmental Factors; Public Health; Urban Health; Respiratory Health; Socioeconomic Factors; Geovalidation.*

# Abstract

**Background** Chronic Respiratory Diseases (CRDs) constitute a substantial global health challenge, contributing significantly to both mortality and morbidity on a worldwide scale. According to the World Health Organization (WHO), CRDs accounted for 4.1 million deaths in 2023 and affected approximately 454.6 million people, equivalent to 5.54% of the global population. Tobacco smoking emerges as the most important risk factor for CRDs at the global level, followed by air pollution, occupational hazards, frequent early childhood incidence of lower respiratory tract infections and genetic predisposition. This study investigated the role of hydrology as a potential determinant of the prevalence and spatial distribution of CRDs while also accounting for other household-level factors.

**Methods** Using remote sensing techniques, the topographical wetness index (TWI) was estimated at 30m resolution and related to spatially referenced CRD prevalence data from questionnaire surveys of 1533 households distributed across 15 income-stratified neighbourhoods in the Tanzanian city of Dar es Salaam, using general linear mixed models and supported by geovalidation and ground truthing.

**Results** CRD prevalence was associated with high TWI scores (Odds Ratio (OR) [95% confidence interval (CI)] = 1.18 [1.04, 1.33] per TWI unit increment,  $p = 0.00925$ ), with stratification revealing that risk was approximately 9-fold greater in particularly flood-prone locations ( $\text{TWI} \geq 15$ ) than elsewhere (OR [95%CI] = 8.63 [2.13, 35]). Increased CRD prevalence was also independently associated with previously described risk factors, specifically the number of people in the household (OR = 1.15 [1.05, 1.25] per person,  $p = 0.00335$ ) and the use of communal skip bins (OR = 4.04 [1.04, 15.80],  $p = 0.0449$ ). Furthermore, lower CRD prevalence was associated with the use of air conditioning (OR = 0.22 [0.06, 0.77],  $p = 0.0174$ ). Interestingly, neighbourhood income was not associated with

CRD prevalence when the effects of all these other risk factors were accounted for, confirming that poverty is an indirect, distal cause of CRDs rather than a direct, proximal one.

**Conclusions** These findings reinforce existing evidence regarding the risk of moist living conditions where mould proliferates. Specifically, they identify local hydrology as an important risk factor in rapidly urbanising cities, where it plays a key role in determining the residential location of poor households who commonly live in low-lying, wet areas due to accessibility and affordability of land.

### 3.1 Introduction

Chronic Respiratory Diseases (CRDs) constitute a substantial global health challenge, contributing significantly to both mortality and morbidity on a worldwide scale. According to the World Health Organization (WHO), CRDs accounted for 4.1 million deaths in 2023 and affected approximately 454.6 million people, equivalent to 5.54% of the global population (Momtazmanesh et al., 2023), while in Tanzania, they accounted for 2% of total deaths in 2019 (WHO, 2019b). Historically, tobacco smoking has been the most important risk factor for CRDs at the global level, followed by air pollution, occupational hazards, frequent early childhood lower respiratory tract infections and genetic predisposition (WHO, 2019a). Over recent years, however, it has become apparent that air pollution has become the most pronounced cause of CRD in towns and cities, with both outdoor elements like dust and particle pollution as well as indoor factors, such as asbestos, paint, cleaning agents, mould and radon, all contributing to chronic obstructive pulmonary disease and asthma (Hendryx et al., 2019). Furthermore, these factors exhibit heterogeneity across very fine scales, depending on the geographic location and socioeconomic circumstances of individuals, households, or settlements (Fu et al., 2024).

In the context of the hot and humid coastal equatorial climate of Dar es Salaam city in Tanzania, which has predominantly low-lying terrain susceptible to waterlogging, hydrology may significantly impact indoor air quality by influencing moisture levels within houses and other residential buildings. Excessive indoor moisture, exacerbated by high temperatures and humidity, provides an ideal environment for mould growth (Fanca et al., 2023). This not only raises aesthetic concerns in many houses, but also poses substantial health risks (Mendell et al., 2011). Mould proliferation under such conditions fosters the presence of dust mites, cockroaches and bacteria, all of which contribute to poor indoor air quality (Hasager et al., 2021). However, all of these factors may have different impacts on disparate socio-economic



groups, all of whom live complex lives in diverse physical environments distributed across the city in microheterogeneous mosaics (Msuya et al., 2024).

Several past studies have established an association between damp and mouldy housing and CRD over time (Burr et al., 1988; Gravesen, 1972; Lumpkins et al., 1973), while others have associated it with the age of the house (de Marco et al., 2013; Li et al., 2020; Mishra et al., 2023) and general air quality (Annesi-Maesano et al., 2021; Bălă et al., 2021; Monoson et al., 2023), but none have yet identified underlying physical geographical factors driving these hazards. This study investigated the role of hydrology as a potential determinant of the prevalence and spatial distribution of CRDs, while also accounting for other household-level factors commonly reported by other studies.

## **3.2 Methods**

### **3.2.1 Study site**

This cross-sectional study, a household survey supplemented with a hydrological survey using remote sensing data, was conducted in 15 income-stratified neighbourhoods (*mitaa*, literally translated as *streets*) of Dar es Salaam, the largest city in Tanzania. The neighbourhoods have a diverse and complex pattern of income and poverty distribution across fine spatial scales (Msuya et al., 2024). Situated on Tanzania's Indian Ocean coast, Dar es Salaam is known for its economic importance and large population (Todd et al., 2019). At the time of the last population and housing census in 2022, Dar es Salaam spanned an area of 1,493 km<sup>2</sup> with a population of 5.4 million residents, accounting for 8.7% of the country's population (URT, 2022). The city experiences a coastal equatorial climate characterised by consistently high temperatures and humidity. The city primarily occupies low-lying terrain along a relatively flat, largely sandy, coastal plain intersected by several small rivers, with many areas within these

valleys prone to water accumulation and flooding (Figure 3.1). Data collection took place between June and September 2021.

### **3.2.2 Participants**

Households were used as the primary units of analysis, with neighbourhoods serving as the most suitable geographic sampling unit because they are both large and small enough to capture heterogeneity within and between such cluster samples. The study aimed to sample representative clusters of neighbourhoods from all across the city, thus maximizing their diversity at this geographic scale rather than deliberately including any particular ethnic groups or population segments. The selected neighbourhoods in the study area spanned most of the social and spatial continuum within the city, ranging from affluent to deprived, inner city to urban periphery and planned to unplanned. Hence, a sample size of at least 1500 households distributed across five income bands in 15 neighbourhoods with 300 households in each neighbourhood income category within the city was considered sufficient to represent the social and spatial spectrum dynamics within the neighbourhoods regardless of the city population. Also based on the old urban planning assumption that neighbourhood population ranges from 5000 to 7000 (Baffoe, 2019), a sample size of around 364 individuals was considered sufficient to achieve prevalence estimates with a 5% margin of error for a neighbourhood with a population of 7000 (Charan & Biswas, 2013).

The sampling strategy employed in this study therefore followed a multi-stage approach, starting by stratifying neighbourhoods into income categories ranging from low to high. A participatory stratification approach based on consensus subjective perspectives of local community representatives, town planners and technical experts (Msuya et al., 2024) was used to categorise every neighbourhood in Dar es Salaam into five income strata (low, mixed low and medium, medium, mixed medium and high and high). In the first stage, three

neighbourhoods were selected from within each income category by population-weighted random sampling obtained from the census data, comprising 15 widely distributed neighbourhoods overall (Figure 3.1). Following this, dwellings were selected systematically at a predefined interval ( $n$ ). The value of  $n$  represented the number of dwellings skipped between surveyed dwellings in each neighbourhood, which depended on the total number of sampled dwellings and the total dwellings ( $n = \text{total dwelling} / \text{total sampled dwellings}$ ), ranging from 70 to 105 households. One household, defined as a group of individuals living together and sharing meals, was randomly selected from within each selected dwelling using a household list and the random selection generator on a mobile device. In cases where household members were absent during the initial visit, interviewers revisited the following day, leaving contact information for the interviewer at the door of the household head. Finally, respondents were selected using one of two distinct approaches, either by (1) listing all household members aged 18 years and above and then allowing an ODK tool to randomly select one respondent for the interview, or by (2) applying the birth date rule, whereby the next household member whose birth date was nearest was interviewed. Similar to the previous stage for the household head, interviewers returned on a subsequent day if household members were unavailable during the initial visit. In accordance with the approved protocols, written consent was obtained from all human participants.

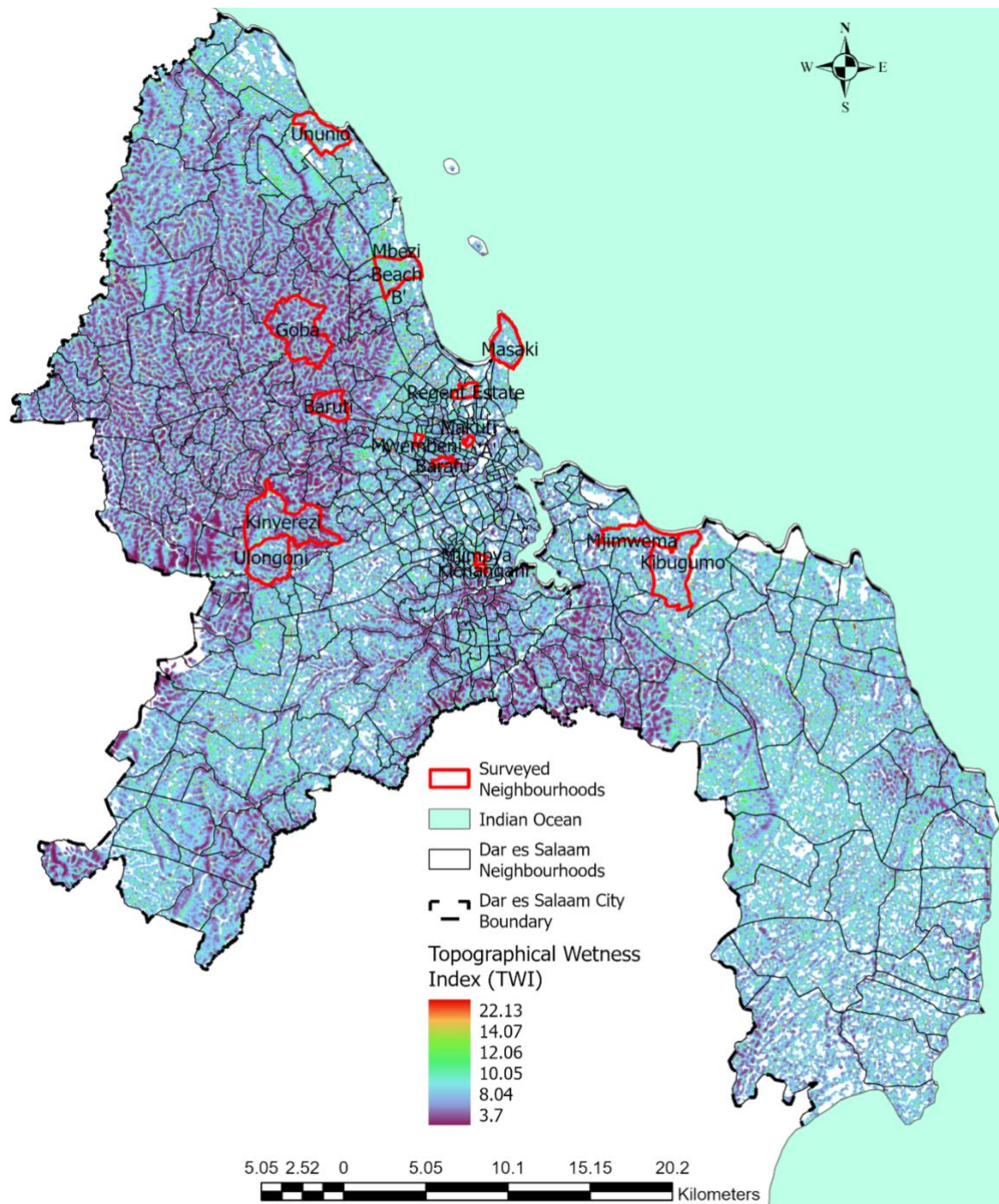


Figure 3.1: Distribution of sampled neighbourhoods ( $n=15$ ) in the survey conducted in Dar es Salaam city and reported herein (Supplemental Table 3), overlaid with a topographical wetness map at a resolution of 30m.

### **3.2.3 Procedures**

A total of 17 experienced Tanzanian research assistants (RAs) were recruited and trained for five consecutive days from 17<sup>th</sup> to 21<sup>st</sup> May 2021 at the Kibaha Conference Centre, Pwani Region, Tanzania. A two-day pilot of the survey tools and feedback session was conducted to improve the survey. The RAs were then divided into small groups of three people, with a supervisor for each group to oversee all research fieldwork activities. A structured questionnaire, consisting of various sections, was employed. These sections covered details such as the household roster (including information on sex, age, education, marital status, relationship to the household head, employment status and long-term illness), as well as aspects related to household characteristics, health, education, income, neighbourhood and gender. During the household survey, respondents were specifically asked whether any household member had been diagnosed with any chronic respiratory disease. These included but were not limited to, asthma, chronic obstructive pulmonary disease (COPD) and interstitial lung diseases. Additionally, respondents were queried about other non-communicable diseases, such as cancer, diabetes, heart diseases, kidney diseases, high blood pressure, back pain, mental health conditions and any other sundry relevant diagnoses.

### **3.2.4 Hydrology data acquisition**

A 30m resolution Digital Elevation Model (DEM) of Dar es Salaam was adopted to generate the Topographical Wetness Index (TWI) using the ArcGIS Pro 3.2.2 hydrology spatial analyst tool. The DEM underwent several preprocessing steps to ensure its suitability for hydrological analysis. These steps included artifact correction and resampling. Subsequently, slope values were computed for each pixel in the DEM using the arctan function, which converted elevation differences between neighbouring pixels into radians (Hojati & Mokarram, 2016). These radians were later transformed into degrees for ease of interpretation. Following the slope calculation, the contributing upslope area for each pixel was determined using flow

accumulation algorithms, primarily implemented through  $D_{\infty}$  flow accumulation methods. This process involved calculating the upstream contributing area per unit width orthogonal to the flow direction. Finally, the TWI was computed using a logarithmic formula that integrates the slope and the contributing upslope area per unit width. Specifically, this entailed calculating the natural logarithm of the ratio between the upslope contributing area and the tangent of the slope angle. The generated TWI values provided information about each pixel's relative wetness or water accumulation potential. The raster calculator tool was used to compute TWI values for each 30×30 meter pixel by incorporating the derived slope and upslope contributing area, obtained from the DEM and flow accumulation data, respectively. (Ali & Abdulateef, 2013).

### **3.2.5 Data analysis**

TWI values for each surveyed household were calculated for each of 1533 spatially referenced household coordinates using the *extract values to points* tool to extract raster values for specific point features in the ArcGIS Pro 3.2.2 *analyst tool*, with the lowest estimated TWI being 5.4 and the highest being 20.1 (Supplemental Figure 1), for driest and wettest households, respectively. Although it was hypothesized *a priori* that TWI was an important underlying distal cause of CRD (Figure 3.2), the following regression analyses were conducted with systematic and unbiased forward stepwise selection procedures to determine whether it was independently associated with disease prevalence even when other factors known to influence risk (Figure 3.2) were objectively accounted for.

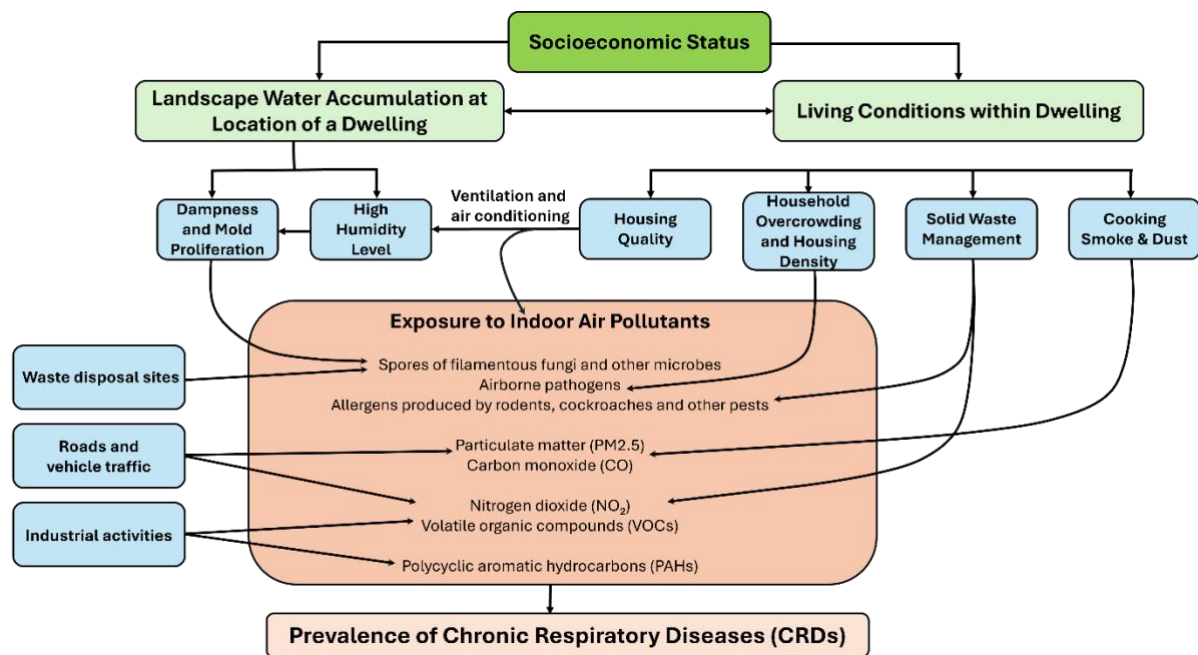


Figure 3.2. A hypothetical causal pathway diagram illustrating the underlying conceptual framework used to inform the interpretation of this analysis, based on careful literature review and consideration of the processes that are understood to influence chronic respiratory disease risk (Falkowska, 2016; Hendryx et al., 2019; Lim et al., 2021; Munyai & Nunu, 2020)

Using R 4.3.3 and RStudio 2023.12 for statistical analysis, binary CRD prevalence outcome data for individual households were related to the TWI estimates for that location together with other recorded factors in the household survey using general linear mixed models (GLMMs). Geographic variation associated with unidentified neighbourhood-specific characteristics was accounted for by including neighbourhood as a random effect. Univariate and then multivariate analyses were conducted to explore the association between CRD prevalence and the studied independent variables, with the best fit multivariate model identified using a systematic forward stepwise selection procedure. The building of the best-fit multivariate model started with univariate analysis, where variables were sequentially added to the model in order of their initial p values, starting from the lowest and proceeding through to the highest. Beginning with an empty model with no predictors, each potential predictor variable provisionally added to the model was evaluated based on its contribution to improving the model fit, using statistical

criteria such as the Akaike Information Criterion (AIC) the Bayesian Information Criterion (BIC), or  $p$ -values whereby the predictor that provided the most significant improvement in the model's fit was retained in the model. This process was repeated iteratively, with the model being re-evaluated after each new predictor was included until no remaining variables offered a statistically significant improvement to the model based on the aforementioned criteria. This forward selection method ensured that the final model included only those predictors that significantly contributed to explaining the variability in the response variable, thus striking a parsimonious balance between model complexity and explanatory power. Note that even variables that did not approach significance in the univariate analysis were each tentatively added in order of their univariate  $p$  values to the multivariate model to explore whether their inclusion could add incremental explanatory power to already robust multivariate models that allow for far more other sources of variance than the original univariate models, thereby uncovering nuanced relationships that would not otherwise be obvious.

While contemporary best statistical practice often constrains such model building processes based on the *a priori* hypothesis or hypotheses that motivated the study (Bojinov & Dominici, 2024; Lederer et al., 2019; McNamee, 2005; Westreich & Greenland, 2013), taking that approach made absolutely no difference to the stepwise model selection process in practice. This occurred because TWI was also identified as the strongest predictor of CRD risk, with the lowest AIC and  $P$  values, in the first round of simple univariate analyses of each individual potential explanatory variable, so it was the first independent variable to be included in the multivariate model at the very outset of the forward stepwise selection procedure applied.

To identify the optimal approach for modeling the variables to maximize statistical power, several different transformations or reclassifications of these variables were included and compared in distinct univariate models to determine which format of each variable yielded the best fit. Several TWI transformations were assessed as potential predictors of CRDs,



specifically the logarithm, square root and binary classification as either above or below 9 (See Results for justification of this cutoff). After interpreting this *a priori* analysis and examining the smoothed curve relationship between CRD prevalence and TWI, a further categorical analysis of the influence of this variable was conducted *post hoc* by stratifying into households at locations where  $TWI \geq 15$  and those where  $TWI < 15$ . The number of people in the household was also assessed as an ordinal categorical variable by classifying it into four groups:  $<5$ , 5 to 9, 10 to 14 and  $\geq 15$  occupants. Moreover, both energy sources were combined and assessed as a single binary variable to represent households using either charcoal or canned gas as relatively clean fuels for cooking. In addition, the neighbourhood income variable was also assessed in a reclassified form, reducing based on their frequency distribution from five categories (low, mixed low and medium, medium, mixed medium and high and high) to three (low, medium and high) by combining low with mixed low and medium as a single low category and mixed medium and high with high as a single high category.

To validate the model results, high-resolution satellite images from May 2021, taken near the time of data collection, were used to georeference the hydrological characteristics of areas where CRD cases were identified. These findings were further corroborated by ground truthing in the same locations. Whereby the findings from the study were verified by physically visiting the same locations where the data had been collected and cases of CRDs identified. This on-site verification compared and confirmed the accuracy of the remote (TWI) and modelled data findings against actual household and neighbourhood hydrological conditions.

### **3.2.6 Ethical considerations**

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. An ethical clearance for the study, a component of the Sustainable Cities project at the Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara

Health Institute (IHI/IRB/NO: 26-2018) and the Medical Research Coordination Committee of the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954).

**Clinical trial number:** not applicable

Written consent, in accordance with the approved protocols, was obtained from all human participants with detailed information about the survey's purpose, procedures, potential risks and benefits, allowing them to make an informed decision about their involvement. Confidentiality was maintained by anonymizing data and securely storing personal information to prevent unauthorized access. To minimize harm, the survey was designed to avoid sensitive topics in the context of the study that could cause distress and participants were given the option to skip questions or withdraw at any time without penalty. Transparency was upheld by clearly communicating the survey's objectives, methods and the use of collected data, ensuring participants understood how their information would be used and the overall aim of the research.

### **3.2.7 Role of the funding source**

Data used in this study were collected from the research conducted as part of the Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods, supported by funding from the United Kingdom Research and Innovation (UKRI) through the Economic and Social Research Council (ESRC) under the UK Government's Global Challenges Research Fund (GCRF), through a project entitled *Sustainable, Healthy and Learning Cities and Neighbourhoods*. The funder had no role in the designing of the study or the collection, analysis and interpretation of data.

## **3.3 Results**

A total of 1533 households with approximately 7,098 residents were interviewed, representing a mean household size of 4.6 members. Out of 1468 surveyed households that responded to the

subsection on non-communicable diseases, 65 reported one or more diagnosed cases of CRD (Supplemental Table 2), making a total of 4.4% prevalence. The age and sex distribution of the study population are presented in Supplemental Table 1 and a detailed descriptive analysis table showing number of outcomes events of each variable investigated in the current study stratified into income categories used in sampling the study neighbourhoods are found in Supplemental Table 3.2. While six of the nine factors investigated were associated with CRD in the univariate analysis, only four were included in the final best-fit multivariate model (Table 3.1). In all these univariate and multivariate models, unidentified neighbourhood-specific characteristics accounted for considerable variation that was captured by a corresponding random effect.

In addition to the simple logit-linear relationship reported in Table 3.1, a number of TWI transformations were also assessed as potential predictors of CRDs. However, all these alternative formats yielded models with poorer goodness of fit ( $AIC \geq 409$ ) than that described in Table 3.1 for the final best-fit model ( $AIC = 407$ ). The number of people in the household was also assessed as an ordinal categorical variable but also yielded a model with poorer goodness of fit ( $AIC \geq 413$ ). Similarly, attempts to recode energy sources yielded a model that failed to converge and reclassification of neighbourhood income into only three categories from five, also resulted in poorer goodness of fit ( $AIC = 409$ ). Hence, all results presented herein are based on variables analysed in their original format and scale because this maximised statistical power.

Reassuringly, even though TWI was assumed beforehand to be a distal case of CRD and every effort was made to keep the multivariate model selection process systematic, objective and unbiased, it exhibited an apparently robust influence upon CRD, being consistently the first explanatory variable to be included and most clearly justified for retention. The final multivariate analysis indicated a clear positive association between hydrological determinants of wetness and household CRD prevalence, whereby the risk of CRD increased by 18% per

TWI unit increment (Table 3.1). Further categorical analysis of TWI after *post hoc* stratification was therefore informed by Figure 3.3, wherein a steep response curve was seen only in the very wettest locations ( $TWI \geq 15$ ). In these particularly flood-prone locations ( $\geq 99$ th percentile), CRD risk was approximately 9-fold greater than elsewhere (OR [95% CI] = 8.63 [2.13, 35]) when the influence of household size, air conditioning and communal waste disposal were all accounted for. Also, the number of people living in the household and CRD prevalence indicated a positive association, with risk increasing by about 15% per extra household member. In addition, the use of communal skip bins in the household was associated with four-fold greater CRD, indicating an important influence on outdoor air quality. On the other hand, however, the use of air conditioning was associated with CRD being reduced approximately four-fold.

While having recently had a birth in the household and the use of charcoal both appeared positively associated with CRD risk in the univariate analysis, neither was included in the final multivariate model. Interestingly, the number of years a household has lived in the dwelling emerged as a CRD risk factor as the addition of other independent variables improved the statistical power of the multivariate model. While univariate analysis indicated no association, the final multivariate model indicated an association that approached significance. Nevertheless, it did not quite reach statistical significance or improve the model AIC and was therefore excluded from the final model (Table 3.1). The use of canned gas was not found to have any association in either univariate or multivariate analysis. Interestingly, neighbourhood income was not associated with CRD prevalence when the effect of all these other risk factors was accounted for, confirming that poverty is an indirect, distal cause of CRDs rather than a direct, proximal one.

Table 3.1: The results of univariate and multivariate logistic regression analyses (GLMM) investigating factors apparently associated with the prevalence of chronic respiratory diseases (CRDs) in Dar es Salaam City, Tanzania.

| Fixed Effects                                  | Statistical Parameter |         |           |                    |         |         |
|------------------------------------------------|-----------------------|---------|-----------|--------------------|---------|---------|
|                                                | Univariate            |         | P         | Multivariate       |         |         |
|                                                | OR [95% CI]           | t-value |           | OR [95% CI]        | t-value | p       |
| <i>Topography and hydrology</i>                |                       |         |           |                    |         |         |
| Topographical Wetness Index (TWI) <sup>a</sup> | 1.16 [1.09, 1.24]     | 4.380   | <<0.00001 | 1.18 [1.04, 1.33]  | 2.603   | 0.00925 |
| <i>Household Characteristics</i>               |                       |         |           |                    |         |         |
| Number of people in the household <sup>b</sup> | 1.14 [1.04, 1.24]     | 2.946   | 0.00322   | 1.15 [1.05, 1.25]  | 2.934   | 0.00335 |
| Recent birth in the household                  | 1.82 [1.08, 3.08]     | 2.233   | 0.0255    | 1.42 [0.76, 2.65]  | 1.097   | 0.273   |
| Any air conditioning                           | 0.40 [0.18, 0.86]     | -2.328  | 0.0199    | 0.22 [0.06, 0.77]  | -2.379  | 0.0174  |
| Use of a communal skip                         | 3.86 [1.01, 14.74]    | 1.972   | 0.0486    | 4.04 [1.04, 15.80] | 2.006   | 0.0449  |
| Years lived in a dwelling                      | 1.00 [1.00, 1.01]     | 0.911   | 0.362     | 1.00 [1.00, 1.01]  | 1.828   | 0.0676  |
| <i>Cooking Energy<sup>c</sup></i>              |                       |         |           |                    |         |         |
| Use of charcoal                                | 1.93 [1.08, 3.44]     | 2.218   | 0.0266    | 1.35 [0.69, 2.62]  | 0.876   | 0.381   |
| Use of canned gas                              | 0.61 [0.34, 1.09]     | -1.669  | 0.0951    | 0.80 [0.40, 1.59]  | -0.641  | 0.522   |
| <i>Neighbourhood Income<sup>d</sup></i>        | 0.84 [0.52, 1.36]     | -0.702  | 0.483     | 0.84 [0.45, 1.56]  | -0.551  | 0.581   |
| Random Effect                                  |                       |         |           | σ                  | SD      |         |
| <i>Street Name</i>                             |                       |         |           | 1.073              | 1.036   |         |

OR: Odds Ratio

95% CI: 95% Confidence Interval

p: Estimated probability of the null hypothesis being true

σ: Variance

SD: Standard Deviation

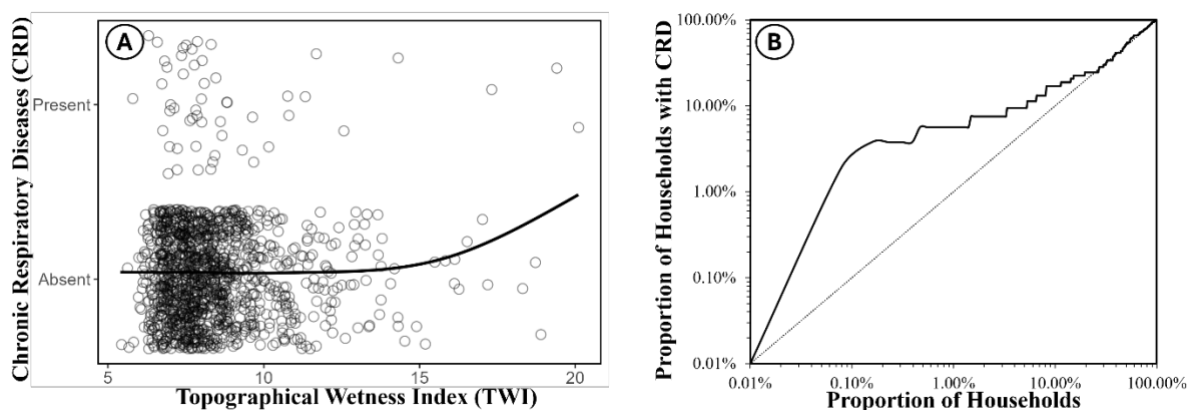
<sup>a</sup> In addition to the simple logit-linear relationship reported here, a number of TWI transformations were assessed as potential predictors of CRDs, specifically the base 10 logarithm, square root and binary classification as either above or below 15. However, all these alternative formats yielded models with poorer goodness of fit ( $AIC \geq 409$ ).

<sup>b</sup> The number of people in the household was also assessed as an ordinal categorical variable by classifying it into four groups:  $\leq 4$ , 5 to 9, 10 to 14 and  $>15$ . However, this yielded a model with poorer goodness of fit ( $AIC \geq 413$ ).

<sup>c</sup> Both energy sources were combined and assessed as one variable to represent households using either charcoal or canned gas for cooking in a binary form. However, no model convergence was attained.

<sup>d</sup> The neighbourhood income variable was also assessed following reclassification to yield 3 categories instead of 5, with mixed low and medium income being combined with low and mixed medium and high income being combined with high, while the medium was retained as it was, making three categories called Low, Medium and High. However, this also did not yield a model with improved goodness of fit either ( $AIC \geq 409$ ).

The results in Table 3.1 demonstrating the clear association of CRD with hydrological likelihood of local water accumulation is further illustrated by Figure 3.3A, which shows an uneven distribution of TWI values across a wide range, with substantial clustering at the lower end, between 6 and 12. The fitted moving average indicates a generally flat trend for low to moderate values of the TWI, suggesting consistently low CRD prevalence within this range. However, a noticeable upward trend in this curve at TWI values above approximately 15 suggests an increase in disease prevalence at higher levels. This consistent non-linear relationship was identified assuming any specific model form strongly implying there is an authentic threshold effect and steady upward trend in risk with increasing TWI. Panel B, log-scaled area under the curve (AUC) graph reinforces this interpretation, with cumulative proportion of households with CRD and the proportion of total households ranked from highest to lowest TWI, exhibiting a steep slope at the beginning of the curve, indicating a high concentration of CRD in a small proportion of households.



**Figure 3.3: Graphical illustration of CRD risk concentration in a relatively small fraction of houses with unusually high topographical wetness index (TWI).** Panel A Jitter plot and smoothed moving average curve (LOESS regression) showing the nonlinear relationship between chronic respiratory disease (CRDs) and topographical wetness index (TWI). Panel B, Log-Scaled area under the curve plot (AUC) plot narrative interpretation showing the

cumulative proportion of households with one or more CRD cases and proportion of total households with both ranked from highest to lowest TWI values.

These results are further supported by cartographic representations of CRD distribution across several areas of Dar es Salaam city, as depicted in Figure 3.4. Many households with reported cases are found in or beside areas with relatively high TWI (panels B and C), while areas without diagnosed cases are predominated by relatively low TWI (Panels D and E). Nevertheless, it is also obvious from Figure 3.4 that some CRD cases are found in areas with relatively low estimates, so further visual investigation of potential risk factors beyond TWI estimates was undertaken.



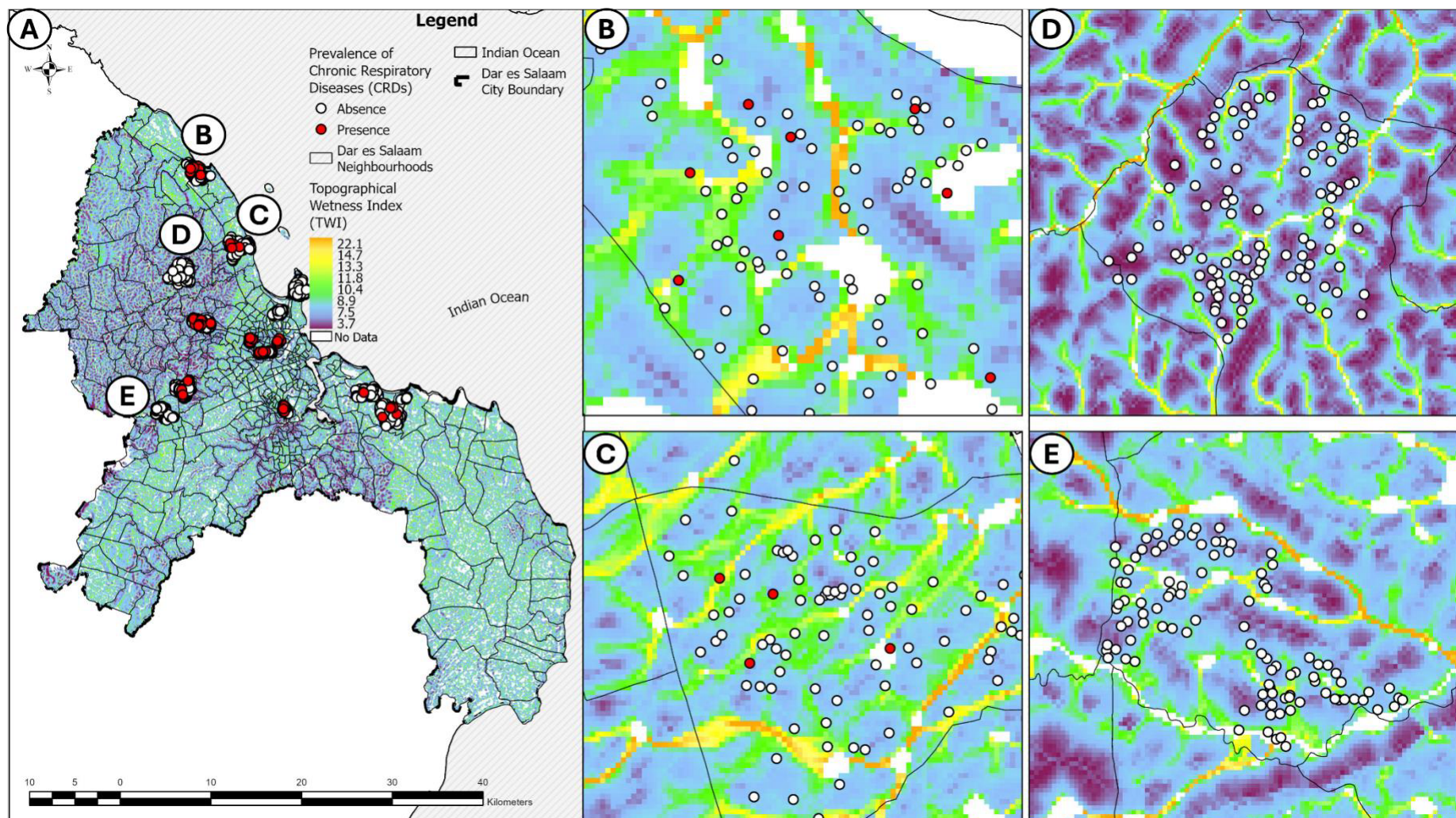
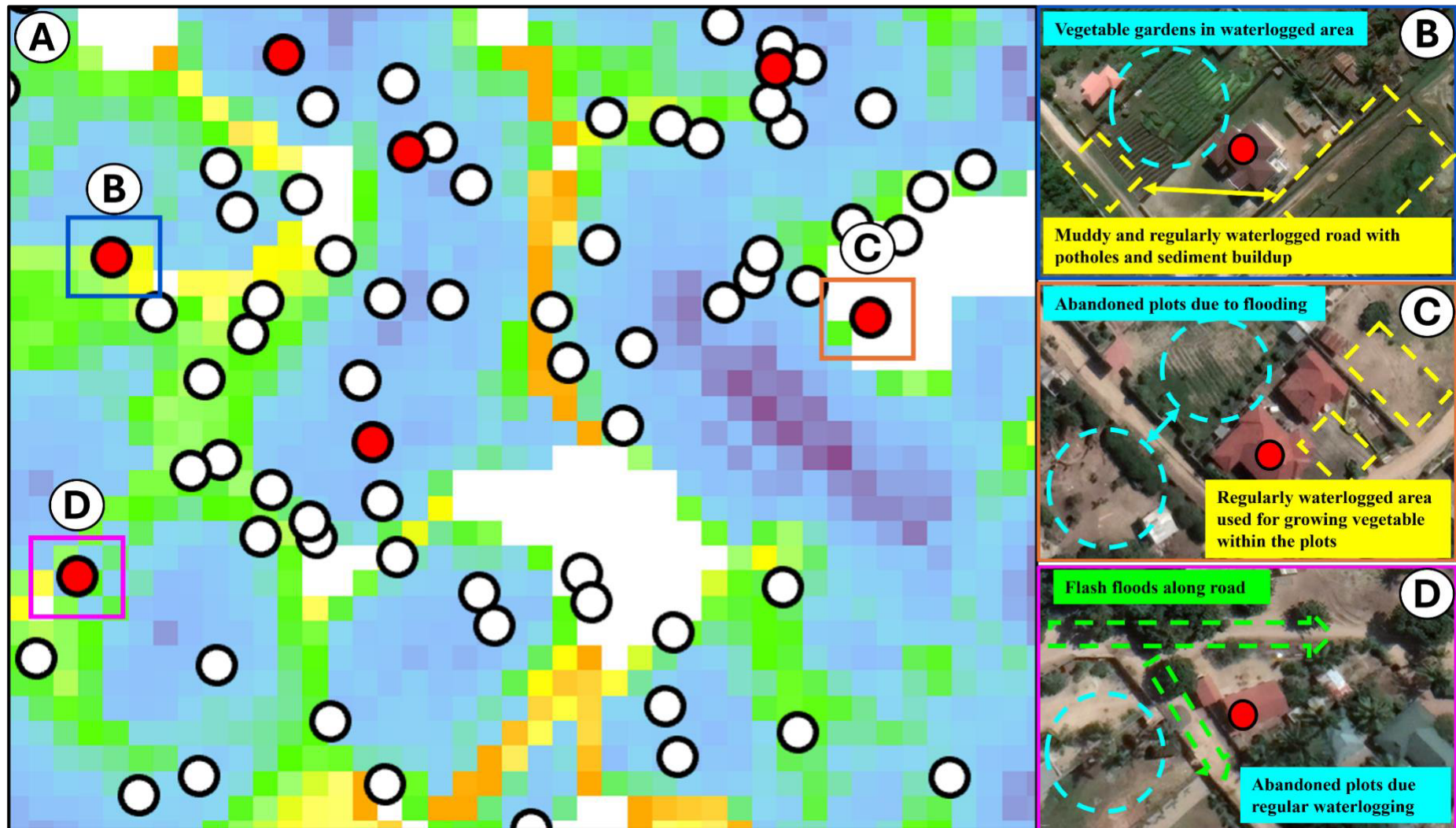


Figure 3.4: **Spatial distribution of chronic respiratory diseases (CRDs) in the surveyed neighbourhood's clusters of households in Dar es Salaam city, (A) with high resolution view of representative areas with either high (B, C) or low (D, E) CRD prevalence and TWI.** The map presents a topographical wetness index (TWI) overlay to show relationships of potential hydrological factors influencing CRD prevalence. Panels B and C shows neighbourhoods with generally elevated TWI where households with reported CRD diagnoses that were usually found in areas with or very near to those with high estimated TWI. Panels D and E illustrate neighbourhoods without reported CRD diagnoses in areas with predominantly low TWI.

Careful examination of high-resolution satellite images, taken close to the time when data were collected (May 2021) to ensure the compatibility, showing the obvious spatial association of CRD cases with visual evidence of regular waterlogging in areas of elevated TWI, (Figure 3.5, panel A).





**Figure 3.5: Visual cartographic geovalidation of distribution of chronic respiratory diseases (CRD) over the topographical wetness index (TWI).** Panel A shows how three cases of CRD are obviously located in areas of high TWI, while panels B, C and D geovalidated this interpretation with high-resolution satellite image showing fine scale landscape features consistent with regular waterlogging and flash floods.

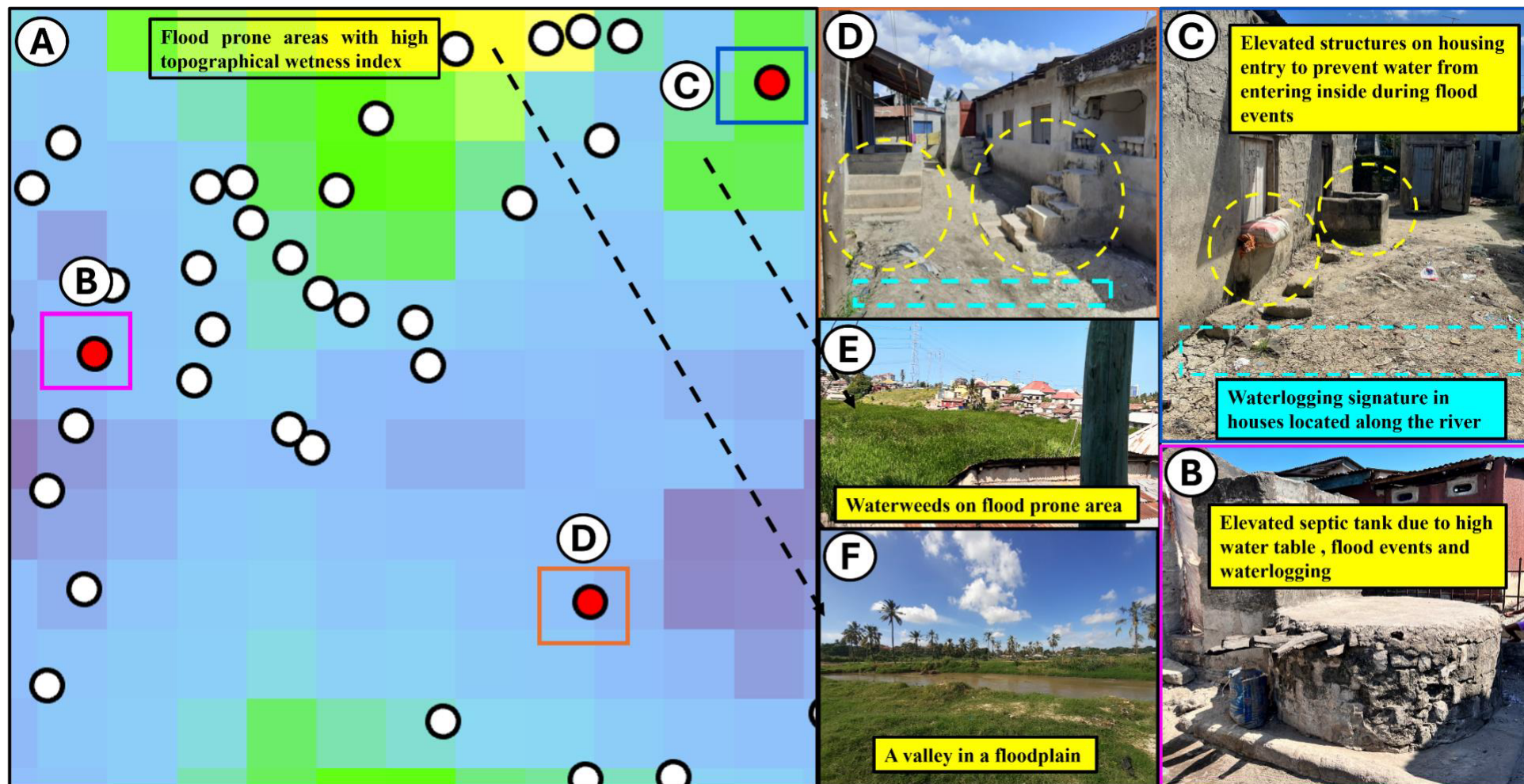
Furthermore, the results in Figure 3.6 showed that coarse scale TWI initially failed to capture the hydrological nature of some households (A), as some with CRD were found in areas with low estimated TWI. However, a clear effect was observed when they were geovalidated with fine scale landscape features (B, C and D).



**Figure 3.6: Further geovalidation that distribution of chronic respiratory diseases (CRD) prevalence is strongly influenced by hydrological phenomena even where they occur at residual scales too fine to be detected by topographical wetness index (TWI).** Panel A shows a series of cases of CRD located in a low TWI that were noted to occur along a rarely straight transect, which proved to be a road when the matching high-resolution image was examined. While panel B, C and D show an overlay with high resolution satellite image geovalidating fine scale hydrological features which were not be captured by TWI showing effect of fine scale hydrological processes that clearly influence CRD.

These obvious instances of clear geographic association between CRD cases and visual indicators of water accumulation were further been reinforced by using both geovalidation and ground truthing (field verification), as illustrated in Figure 3.7.







**Figure 3.7: Geovalidation and ground truthing (field verification) of hydrological conditions in different housing blocks with evidence of diverse housing typologies, construction methods and water accumulation in areas with reported diagnosed cases of chronic respiratory diseases (CRD).** Panel A show a block which is relatively wet, flood prone area with high TWI with its typical housing typologies and surrounding environment in panel B, C D, E and F. Panel D and C presents construction method used to protect water from entering the houses during flood but also showing evidence of water accumulation on the ground. In addition to that even septic tanks and soak aways pits have been elevated due to high water table and numerous flood incidents (panel B). But also, some of the houses with CRD are found within the catchment areas of the valleys (60 meters), as it can be seen in panel A with evidence of water weeds and flooding valley in panel E and F.

Hence, all these results confirmed by geovalidation and ground truthing with reference to the model results in Table 3.1, indicated that the presence of CRD is not merely a random occurrence rather than presentation of evident spatial pattern closely associated with hydrology.

### **3.4 Discussion**

This study demonstrated the role of hydrology as a clearly important fine-scale determinant of CRD prevalence while also accounting for other household-level factors related to air quality in indoor and outdoor environments. The association of CRD prevalence with hydrological conditions, as estimated based on water accumulation likelihood (TWI), apparently confirms it to be an important underlying cause of persistent dampness and moisture in housing structures built in low-lying terrain (Figure 3.4). Such conditions clearly not only affect the building's aesthetics, but also indoor air quality and respiratory health. A wide range of bacteria and fungi, including filamentous fungi, often referred to as mould, proliferate inside buildings that are continuously moist. These microbes discharge toxic volatile organic compounds (VOCs), spores and broken cells into the atmosphere, all of which are harmful to human health

and respiratory health in particular (Hernberg et al., 2014; Heseltine & Rosen, 2009). These results corroborate the findings of a great deal of the previous work on the risks of dynamic temporal excessive rainfall and flooding to respiratory health,(Mulder et al., 2019; Paterson et al., 2018; The Lancet Respiratory, 2024) by bridging the gap in understanding the topographic features which exacerbate the static spatial risk of CRD.

The findings of this study also support existing knowledge relating to the influence of overcrowding on indoor air quality and CRD risk. For example, several studies have shown that there is a connection between indoor air quality and household size (Gilbey et al., 2023). Although there may not be a direct causal relationship between the number of individuals living in a household and CRD, cooking habits, fuel use and exposure to indoor pollution, all likely contribute to this relationship as the actual proximal causes, with the likelihood of negative health consequences from indoor air pollution increasing with household size (Kovesi et al., 2007; Lim et al., 2021).

On the other hand, one risk factor identified in this study relates to outdoor air quality, specifically the use of communal skips for disposing of household waste. Similar to other reports, our findings indicated a notable association between the use of a communal skip and CRD prevalence, implying direct impacts of waste disposal practices upon respiratory health (Boadi & Kuitunen, 2005). Communal skips serve as prominent collection points within neighbourhoods, allowing households to dispose of several types of waste. However, the accumulation of waste within these bins can significantly affect air quality (Boadi & Kuitunen, 2005; Gao et al., 2023). The proximity of communal skips to residential buildings may contribute to outdoor air pollution by releasing VOCs, particulate matter and other pollutants during the decomposition of waste materials (Munyai & Nunu, 2020). While it may appear intuitive to attribute outdoor air pollution solely to industrial sources or vehicular emissions, this study underscores the role of waste disposal practices in elevating pollution levels, with

the risk of CRD in households using communal skip bins being four-fold higher. This could have been caused by the malfunctioning municipal services for collecting waste from communal skip bins, leading to the accumulation and overflow of refuse over time (Kassim & Kayaga, 2016; Mhache, 2012). VOCs emit toxic pollutants like ammonia, methane and hydrogen sulphides, that compromise air quality and intensify respiratory problems in residential neighbourhoods (Domingo et al., 2020; Falkowska, 2016; Ferronato & Torretta, 2019).

The exhaustive, objective forward stepwise selection process applied revealed that, when all the other significant predictors of prevalence were accounted for, household duration of residence in the same dwelling approached significance as a risk factor for CRD (Table 3.1). While subtly different in terms of the question asked, this finding is nevertheless broadly consistent with existing evidence that CRD risk increases as buildings age and deteriorate. Unless rigorously maintained, ageing buildings become more susceptible to mould growth and poor air quality more generally, due to factors like deteriorating insulation, increased moisture penetration and inadequate ventilation (Chaudhari et al., 2023).

However, one of the findings presented in Table 3.1 challenges some established perspectives in the field of respiratory health. While using air conditioning is generally thought to exacerbate respiratory illness, Table 3.1 indicates that it actually reduces CRD risk more than four-fold in Dar es Salaam. Fortunately, these surprising findings may be rationalized by understanding the physical effects of air conditioning on the indoor atmosphere in such a coastal equatorial climate. While ambient relative humidity (RH) levels in Dar es Salaam and many other tropical cities routinely exceed 60% saturation, providing a favourable environment for the formation of mould (Bomberg & Brown, 1993; Coppock & Cookson, 1951), air conditioning removes moisture from the air through cooling and consequent condensation. Maintaining indoor RH levels within the recommended range of 40% to 60% not only keeps the occupants

immediately comfortable, but it also prevents mould proliferation within that dwelling (Alaidroos & Mosly, 2023; Jones et al., 2022; Wolkoff, 2018) (Yu et al., 2009). Furthermore, modern air conditioning units equipped with specially designed *dry mode* features deliberately dehumidify the indoor environment by operating at lower fan and compressor speeds (Afram & Janabi-Sharifi, 2014). Having said that, various details of how air conditioning systems operate may result in negative impacts on respiratory health, such as short cycling, refrigerant leaks, dirty air filters, poor maintenance, dysfunctional humidity control, excessive cooling, improper sizing and the presence of allergens or existing mould growth, as well as pre-existing health conditions, are important to consider before simplistically recommending it as a panacea for respiratory health in the tropics (Chirico et al., 2020; Lenzer et al., 2020).

On the other hand, while several other variables initially appeared to be significant in univariate analysis, they did not even approach significance when other, more robust, predictors of CRD prevalence were accounted for by more powerful and nuanced multivariate models (Table 3.1). Also, having had a recent birth in the household was not identified as a risk factor for CRD when the effects of other clear predictors were accounted for by the multivariate analysis presented herein (Table 3.1). While this might initially appear to contradict established evidence for higher risk of CRD among newborns, (Buchwald et al., 2019; Marangu & Zar, 2019) this may be readily explained by intuitively obvious covariance between the presence of newborns and the overall number of people in the household, presumably resulting in the latter assimilating variance associated with the former in the model presented in Table 3.1.

Furthermore, despite many studies describing the role of the source of cooking energy as a contributor to air pollution in households that is clearly associated with CRD (Chan et al., 2019; Jindal et al., 2020; Langbein, 2017; Torres-Duque et al., 2008), no such association was observed here. While charcoal use was associated with CRD risk in the univariate analysis, no such association was observed when other risk factors were accounted for in the multivariate

analysis (Table 3.1). More conclusively, the use of canned gas was not found to have any association in either univariate or multivariate analysis (Table 3.1).

In addition, while studies have shown that poverty and deprivation are associated with increased CRD risk, no such association was observed here (Table 3.1) (Axelsson Fisk & Merlo, 2017; Lee et al., 2019). While income often appears to be a dominant, sometimes even singular risk factor for illnesses in general, that is because it is a broadly relevant but nevertheless indirect and distal cause of most diseases, that operates indirectly through a diversity of more direct, proximal causes. It is therefore interesting that in this analysis, which accounts for variations in socioeconomic status at neighbourhood but not household level and also for fine-scale variations in environmental risk factors, no association of CRD with this broadly important determinant of health was identified. While this might initially seem at odds with the existing evidence base, it may also be explicable in terms of the close association of poverty and CRD with environmental risk factors at scales of individual households and their immediate surroundings.

On the other hand, this well-supported evidence, derived from geovalidation using high resolution satellite imagery and on-the-ground observations (ground truthing), not only validates the association between CRDs and hydrology, but also underscores the importance of not solely relying on coarse resolution digital elevation models (DEMs) data for studying hydrology, as fine scale features can be overlooked as seen in Figure 3.6. Hence in absence of fine resolution data, comprehensive validation methods are required to reach conclusion in this type of studies, considering the current observed evidence that shows fine scale hydrological processes may capture effect of CRD than TWI.

While place of residence is in principle a matter of personal choice, in practice, deprived households are often compelled to live clustered alongside each other in areas characterised by

challenging hydrological conditions, due to socioeconomic factors and family history. For instance, deprived communities are typically composed largely of households who cannot afford housing in less vulnerable areas, forcing them to settle in known flood-prone areas. Moreover, urbanisation and population growth often lead to increased demand for housing, driving the expansion of settlements into floodplain areas, due to limited application of planning and development controls. More detailed fine-scale data on relevant characteristics of locations and buildings, such as maximum flood level, moisture content, mould formation and airborne concentrations of fungal spores could therefore be important to record in future observational and interventional studies of the relationship between hydrology and CRD.

This study had several limitations that should be considered when interpreting the results. One significant limitation was the sample size, which may have affected the statistical power of the modeling. While the odds ratio confidence intervals for TWI and the number of household members were reasonably narrow, those for air conditioning and communal skip use were very wide, so it is certainly possible that some other important risk factors were missed. A larger sample size might therefore have provided more robust, insightful and reliable results. Additionally, the coarse resolution of socioeconomic status data, specifically related to poverty and deprivation at the neighbourhood level, may well have obscured finer-scale variations and nuances in these socioeconomic factors. Finally, while individual-level data could have offered greater insight and statistical power, this study only collected data at the household level, so this may have limited the granularity and nuance of the analysis.

### **3.5 Conclusion**

Despite these study limitations, the results presented nevertheless indicate that hydrology is one of the most important drivers of CRD in the low-lying, sandy, hot and humid environment of Dar es Salaam city. Specifically, factors such as poor surface water drainage, high groundwater tables, and frequent flooding contribute to prolonged dampness and mould growth

in residential structures, which in turn exacerbate respiratory health risks. These conditions are somehow intensified by inadequate stormwater management and the accumulation of stagnant water which also foster unsanitary conditions that increase exposure to environmental pollutants linked to CRDs. These hydrological characteristics collectively shape the micro-environmental conditions that heighten the vulnerability of residents in low-lying settlements.

In addition to a number of known risk factors for CRD, this study identified a clear link between areas prone to accumulate and retain water, where houses and residential buildings are consequently likely to suffer from chronic dampness, mould proliferation and poor indoor air quality. The observed interaction between hydrological conditions and CRD further emphasizes the necessity for comprehensive urban planning and astute construction methods that address both environmental and public health concerns.

### **3.6 Abbreviations**

**AIC:** Akaike Information Criterion

**BIC:** Bayesian Information Criterion

**CI:** Confidence Interval

**COPD:** Chronic Obstructive Pulmonary Disease

**CRDs:** Chronic Respiratory Diseases

**DEM:** Digital Elevation Model

**ESRC:** Economic and Social Research Council

**GCRF:** Government's Global Challenges Research Fund

**GLMM:** Generalized Linear Mixed Model

**IHI:** Ifakara Health Institute

**IRB:** Institutional Review Board

**NIMR:** National Institute for Medical Research in Tanzania

**ODK:** Open Data Kit

**OR:** Odds Ratio

**RH:** Relative Humidity

**SD:** Standard Deviation

**TWI:** Topographical Wetness Index

**UKRI:** United Kingdom Research and Innovation

**VOCs:** Volatile Organic Compounds

**WHO:** World Health Organization



### **3.7 Declarations**

#### **3.7.1 Ethics approval and consent to participate.**

Ethical clearance for the study, a component of the Sustainable Cities project at the Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara Health Institute (IHI/IRB/NO: 26-2018) and the Medical Research Coordination Committee of the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954).

Written consent, in accordance with the approved protocols, was obtained from all human participants with detailed information about the survey's purpose, procedures, potential risks and benefits, allowing them to make an informed decision about their involvement. Confidentiality was maintained by anonymizing data and securely storing personal information to prevent unauthorized access. To minimize harm, the survey was designed to avoid sensitive topics in the context of the study that could cause distress and participants were given the option to skip questions or withdraw at any time without penalty. Transparency was upheld by clearly communicating the survey's objectives, methods and the use of collected data, ensuring participants understood how their information would be used and the overall aim of the research.

#### **3.7.2 Availability of data and materials**

The data supporting the findings of this study are openly available in GCRF Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods: Household Survey and Neighbourhood Focus Group Data from Seven Asian and African Countries, 2021- 2022 at <http://dx.doi.org/10.5255/UKDA-SN-855998> (Wang et al., 2023)

Wang, Y. P., Kintrea, K., Osborne, M., Schweisfurth, M., Mitchell, R., Kamete, A., ... & Jinqiao, L. (2023). GCRF Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods: Household Survey and Neighbourhood

### **3.7.3 Competing interests**

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### **3.7.4 Funding**

This research was conducted as part of the Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods, supported by funding from United Kingdom Research and Innovation (UKRI) through the Economic and Social Research Council (ESRC) under the UK Government's Global Challenges Research Fund (GCRF) through a project entitled *Sustainable, Healthy and Learning Cities and Neighbourhoods* (reference ES/P011020/1).

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The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

### **3.7.5 Authors' contributions**

IM contributed to the conceptualization of the study, data curation, formal analysis, methodology, writing of the original draft and reviewed and edited the manuscript. GFK contributed to formal analysis, methodology, validation, writing of the original draft and reviewed and edited the manuscript. The investigation was carried out collaboratively by IM,

FL and IRM. The study's methodology was designed IM, FL and IRM, who also oversaw project administration. Supervision was provided by GFK and JO. Visualization of the data was handled by IM. The original draft of the manuscript was written by IM and review & editing were completed by GFK and JO and were also involved in the decision to submit the manuscript. All other authors were involved in data curation and reviewed and edited the manuscript.

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# Appendices

## Appendix A: Supplementary Tables

Supplemental Table 1: The age and sex distribution of residents in Dar es Salaam city corresponds to that of the sampled households.

Supplemental Table 2: Number of outcomes events of each variable investigated in the current study stratified into income categories used in sampling the study neighbourhoods (mitaa, literally translated as streets).

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## Appendix B: Supplementary Figures

Supplemental Figure 1: Raster histogram illustrating the frequency distribution of the topographical wetness index (TWI) within Dar es Salaam city

## Appendix A: Supplementary Tables

Supplemental Table 1: **The age and sex distribution of residents in Dar es Salaam city corresponds to that of the sampled households.**

| Age          | Males       |            | Females     |            | Total       |            |
|--------------|-------------|------------|-------------|------------|-------------|------------|
|              | n           | %*         | n           | %*         | n           | %*         |
| 1-4          | 373         | 13.5       | 376         | 10.7       | <b>749</b>  | 12.1       |
| 5-9          | 359         | 11.4       | 400         | 11         | <b>759</b>  | 11.2       |
| 10-14        | 325         | 10.2       | 333         | 8.8        | <b>658</b>  | 9.5        |
| 15-19        | 285         | 9.2        | 327         | 10         | <b>612</b>  | 9.6        |
| 20-24        | 319         | 11.9       | 369         | 14         | <b>688</b>  | 13         |
| 25-29        | 252         | 9.6        | 371         | 12         | <b>623</b>  | 10.9       |
| 30-34        | 254         | 9.3        | 336         | 11         | <b>590</b>  | 10.1       |
| 35-39        | 215         | 6.1        | 280         | 5.9        | <b>495</b>  | 6          |
| 40-44        | 200         | 5.5        | 243         | 5.4        | <b>443</b>  | 5.4        |
| 45-49        | 191         | 5          | 206         | 4.1        | <b>397</b>  | 4.5        |
| 50-54        | 168         | 2.9        | 143         | 2          | <b>311</b>  | 2.4        |
| 55-59        | 90          | 1.4        | 99          | 1.3        | <b>189</b>  | 1.4        |
| 60-64        | 96          | 1.5        | 112         | 1.4        | <b>208</b>  | 1.5        |
| 65-69        | 71          | 1.1        | 81          | 1          | <b>152</b>  | 1          |
| 70-74        | 63          | 0.8        | 42          | 0.4        | <b>105</b>  | 0.6        |
| 75-79        | 23          | 0.3        | 26          | 0.3        | <b>49</b>   | 0.3        |
| 80+          | 18          | 0.3        | 52          | 0.6        | <b>70</b>   | 0.5        |
| <b>Total</b> | <b>3302</b> | <b>100</b> | <b>3796</b> | <b>100</b> | <b>7098</b> | <b>100</b> |



Supplemental Table 2: **Number of outcomes events of each variable investigated in the current study stratified into income categories used in sampling the study neighbourhoods (*mitaa*, literally translated as *streets*).**

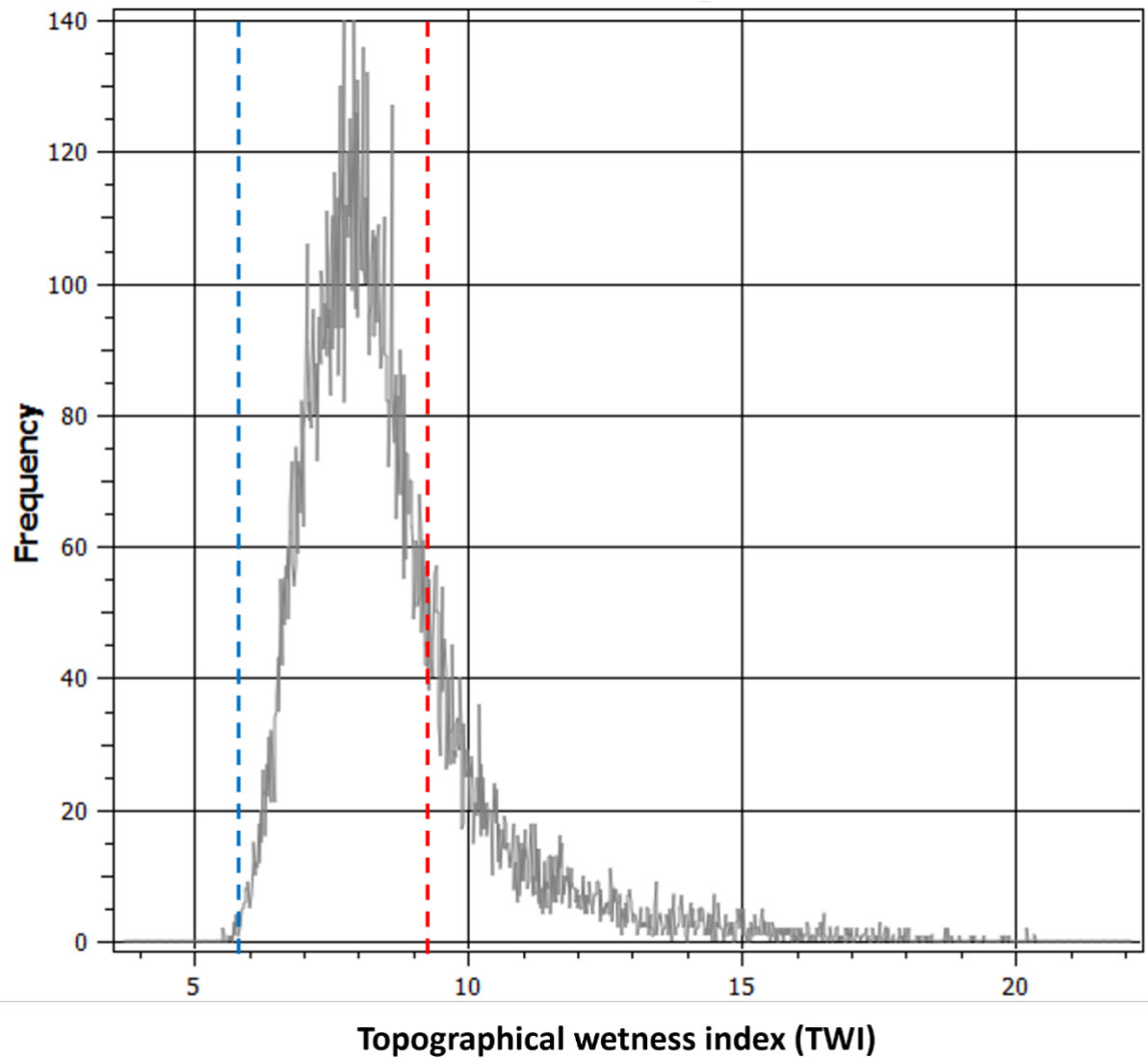
| <b>Variables</b>                         | <b>Low</b> | <b>Mixed Low &amp; Medium</b> | <b>Medium</b> | <b>Mixed Medium &amp; High</b> | <b>High</b> | <b>Total</b> |
|------------------------------------------|------------|-------------------------------|---------------|--------------------------------|-------------|--------------|
| <b>Topographical wetness Index</b>       |            |                               |               |                                |             |              |
| ≤8                                       | 140        | 179                           | 196           | 89                             | 96          | <b>700</b>   |
| ≥9                                       | 55         | 67                            | 70            | 52                             | 55          | <b>299</b>   |
| <b>Chronic respiratory diseases</b>      | 8          | 17                            | 17            | 19                             | 4           | <b>65</b>    |
| <b>Number of People in the Household</b> |            |                               |               |                                |             |              |
| 1-2                                      | 17         | 27                            | 28            | 15                             | 56          | <b>143</b>   |
| 3-4                                      | 71         | 77                            | 89            | 92                             | 138         | <b>467</b>   |
| 5+                                       | 170        | 207                           | 209           | 219                            | 118         | <b>923</b>   |
| <b>Recent Birth in the Household</b>     | 89         | 102                           | 115           | 79                             | 43          | <b>428</b>   |
| <b>Any Air Conditioning</b>              | 62         | 10                            | 61            | 117                            | 231         | <b>481</b>   |
| <b>Use of Communal Skip Bins</b>         | 2          | 1                             | 12            | 5                              | 1           | <b>21</b>    |
| <b>Years Lived in Dwelling</b>           |            |                               |               |                                |             |              |
| ≤10                                      | 160        | 139                           | 163           | 165                            | 178         | <b>805</b>   |
| ≥10                                      | 98         | 172                           | 136           | 161                            | 134         | <b>701</b>   |
| <b>Cooking Energy</b>                    |            |                               |               |                                |             |              |
| Canned gas                               | 83         | 83                            | 154           | 263                            | 279         | <b>862</b>   |
| Charcoal                                 | 164        | 204                           | 139           | 51                             | 18          | <b>576</b>   |
| <b>Number of respondents</b>             | <b>271</b> | <b>298</b>                    | <b>326</b>    | <b>326</b>                     | <b>312</b>  | <b>1,533</b> |

Supplemental Table 3: Demographic, spatial and socioeconomic characteristics of sampled neighbourhoods

| S/n | District  | Ward      | Street          | Population<br>(Census 2012) | Area<br>(Kilometre square) | Population density<br>People/Kilometre square | Income Category       | No. household surveyed |
|-----|-----------|-----------|-----------------|-----------------------------|----------------------------|-----------------------------------------------|-----------------------|------------------------|
| 1   | Ilala     | Kinyerezi | Kinyerezi       | 27200                       | 11.82                      | 2300.48                                       | Medium                | 135                    |
| 2   | Ilala     | G/Mboto   | Ulongoni        | 27624                       | 6.05                       | 4562.41                                       | Mixed low and medium  | 104                    |
| 3   | Kigamboni | Mjimwema  | Mjimwema        | 7413                        | 4.17                       | 1779.12                                       | Medium                | 91                     |
| 4   | Kigamboni | Mjimwema  | Kibugumo        | 4217                        | 8.91                       | 473.45                                        | Mixed low and medium  | 103                    |
| 5   | Kinondoni | Kawe      | Mbezi Beach 'B' | 16531                       | 4.40                       | 3755.40                                       | High                  | 105                    |
| 6   | Kinondoni | Magomeni  | Makuti 'A'      | 6826                        | 0.25                       | 27596.75                                      | Medium                | 100                    |
| 7   | Kinondoni | Kunduchi  | Ununio          | 7187                        | 4.35                       | 1650.46                                       | Mixed medium and high | 111                    |
| 8   | Kinondoni | Mikocheni | Regent Estate   | 2989                        | 1.08                       | 2775.82                                       | High                  | 73                     |
| 9   | Kinondoni | Msasani   | Masaki          | 7619                        | 3.98                       | 1913.10                                       | High                  | 134                    |
| 10  | Temeke    | Azimio    | Mji Mpya        | 9071                        | 0.35                       | 26153.12                                      | Mixed low and medium  | 91                     |
| 11  | Temeke    | Azimio    | Kichangani      | 8180                        | 0.20                       | 40350.63                                      | Low                   | 56                     |
| 12  | Ubungo    | Kimara    | Kimara Baruti   | 13269                       | 3.02                       | 4393.78                                       | Mixed medium and high | 110                    |
| 13  | Ubungo    | Manzese   | Mwembeni        | 9166                        | 0.25                       | 37016.40                                      | Low                   | 99                     |
| 14  | Ubungo    | Goba      | Goba            | 9471                        | 10.20                      | 928.37                                        | Mixed medium and high | 105                    |
| 15  | Ubungo    | Mburahati | Barafu          | 15912                       | 0.51                       | 31263.02                                      | Low                   | 116                    |

## Appendix B: Supplementary Figures

Supplemental Figure 1: Raster histogram illustrating the frequency distribution of the topographical wetness index (TWI) within Dar es Salaam city, derived from a Digital Elevation Model (DEM) with a resolution of 30 meters, a blue dotted line indicating tenth percentile (TWI  $\approx 5.4$ ) and a red dotted line indicating ninetyeth percentile (TWI  $\approx 9.2$ ).



## 4 CHAPTER FOUR

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**Exploring the Normalised Difference Vegetation Index (NDVI) as a green vegetation proxy and Land Surface Temperature (LST) as an indicator of thermal conditions as independent determinants of household hypertension prevalence across diverse neighbourhoods of Dar es Salaam city in Tanzania: A cross-sectional study.**

# Preface

**Title:** Exploring the Normalised Difference Vegetation Index (NDVI) as a green vegetation proxy and Land Surface Temperature (LST) as an indicator of thermal conditions as independent determinants of household hypertension prevalence across diverse neighbourhoods of Dar es Salaam city in Tanzania: A cross-sectional study.

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# Abstract

**Background** Urban environmental factors associated with climate change, such as increased temperatures and reduced green spaces, are thought to be associated with a rising burden of depression, anxiety and hypertension in towns and cities, particularly in densely built-up areas in both developing and developed countries. Here, the influence of green vegetation cover and ambient temperature on hypertension prevalence across diverse income neighbourhoods of Dar es Salaam city in Tanzania were assessed, while allowing for the potentially confounding contributions of several other known household risk factors.

**Methods** Estimates of normalised difference vegetation index (NDVI) and land surface temperature (LST) at a resolution of 30 meters were derived from Landsat 9 images available from the United States Geological Survey. These environmental metrics of green vegetation cover and ambient temperature, respectively, were then related to spatially referenced hypertension prevalence data collected through a large-scale household survey across 15 different neighbourhoods distributed across Dar es Salaam. The associations were analysed using general linear mixed models, allowing for the effects of all the various household-level risk factors that were also captured by these surveys.

**Results** An association was found between NDVI and hypertension prevalence, with the odds of disease occurrence being 87% lower in households sitting in areas with high NDVI as compared to those in low. The risk decreased by approximately 33.4% for every 0.1 unit increase in NDVI, indicating that vegetation may have a protective effect against the disease (CI [0.00, 0.29],  $p = 0.00188$ ). On the other hand, the analysis indicated a borderline association between the LST and hypertension, with the effect estimate showing no clear difference (CI [0.84, 1.00],  $p = 0.05322$ ). In line with previous research, the actual impact on the disease became evident only after adjusting for other confounding factors associated with.

Additionally, contrary to our initial assumptions, no association was observed on income as a confounding factor for household hypertension in the current study.

**Conclusion** These findings emphasize the need to integrate green spaces and temperature mitigation strategies in urban design for public health, especially in rapidly growing cities like Dar es Salaam with several climate change-related events, while also considering socioeconomic stressors which disproportionately affect city residents.

## 4.1 Introduction

Hypertension, also known as high blood pressure, is a significant contributor to premature mortality worldwide. According to the World Health Organization (WHO), approximately 1.28 billion adults aged 30-79 years suffer from hypertension globally, about two thirds of whom reside in low and middle-income countries (LMICs).(Kario et al.) The prevalence of hypertension has risen steadily over recent decades, increasing from 594 million cases in 1975 to 1.13 billion cases in 2015 (Zhou et al., 2017). Most LMICs have tropical or subtropical climates and account for a disproportionately high proportion of global hypertension burden, indicating elevated risk in these regions compared to other parts of the world (Cohen et al.). Known modifiable risk factors for hypertension include modifiable risk factors that encompass unhealthy diets, physical inactivity, tobacco use, alcohol consumption and being overweight or obese, while non-modifiable ones include genetics, old age and co-existing health conditions like diabetes (Zhou et al., 2021). Furthermore, several studies have established an underlying connection between various socio-economic stressors and hypertension (Wahid et al., 2023). Factors such as low income, inadequate housing and unstable employment have been consistently linked to higher blood pressure levels (Commodore-Mensah et al., 2021; de Mestral & Stringhini).

Furthermore, growing concerns about climate change as a public health threat in rapidly urbanising LMICs has stimulated interest in environmental determinants of elevated hypertension risk (Maibach et al.; Wills-Karp, 2024). Specifically, increased temperatures and reduced green spaces are suspected to be associated with a rising burden of hypertension in towns and cities, adding further nuance to the already complex web of interrelated determinants of risk (Peters & Schneider, 2021; Zhang et al.). Additionally, research has shown that the lack of green spaces and urban heat islands contribute significantly to mental health issues in urban



environments (Dadvand et al., 2016). The absence of natural environments can increase the risk of depression and anxiety, while the intensified heat in urban areas further exacerbates these conditions, both of which are known to contribute to hypertension (Kuneš et al., 1991; Park et al., 2020).

The relationship between environmental factors and hypertension is inherently complex, influenced by a range of interacting physiological, behavioural, and contextual variables (Rossios et al., 2023). While elevated temperatures can contribute to increased cardiovascular strain and fluctuations in blood pressure, the effects are neither linear nor uniform across populations. Factors such as acclimatisation, age, occupation, housing conditions, and access to cooling or healthcare resources can mediate individual vulnerability. Moreover, temperature interacts with other environmental stressors including air pollution, humidity, and psychosocial stress to shape hypertension risk in multifaceted ways (Rios et al., 2023).

In recognition of the above acknowledged complexity of associating environmental factors with hypertension, this study adopts a balanced interpretation that accounts for the multifactorial nature of these relationships. The study reported herein therefore investigates the influence of heterogeneities in the urban environment and associated socio-economic factors on the prevalence of hypertension across a diversity of different neighbourhoods of Dar es Salaam city in Tanzania. Specifically, it examines the relationship between urban vegetation and temperature, respectively utilizing the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) as indicators that are freely available at fine geographic scales, while also considering known household risk factors captured in a survey of non-communicable diseases, to dissect the multi-layered interactions between all these potential contributors to hypertension in this urban tropical setting.

## **4.2 Method**

### **4.2.1 Study Site**

The study was conducted in Dar es Salaam city in Tanzania, where both population and housing densities limit the availability of green spaces, thereby exacerbating the extreme high temperatures that occur in this coastal tropical setting (Group, 2016). The cross-sectional household survey described below was carried out in 15 different neighbourhoods scattered across the city that were previously stratified by income (Figure 4.1) (Msuya et al., 2024), using a participatory approach conducted prior to the household survey. The approach was based on consensus subjective perspectives of local community representatives, town planners and technical experts (Msuya et al., 2024) .

### **4.2.2 Household surveys**

Between June and September 2021, a total of 1533 participating households from across 15 neighbourhoods were involved in a clustered cross-sectional questionnaire survey (Figure 4.1), as described in detail by Msuya et al (2025) (Msuya et al., 2024). A multi-stage sampling frame was used, with three neighbourhoods selected from each of five distinct income strata by population-weighted random sampling based on data from the 2012 National Population and Housing Census (NBS, 2016).

In accordance with the approved protocols, written consent was obtained from all participating heads of households or other suitable household representatives, following which they were engaged in answering questions written on a structured questionnaire with multiple sections (Wang et al., 2023). In addition to covering other non-communicable diseases, such as cancer, diabetes, heart disease, kidney disease, back pain and mental health conditions, respondents were specifically asked whether any household member had been diagnosed with high blood pressure. For household who reported one or more cases of hypertension, the diagnosis was

clarified by asking whether the relevant household member had been diagnosed based on the standard criteria that require blood pressure readings to be consistently high across multiple visits, typically two to three separate occasions over several weeks or months (Lüdecke et al., 2021).

Ethical clearance for the study, a component of the Sustainable Cities project at the Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara Health Institute (IHI/IRB/NO: 26-2018) and the Medical Research Coordination Committee of the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954).

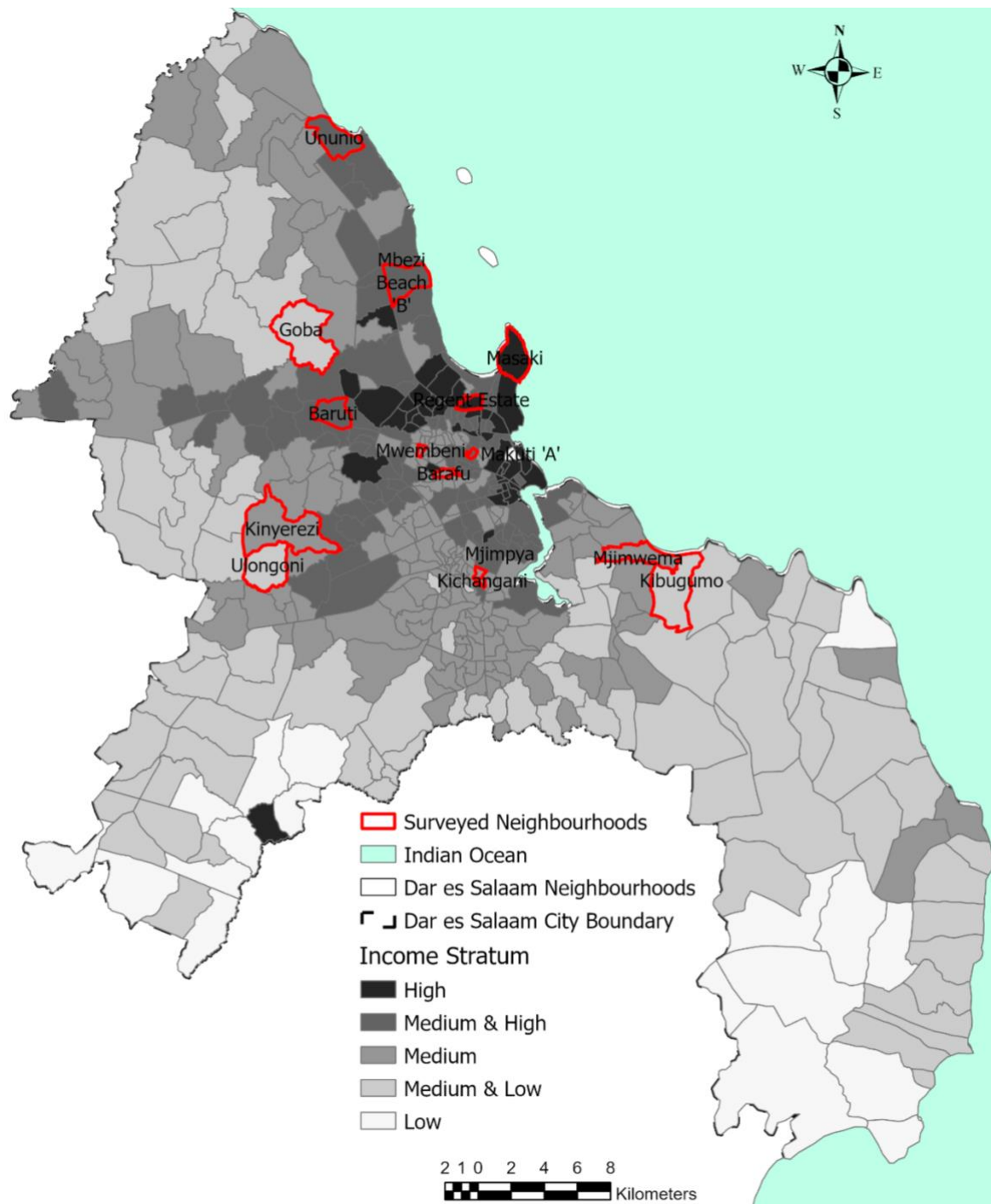


Figure 4.1: Location of 15 surveyed neighbourhoods and their income stratum

#### 4.2.3 Normalised Difference Vegetation Index (NDVI)

In the context of rapidly growing cities with ongoing informal land use changes and inadequate systems for monitoring urban development, reliable ground-based data on green spaces are

often lacking, so satellite imagery can be invaluable. The NDVI has emerged as a prominent remotely sensed indicator of vegetation greenness and density at fine geographic scales (Dutta et al., 2021). NDVI assesses vegetation cover by comparing the difference between the intensities with which near-infrared (NIR) light, which vegetation reflects strongly and red light, which vegetation absorbs. NDVI values range from -1 to +1, with high values indicating healthier vegetation, while low values correspond to little or no vegetation (Mwakapuja et al., 2013). To obtain these data, Landsat 9 images with a 30-meter resolution were generated on the 2<sup>nd</sup> of April 2021 (Freely provided by the United States Geological Survey; identifier *LANDSAT\_PRODUCT\_ID = LC08\_L1TP\_166065\_20210328\_20210402\_02\_T1*) and acquired on the 17<sup>th</sup> of May 2024. The reason for acquiring images from 2021 was to align them with household data collected in the same year. Although this represents a time difference between the image acquisition and household data collection, which occurred from June to September, the April image was chosen for its lower cloud cover and consequently higher quality. Also, April is typically the peak of the main rains in Tanzania, during which most forms of vegetation are at their greenest and provide the clearest possible signal to remote sensing tools.

Before generating the NDVI, the image underwent several preprocessing steps. These included clipping it to the study area boundaries, cloud masking, radiometric calibration, atmospheric correction and converting the data to surface reflectance. These steps ensured the image quality and accuracy needed for the analysis. The image has eleven spectral bands, out of which only the NIR (Band 5) and Red (Band 4) bands were used to calculate NDVI with the *raster calculator tool* of the ArcGIS Pro 3.2.2:

$$NDVI = \frac{NIR - Red}{NIR + Red} = \frac{Band\ 5 - Band\ 4}{Band\ 5 + Band\ 4} \quad (4.1)$$

Where RED = Digital number values from the RED band and NIR = Digital number values from the NIR band (Xu & Guo, 2014).

The generated GeoTIFF NDVI image was then saved for further analysis. This NDVI image serves as a key input for subsequent steps, such as the calculation of the Land Surface Emissivity (LSE) and the final Land Surface Temperature (LST).

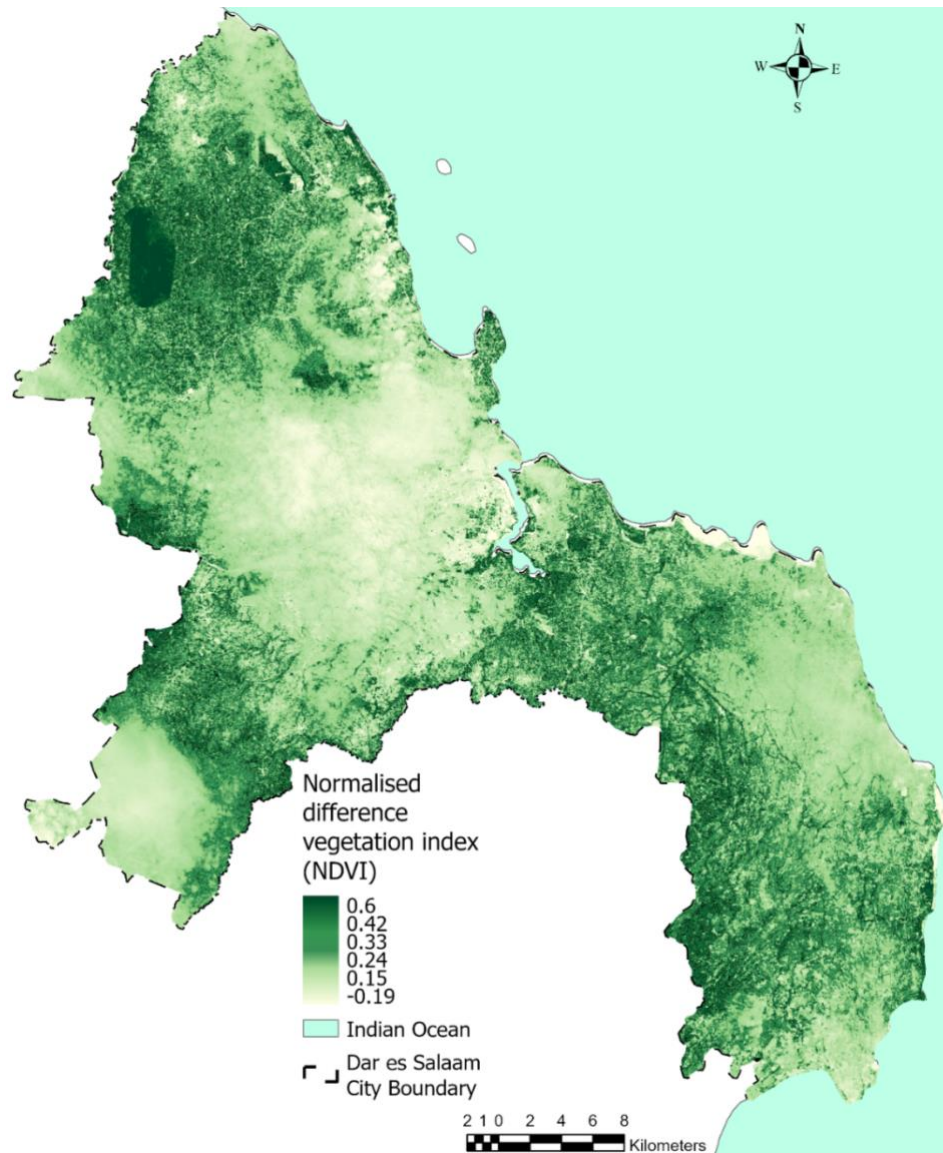


Figure 4.2: Dar es Salaam normalised difference vegetation index (NDVI) generated from Landsat 9 satellite image (United States Geographic Survey) with 30m resolution, image dated 2<sup>nd</sup> April 2021.

#### 4.2.4 Land Surface Temperature (LST)

In addition to analysing the NDVI as a proxy for urban greenery, this study incorporates Land Surface Temperature (LST) estimates as an indicator of mean ambient temperature. LST quantifies thermal emissions from the Earth's surface, providing crucial information about land-atmosphere interactions and other environmental processes. To investigate micro-variations in LST, the same Landsat 9 images used to generate the Normalized Difference Vegetation Index (NDVI) were utilized, but different calculations were applied based on different spectral bands. The first step involved the calculation of Top of Atmospheric Spectral Radiance (TOA), where Thermal Infra-Red Digital Numbers from Landsat 9 were converted to TOA spectral radiance, using radiance rescaling factors provided in the metadata. Subsequently, the TOA spectral radiance was converted to TOA brightness temperature (BT), using the thermal constants from the metadata. The NDVI, which had already been calculated, was then adopted for further analysis. The proportion of vegetation (PV) and emissivity (E), measuring the average emissivity of an element on the Earth's surface (Land Surface Emissivity, LSE), was derived from the NDVI (Meng et al., 2022). Finally, the LST was calculated using the TOA brightness temperature, the wavelength of emitted radiance and the land surface emissivity, applying equation 4.2:

$$LST = BT / (1 + (\lambda * BT / c2) * \ln(E)) \quad (4.2)$$

Where BT is the TOA brightness temperature,  $\lambda$  is the wavelength of emitted radiance,  $c2$  is a constant that depends on  $\lambda$ , E is the land surface emissivity (Dash, 2005).

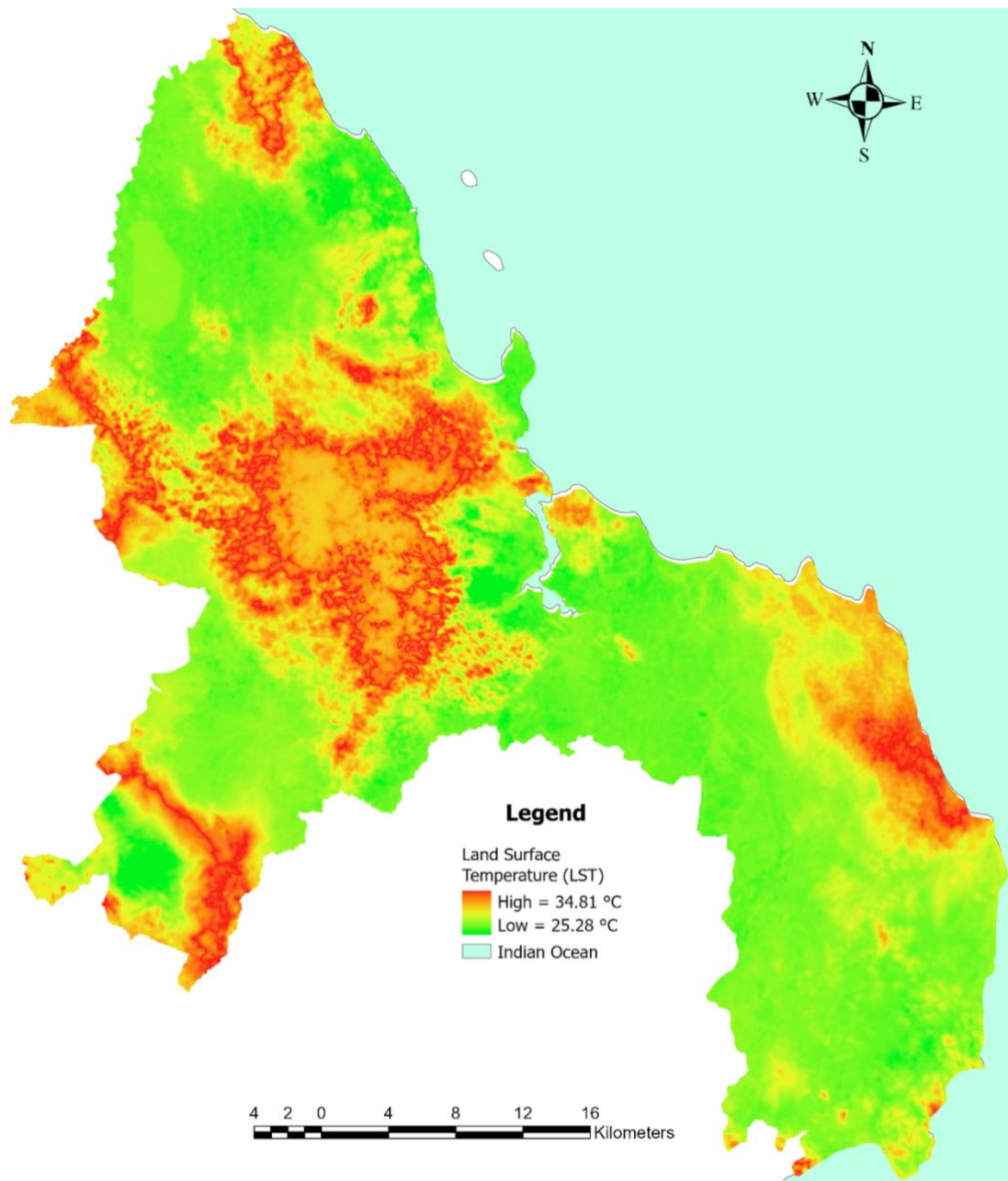


Figure 4.3: Dar es Salaam Land surface temperature (LST), generated from Landsat 9 satellite image (United States Geological Survey) with 30m resolution, image dated 2<sup>nd</sup> April 2021.

NDVI and LST values were then extracted for each of the spatially referenced 1533 surveyed households in Dar es Salaam using the *Extract Values to Points tool* in ArcGIS Pro 3.2.2 to retrieve raster values corresponding to specific locations of interest. The resulting dataset had all relevant socioeconomic and environmental data linked together for further analysis.



### 4.3 Data analysis

Using R 4.4.2 and RStudio 2024.09, binary hypertension prevalence outcome data for individual households were statistically associated with the environmental risk factors which were the independent variables of interest (NDVI & LST), including household-level socioeconomic stressors, such as age, tenure characteristics, employment, property ownership, migration status, housing type and co-existing conditions like diabetes, as well as neighbourhood-level income stratum (Msuya et al., 2024), as additional potential causes of the disease. All variables were selected based on evidence of their association with hypertension and known roles as proximal or distal causes of the disease, as reported by a range of other studies (Leng et al., 2015). The associations of household-level hypertension with all these independent variables were analysed using Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM), with the latter treating neighbourhood as a random effect to capture area-wide spatial variability that could not be accounted for by the other environmental covariates estimated by remote sensing. The dependent variable (presence or absence of one or more formally diagnosed cases of hypertension within the household; See *Household Surveys*) was treated as a binomial outcome for each household and related to the independent variables using a logistic link function.

The modelling started with bivariate analysis of each possible explanatory variable, using both GLM and GLMM as alternative model structures, followed by multivariate analysis of unadjusted followed by adjusted models using the same. In both the GLM and GLMM models, a forward stepwise selection procedure was applied on which the model first included the two remote sensed variables of interest, added in the reverse order of their p values from the univariate analyses and then adding other potential explanatory variables one at a time, again in reverse order of their significance in the univariate analyses (McNamee, 2005). Each

possible explanatory variable other than NDVI and LST were either removed or retained within the multivariate model based on significance and evidence for improvement of model fit, specifically reduced AIC. Although a significance threshold of  $p \geq 0.05$  was applied, independent variables were retained in the model so long as they at least approached significance ( $p \geq 0.10$ ) and improved the model fit.

The final multivariate models, in both GLM and GLMM form, were selected based on the goodness of fit, parsimony and the ability to explain variance and finally the four were compared using the *compare performance* function from the *performance* R package (Lüdtke et al., 2021) which allows to compare models with different structures such as GLM and GLMM. This function was employed to assess models based on several performance metrics, such as AIC, BIC, R-squared and other relevant indicators, to determine the best-fitting model for the data. The comparison provided a comprehensive evaluation of each model's statistical fit, predictive accuracy and complexity, with model performance indices represented graphically to inform the selection of the final model.

#### **4.4 Results**

Out of the 1533 surveyed households, 264 reported one or more diagnosed cases of hypertension, representing an overall prevalence of 20.8% across the sampled study neighbourhoods. The lowest NDVI value estimated for any the households surveyed was 0.049 and the highest was 0.491, while the lowest LST was 25.9 °C and the highest was 34.5 °C. The distribution of age and sex within the surveyed study population is detailed in Appendix 1 and the demographic, spatial and socioeconomic characteristics of the sampled neighbourhoods is outlined in Appendix 2.

The final best-fit adjusted GLMM was selected ahead of the best-fit adjusted GLM model based on their comparative AIC estimates and all the other indices as presented in Table 4.1.

Although the random effect to account for sundry causes of neighbourhood-level geographic variation other than income was clearly worth retaining in the GLMMs, it nevertheless accounted for a notably modest fraction of variance in the final multivariate model (Table 4.2).

Table 4.1: Comparison of model performance metrics for Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM), unadjusted and adjusted. The table displays AIC, AICc, BIC, RMSE, Sigma, conditional and marginal  $R^2$ , Intraclass Correlation Coefficient (ICC), Log Loss and Tjur's  $R^2$ . Graphical representation of selected model is presented in Appendix 3.

|    |                        | Performance Indices |                |                |       |       |                        |                        |       |                       |
|----|------------------------|---------------------|----------------|----------------|-------|-------|------------------------|------------------------|-------|-----------------------|
|    | Indices                | AIC (weights)       | AICc (weights) | BIC (weights)  | RMSE  | Sigma | R <sup>2</sup> (cond.) | R <sup>2</sup> (marg.) | ICC   | Tjur's R <sup>2</sup> |
|    | <i>Model</i>           |                     |                |                |       |       |                        |                        |       |                       |
| 1. | <b>GLM unadjusted</b>  | 1398.1 (<.001)      | 1398.1 (<.001) | 1414.1 (<.001) | 0.376 | 1.000 |                        |                        |       | 0.007                 |
| 2. | <b>GLM adjusted</b>    | 1158.5 (0.228)      | 1158.6 (0.233) | 1206.3 (0.984) | 0.344 | 1.000 |                        |                        |       | 0.187                 |
| 3. | <b>GLMM unadjusted</b> | 1387.8 (<.001)      | 1387.9 (<.001) | 1409.2 (<.001) | 0.372 | 1.000 | 0.047                  | 0.009                  | 0.038 |                       |
| 4. | <b>GLMM adjusted</b>   | 1156.1 (0.772)      | 1156.2 (0.767) | 1214.5 (0.016) | 0.342 | 1.000 | 0.302                  | 0.299                  | 0.005 |                       |

**AIC:** Akaike Information Criterion. Lower AIC values indicate a better fit.

**AICc:** Corrected AIC for small sample sizes.

**BIC:** Bayesian Information Criterion. Lower BIC values indicate a better fit.

**RMSE:** Root Mean Square Error. Lower RMSE indicates better predictive accuracy.

**Sigma:** The residual standard deviation of the model.

**$R^2$  (cond.):** Conditional  $R^2$ , proportion of variance explained by both fixed and random effects in mixed models.

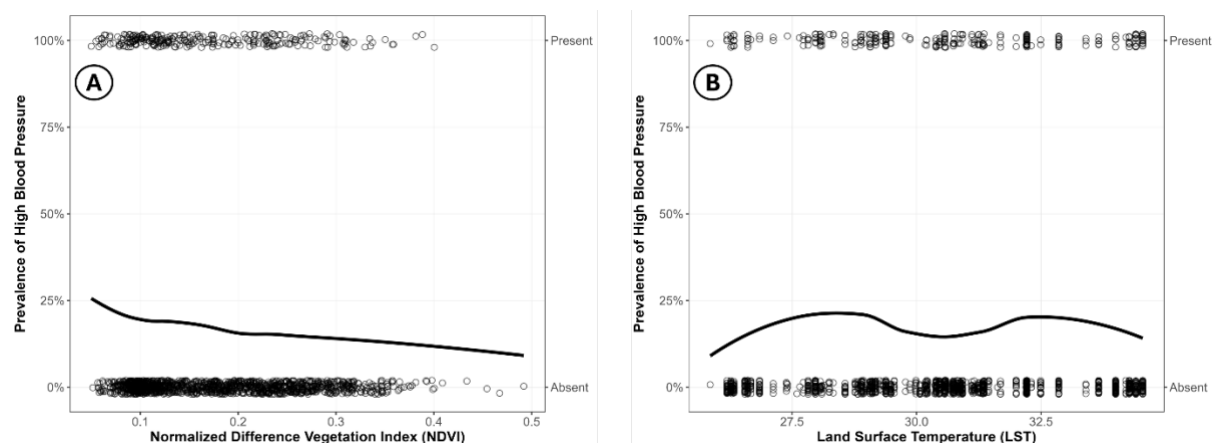
**$R^2$  (marg.):** Marginal  $R^2$ , proportion of variance explained by only the fixed effects in mixed models.

**ICC:** Intraclass Correlation Coefficient, quantifying the proportion of variance due to random effects, indicating model clustering.

**Tjur's  $R^2$ :** A pseudo- $R^2$  for logistic regression, measuring the difference in average predicted probabilities between observed outcome categories

Bivariate analyses indicated no clear association between NDVI or LST and hypertension, although NDVI approached significance. In addition, bivariate analyses indicated that 15 out of the 16 other potential explanatory variables assessed were associated with hypertension and the remaining one approached significance. On the other hand, the final multivariate model indicates that both NDVI and LST are independently associated with hypertension, even after seven other contributing factors found to be associated with occurrence of the disease were accounted for (Table 4.2).

Specifically, the risk of hypertension occurrence was approximately eight times lower in households sitting in areas with highest observed values of NDVI than in those with low values, with the risk steadily decreasing by approximately one third for every 0.1 unit increase in NDVI (Figure 4.4A). The magnitude of this effect size in a multivariate model that also accounts for the effect of LST indicates that green spaces may have a considerable protective effect against hypertension that goes beyond merely reducing ambient temperature. Indeed, the same multivariate analysis indicated an association between the LST and hypertension prevalence that closely approached significance and was independent of the simultaneously estimated effect of NDVI (Figure 4.4A).



**Figure 4.4:** Graphical illustration of the relationship between hypertension prevalence and (A) Normalized Difference Vegetation Index (NDVI) or (B) Land Surface Temperature (LST)

across surveyed neighbourhoods of Dar es Salaam (Figure 4.1). Both panels represent jitter plots of the household-level prevalence data overlaid by the fitted relationships with NDVI (**A**) and LST (**B**), as estimated by the final best-fit multivariate model fit detailed in table 4.2.

Consistent with the findings of others (Charles et al., 2017), univariate analyses indicated that four indicators of co-existing conditions (Age and three categories of other chronic diseases) appeared to be strongly associated with increased hypertension risk (Table 4.1). Reassuringly, these strong associations persisted in the final best-fit multivariate model, with the risk of hypertension being approximately eight-fold higher in households with diagnosed cases of diabetes, five-fold higher in households with diagnosed cases of heart disease and six-fold higher when the age of the head of the household was 40 or more years.

In addition, the multivariate analysis indicates that several other risk factors for hypertension, a few of which are already well known (Rosenthal & Alter, 2012; Rumball-Smith et al., 2014), also appear to have independent effects on risk of this condition. Specifically, having an employed household head was associated with three-fold lower hypertension risk, while having property-generated income appeared associated with an increase in risk by approximately half. Interestingly, living in a co-planned cluster of houses, which are typically developed as estates with amenities that include open spaces, apparently reduced hypertension risk by half.

In contrast, several other potential risk factors that were strongly associated with hypertension risk in simplistic univariate analyses had no obvious effects when included in multivariate models, indicating that they were merely covariant with the other, more directly relevant factors described above. For example, the income category of the neighbourhood where the household was sampled showed no significant association with hypertension. This suggests that community-wide poverty level, while often linked to broader social determinants of health, is not an immediate or direct cause of hypertension in itself in this context. Instead, its relationship

with hypertension may be more distal and complex, acting through a multiplicity of interconnected processes rather than simple, direct, proximal causality. Similarly, neither tenure nor migration status, ownership of a pension, bonds or a refrigerator, or living in a detached house had any obvious influence upon hypertension risk once all the apparently more relevant factors were accounted for in multivariate analyses as described above.

Table 4.2: The results of univariate and multivariate logistic regression analyses (GLMM) investigating environmental and household factors determining the prevalence of high blood pressure (hypertension) in Dar es Salaam City, Tanzania. The analysis explores the normalised difference vegetation index (NDVI) as a green vegetation proxy and land surface temperature (LST) as an indicator of thermal conditions associated with household hypertension prevalence in diverse income neighbourhoods in line with other reported non-modifiable and modifiable household risk factors as confounders. The neighbourhood where the households were surveyed (Figure 4.1) was accounted for as a random effect. Bolded values represent statistically significant results ( $p \leq 0.05$ ), for associations between the independent variable in question and hypertension prevalence.

| Independent variables                                | Univariate         |         |           | Multivariate      |         |        |                   |         |           |
|------------------------------------------------------|--------------------|---------|-----------|-------------------|---------|--------|-------------------|---------|-----------|
|                                                      | OR [95% CI]        | t-value | p         | Unadjusted        |         |        | Adjusted          |         |           |
|                                                      |                    |         |           | OR [95% CI]       | t-value | p      | OR [95% CI]       | t-value | p         |
| Fine scale environmental factors of primary interest |                    |         |           |                   |         |        |                   |         |           |
| Normalised Vegetation Index (NDVI)                   | 0.13 [0.01, 1.38]  | -1.7    | 0.09      | 0.06 [0.00, 0.86] | -2.072  | 0.0382 | 0.04 [0.00, 0.56] | -2.4    | 0.01623   |
| Land Surface Temperature (LST)                       | 0.99 [0.90, 1.09]  | -0.1    | 0.89      | 0.94 [0.85, 1.04] | -1.123  | 0.2614 | 0.92 [0.84, 1.00] | -1.9    | 0.05322   |
| Household Characteristics                            |                    |         |           |                   |         |        |                   |         |           |
| Co-existing conditions                               |                    |         |           |                   |         |        |                   |         |           |
| Any household member diagnosed with diabetes         | 8.33 [5.51, 12.60] | 10      | <<0.00001 |                   |         |        | 5.70 [3.67, 8.88] | 7.7     | <<0.00001 |
| Household head age ≥40 years                         | 6.83 [4.33, 10.76] | 8.3     | <<0.00001 |                   |         |        | 4.63 [2.72, 6.99] | 6.1     | <<0.00001 |
| Any household member diagnosed with heart diseases   | 5.58 [3.38, 9.21]  | 6.7     | <<0.00001 |                   |         |        | 3.27 [1.89, 5.66] | 4.2     | 0.00002   |
| Any household member with long-term illness          | 2.96 [2.09, 4.20]  | 6.1     | <<0.00001 |                   |         |        | 1.54 [0.89, 2.67] | 2.1     | 0.03111   |
| Tenure characteristics                               |                    |         |           |                   |         |        |                   |         |           |
| Owns the house or apartment in full                  | 3.20 [2.28, 4.51]  | 6.7     | <<0.00001 |                   |         |        | 1.35 [0.93, 1.98] | 1.6     | 0.1178    |
| Rents the house or apartment                         | 0.31 [0.21, 0.46]  | -5.8    | <<0.00001 |                   |         |        | 0.94 [0.50, 1.79] | -0.2    | 0.8555    |
| Employment and property ownership                    |                    |         |           |                   |         |        |                   |         |           |
| Household head is employed                           | 0.31 [0.21, 0.45]  | -5.9    | <<0.00001 |                   |         |        | 0.36 [0.23, 0.57] | -4.5    | 0.00001   |
| Any household member with property income            | 1.93 [1.45, 2.56]  | 4.5     | 0.00001   |                   |         |        | 1.57 [1.15, 2.15] | 2.9     | 0.00411   |



|                                               |                   |      |         |                   |        |         |
|-----------------------------------------------|-------------------|------|---------|-------------------|--------|---------|
| Any household member with a pension fund      | 1.62 [1.20, 2.18] | 3.2  | 0.00165 | 1.27 [0.91, 1.77] | 1.4    | 0.1553  |
| Any household member with bonds               | 1.97 [1.29, 3.01] | 3.1  | 0.00171 | 1.45 [0.91, 2.30] | 1.6    | 0.1145  |
| Any member with a fridge                      | 1.49 [1.06, 2.10] | 2.3  | 0.0204  | 1.01 [0.69, 1.46] | 0.04   | 0.96646 |
| <i>Migration status</i>                       |                   |      |         |                   |        |         |
| Never moved                                   | 1.77 [1.24, 2.54] | 3.1  | 0.00185 | 1.14 [0.76, 1.71] | 0.6    | 0.53746 |
| Internal migrant                              | 0.74 [0.55, 1.01] | -1.9 | 0.0598  | 0.94 [0.67, 1.32] | -0.4   | 0.71296 |
| <i>Housing typologies</i>                     |                   |      |         |                   |        |         |
| Cluster of co-planned houses                  | 0.41 [0.22, 0.78] | -2.7 | 0.00691 | 0.44 [0.22, 0.90] | -2.3   | 0.02396 |
| Detached house                                | 1.50 [1.11, 2.03] | 2.7  | 0.00768 | 1.08 [0.77, 1.52] | 0.4    | 0.65496 |
| <b>Neighbourhood-level geographic factors</b> |                   |      |         |                   |        |         |
| Neighbourhood income                          | 1.16 [0.98, 1.36] | 1.8  | 0.073   | 1.08 [0.94, 1.25] | 1.1    | 0.2919  |
|                                               |                   |      |         | $\sigma$          | SD     |         |
| Neighbourhood-level random effect             |                   |      |         | 0.01703           | 0.1305 |         |

OR: Odds Ratio

95% CI: 95% Confidence Interval

p: p-value

$\sigma$ : Variance

SD: Standard Deviation

## 4.5 Discussion

This study emphasizes the importance of examining environmental exposures alongside other modifiable and non-modifiable confounding risk factors. Specifically, it underscores the need to consider the combined effects of multiple variables upon diseases with complex causal chains (Houghton & Paniagua-Avila, 2023). The observed association between NDVI, LST and hypertension, after controlling for immediate household risk factors, suggests that these environmental variables both contribute independently to variations of hypertension prevalence in hot, humid tropical cities. Increased vegetation cover, as measured by NDVI, was associated with a reduction in household hypertension prevalence, whereas rising temperatures, as indicated by LST, had no clear effect upon this epidemiological outcome.

These results are consistent with those of a previous prospective cohort study in China, which indicated that for each 0.1 unit increase in NDVI there was a 40% reduction in hypertension risk (Wensu et al., 2022), comparing well with our estimate of 33% after adjusting for other risk factors. Furthermore, the trend illustrated in Figure 4.4A is also consistent with finding of this complementary study (Wensu et al., 2022) that variability of NDVI has the greatest influence upon hypertension *in absolute terms* at the very lowest end of the range of the former and highest end of the range for the latter. However, by examining this trend using a square root axis, Figure 4.4 reveals that hypertension risk continues to decline steadily with increasing NDVI across the full range of values observed in Dar es Salaam but does so *in proportional terms*. Such an approximately log-linear downward trend could be understandably misinterpreted as a flattening out of hypertension prevalence at relatively high values of NDVI if plotted against a simple linear axis. So, figure 4.4 is actually fully compatible with the conclusions of Wensu et al. (2022) but adds some nuance by identifying a consistent, steady exponential decay in risk up to and including the highest levels of green land cover seen in this representative east African city.

The apparent influence of LST upon hypertension risk is far less clear, with the estimated effect size only approaching statistical significance and accounting for a 0.92-fold increase in risk over the full range of temperature values observed in Dar es Salaam. Although this evidence reported herein for a single city in east Africa is therefore quite uncertain, it is nevertheless inconsistent with the finding of a larger scale global study indicating that a 5°C increase in maximum daily temperature was associated with a modest 3% decrease in hospital admissions associated with hypertension (Bauer et al., 2022).

Despite the differences observed in the current study, our findings suggest that the protective association of NDVI with hypertension is stronger and independent of LST, which is a novel contribution to the existing literature. While the mechanisms underlying this relationship require further confirmation, prior studies offer plausible explanations. First, increased vegetation cover, as indicated by NDVI, reflects the availability of public spaces in urban areas, which can promote physical activity and reduce household and neighbourhood level inactivity (Korpisaari et al., 2024; Xia et al., 2024). Second, vegetation acts as a natural buffer, mitigating surface temperatures a factor already linked to increased hypertension prevalence in urban environments (Keith et al., 2024). Finally, vegetation enhances air quality, which is an important consideration given the established association between poor air quality and elevated hypertension risk in cities (Giorgini et al., 2015).

While the two environmental exposures showed an association with cardiovascular health, the non-modifiable coexisting conditions, such as diabetes, heart disease, long-term illness and the age of the head of household, were the most important confounding factors that also influenced the prevalence of hypertension in the surveyed households. These strong associations are consistent with a large body of existing evidence, which indicated that these factors contribute

to a baseline level of cardiovascular risk, which can be exacerbated by both environmental and other household conditions (Münzel et al., 2021).

For instance, the co-occurrence of diabetes and hypertension is well-documented, with insulin resistance and metabolic dysregulation contributing to elevated blood pressure (Hezam et al., 2024; Sinha & Haque, 2022). Diabetic individuals are more susceptible to vascular damage, which compounds the impact of hypertension (Petrie et al., 2017). In this context, the presence of diabetes was significantly associated with an increased risk of hypertension across all households, independently of the two major environmental factors that were also considered. However, environmental variables such as NDVI and LST may further influence this association. For example, individuals with diabetes residing in areas with higher LST and low NDVI may be more vulnerable to hypertension due to the additional cardiovascular strain induced by heat exposure (Poulsen et al., 2021).

Of course, heart disease is also a critical non-modifiable factor that normally coexists with hypertension for obvious reasons, creating a feedback loop where each condition exacerbates the other (Fuchs & Whelton, 2020). When examined alongside environmental factors, households with existing heart disease may be more sensitive to adverse conditions like high LST, which can further stress the cardiovascular system (Liu et al., 2022). Meanwhile, areas with higher NDVI indicating better vegetation cover, could potentially mitigate this risk by providing a cooler micro-environment than the mean overall temperature, which people naturally gravitate toward and improve opportunities for physical activity.

Perhaps the most epidemiologically relevant nonmodifiable preexisting condition identified herein is age, although only the age of the household head was considered in this study. Hypertension increases with age due to the natural stiffening of blood vessels (Kohn et al., 2015; Sun, 2015), so it is unsurprising that households with older heads had elevated

prevalence of this chronic disease. Also, older individuals may be more susceptible to environmental stressors like high LST due to reduced thermoregulation capacity and increased vulnerability to heat-related cardiovascular events (Ndlovu & Chungag, 2024). On the other hand, the beneficial effects of higher NDVI, such as improved air quality and lower temperatures, may be particularly important for older populations, offering a potential protection against the development or worsening of hypertension in this demographic stratum that also experiences exacerbated risk due to several other non-modifiable factors (Ndlovu & Chungag, 2024).

However, this study also identified additional modifiable risk factors for household hypertension prevalence that have only rarely been reported before, indicating that lifestyle, economic stability and housing conditions have significant implications for cardiovascular health in urban settings. Most striking was the employment status of the head of household, which emerged clearly as a major modifiable risk factor; simply, being employed appears to reduce hypertension risk approximately three-fold. In reference to social stressors, which in some other studies have been reported to not only be associated with cardiovascular health but also mental health in urban areas, unemployment or underemployment can obviously lead to financial stress, a well-known contributor to elevated blood pressure (Tsutsumi et al., 2001). In contrast, employment often provides a sense of purpose and reduces economic stress, with obvious cardiovascular health benefits (Aijaz et al., 2022).

Interestingly, households with property that generates income are often assumed to be more financially resilient, potentially reducing anxiety-related health risks like hypertension (Munford et al., 2020). However, here we found quite the opposite, with 60% higher risk apparent in households in which any member had property-related income. A possible explanation for this might be the older adults are generally more likely to own property

compared to younger generations (Marcinkiewicz, 2023), with age being an obvious risk factor for hypertension. Furthermore, while having an additional income source can alleviate economic pressure, managing property, especially in dense urban areas, can also increase workloads and increase anxiety, potentially leading to higher blood pressure. Additionally, these properties are often located in high-density urban areas with limited green space (low NDVI) and higher LST, which could negate some of the protective effects of the extra income. More obviously, the availability of disposable income may facilitate poor eating and drinking habits, which are well known to cause hypertension. Thus, while property ownership generally correlates with better financial standing, its impact on health outcomes like hypertension may depend on the specific environmental and social context in which it occurs.

Living in houses built within planned clusters by private or government developers, typically comprising estates with shared amenities, was found to approximately halve hypertension risk. While this particular finding is new and perhaps surprising, there are several potential explanations for it in the context of cities with high population and housing density. Firstly, such clustered housing can create a more communal environment, thereby reducing isolation and promoting social interaction, both of which are linked to poor mental and cardiovascular health (Appiah et al., 2022; Lagisetty et al., 2016). In addition, it is likely that residents in most of these communities are younger and therefore at a lower risk for the disease. Furthermore, these areas often benefit from higher levels of vegetation, as communal green spaces are more likely to be included in housing clusters (Bäcklin et al., 2024), increasing NDVI and providing a cooling effect, thereby reducing LST (Perini & Magliocco, 2014). While these environmental factors might contribute to lowering the overall burden of hypertension in clustered housing communities, the multivariate modelling results suggest that such planned housing estates have substantial benefits that are independent of and go beyond them.

Contrary to conventional expectations and findings from past studies which established income as confounding factors in hypertension (Abba et al., 2021; Schutte et al., 2021), this study did not find a significant difference in neighbourhood level income where the households were sampled and the disease present. This indicates that, despite income disparities, environmental stressors affect all groups equally. This contradictory yet important finding points out the complex relationship between socioeconomic status, lifestyle and environmental factors in shaping hypertension risk, while questioning the existing evidence of poverty and cardiovascular health in cities of developing countries with different cultural set up. #

The findings of this study align with existing evidence suggesting that the association between environmental conditions and hypertension is multifaceted and context dependent. As noted by Park et al., (2020) both increases and decreases in ambient temperature can influence blood pressure regulation through physiological stress responses, including vasoconstriction, dehydration, and altered cardiac output. However, these effects are further moderated by individual and environmental factors such as age, chronic disease burden, acclimatisation, housing quality, and behavioural adaptation. In the context of Dar es Salaam, where exposure to heat and humidity is sustained and often compounded by inadequate housing ventilation and limited access to cooling, such interactions may amplify cardiovascular strain (Liu et al., 2022). Nonetheless, it is important to recognise that these pathways operate within a complex system of social and infrastructural determinants, making it difficult to isolate temperature as a singular causal factor. The current study therefore emphasizes the need for integrative approaches that consider both environmental exposures and contextual vulnerabilities in understanding and mitigating hypertension risks in tropical urban environments.

This study had several limitations that should be considered when interpreting the results. First, the absence of individual-level health, demographic or socioeconomic data, as often recorded in other epidemiological studies, limited our ability to account for personal factors such as the wide range of individual ages, lifestyle behaviours and vulnerabilities that could influence hypertension outcomes. This lack of granularity may have led to potential misclassification or underestimation of certain associations. Second, while we considered outdoor environmental factors such as LST and NDVI, we did not have data on indoor air quality, temperature or humidity, all of which are critical components of thermal comfort that could significantly affect hypertension risk in urban areas where people spend most of their time indoors. Additionally, the absence of data on public spaces and tree counts at the finer scale of individual plots limited our ability to precisely measure the quality and accessibility of green spaces. This is important because the benefits of vegetation are not just dependent on the overall presence of green areas, but also on their spatial distribution, density, accessibility and usability, which can differ significantly even within small urban clusters. Lastly, the coarse resolution of socioeconomic stratification at neighbourhood level may have obscured finer-scale variations and associations in these socioeconomic factors. Without detailed individual or household-level socioeconomic data, it was difficult to capture the full spectrum of social determinants that may modulate the effects of environmental exposures and other risk factors for hypertension. This limitation may have contributed to an oversimplified picture of how poverty, employment and housing conditions intersect with environmental risk factors in influencing hypertension prevalence. Overall, these data limitations suggest that future studies should prioritize collecting more detailed individual and environmental data at quite fine geographic scales, to provide a clearer understanding of the interactions between environmental exposures and hypertension in such heterogeneous urban settings.



## **4.6 Conclusion**

Environmental variables like NDVI and LST can either mitigate or intensify the risk of hypertension in tropical cities where vulnerable populations live in densely packed urban environments with high temperatures and low vegetation cover. The finding presented herein imply that access to green spaces and opportunities for outdoor activity can provide natural stress relief and reduce hypertension. Furthermore, the results indicate that modifiable risk factors like employment status, property ownership, housing typology and income levels are profoundly connected with environmental conditions, whereby vegetation cover and temperature regulation not only affect physical health directly but also moderate the socioeconomic pressures associated with urban living. The design of effective public health interventions correspondingly requires a holistic understanding of how environmental and socioeconomic factors interact. While health promotion behaviours are emphasised to inhibit urban lifestyle linked to hypertension, improved urban planning will clearly be required to address important environmental causes of hypertension. Future strategies should therefore focus on integrating these elements, particularly in densely populated urban areas, where both environmental and lifestyle stressors converge. By addressing both environmental quality and socioeconomic conditions, public health initiatives can more effectively target some of the commonly ignored root causes of hypertension, improving outcomes for at-risk populations and contributing to healthier urban environments.

## **4.7 Contributors**

The statistical analysis was conducted by IM. GFK and IM collaborated on the first draft, synthesising research results with IM's input to create a thorough story. FL and IRM participated in the data collection process for the study's household survey design. JO enhanced

the draft manuscript with edits and inputs. GFK also contributed to the study conceptualisation with IM.

Not all authors had full access to all the data in the study, but they had final responsibility for the decision to submit for publication. Data were accessed and verified by IM and GFK.

#### **4.8 Declaration of interests**

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

##### **4.8.1 Data Sharing**

The data supporting the findings of this study are openly available in GCRF Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods: Household Survey and Neighbourhood Focus Group Data from Seven Asian and African Countries, 2021- 2022 at <http://dx.doi.org/10.5255/UKDA-SN-855998>. The imagery data used can be accessed through the United States Geological Survey (USGS) portal <https://earthexplorer.usgs.gov/>.

##### **4.8.2 Role of the funding source**

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# Appendixes

Appendix 1: The age and sex distribution of residents in Dar es Salaam city corresponds to that of the sampled households.

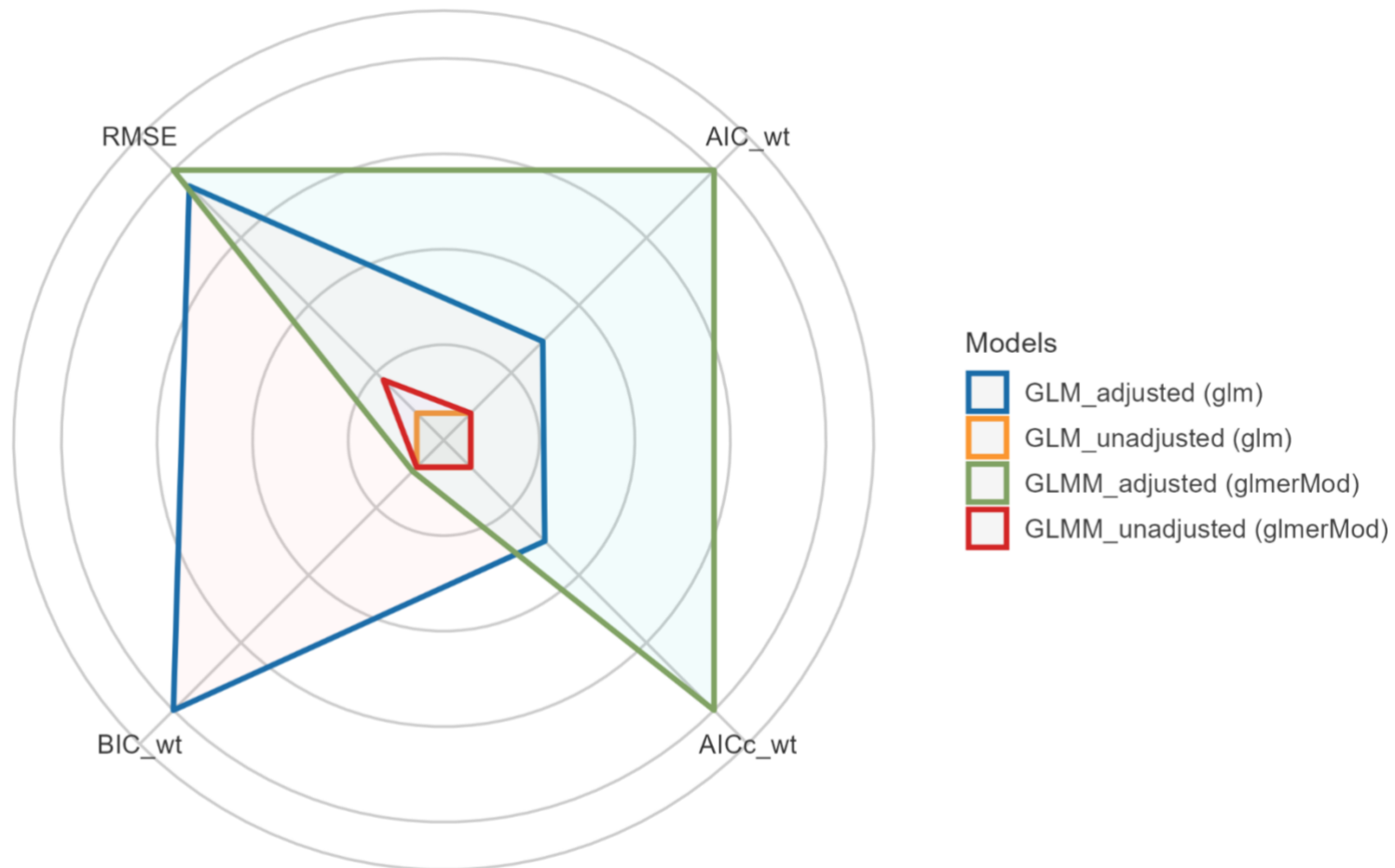
| Age          | Males       |            | Females     |            | Total       |            |
|--------------|-------------|------------|-------------|------------|-------------|------------|
|              | n           | %*         | n           | %*         | n           | %*         |
| 1-4          | 373         | 13.5       | 376         | 10.7       | <b>749</b>  | 12.1       |
| 5-9          | 359         | 11.4       | 400         | 11         | <b>759</b>  | 11.2       |
| 10-14        | 325         | 10.2       | 333         | 8.8        | <b>658</b>  | 9.5        |
| 15-19        | 285         | 9.2        | 327         | 10         | <b>612</b>  | 9.6        |
| 20-24        | 319         | 11.9       | 369         | 14         | <b>688</b>  | 13         |
| 25-29        | 252         | 9.6        | 371         | 12         | <b>623</b>  | 10.9       |
| 30-34        | 254         | 9.3        | 336         | 11         | <b>590</b>  | 10.1       |
| 35-39        | 215         | 6.1        | 280         | 5.9        | <b>495</b>  | 6          |
| 40-44        | 200         | 5.5        | 243         | 5.4        | <b>443</b>  | 5.4        |
| 45-49        | 191         | 5          | 206         | 4.1        | <b>397</b>  | 4.5        |
| 50-54        | 168         | 2.9        | 143         | 2          | <b>311</b>  | 2.4        |
| 55-59        | 90          | 1.4        | 99          | 1.3        | <b>189</b>  | 1.4        |
| 60-64        | 96          | 1.5        | 112         | 1.4        | <b>208</b>  | 1.5        |
| 65-69        | 71          | 1.1        | 81          | 1          | <b>152</b>  | 1          |
| 70-74        | 63          | 0.8        | 42          | 0.4        | <b>105</b>  | 0.6        |
| 75-79        | 23          | 0.3        | 26          | 0.3        | <b>49</b>   | 0.3        |
| 80+          | 18          | 0.3        | 52          | 0.6        | <b>70</b>   | 0.5        |
| <b>Total</b> | <b>3302</b> | <b>100</b> | <b>3796</b> | <b>100</b> | <b>7098</b> | <b>100</b> |



Appendix 2: Demographic, spatial and socioeconomic characteristics of sampled neighbourhoods

| S/n | District  | Ward      | Street          | Population<br>(Census 2012) | Area<br>(Kilometre square) | Population density<br>People/Kilometre square | Income Category       | No. household surveyed |
|-----|-----------|-----------|-----------------|-----------------------------|----------------------------|-----------------------------------------------|-----------------------|------------------------|
| 1   | Ilala     | Kinyerezi | Kinyerezi       | 27200                       | 11.82                      | 2300.48                                       | Medium                | 135                    |
| 2   | Ilala     | G/Mboto   | Ulongoni        | 27624                       | 6.05                       | 4562.41                                       | Mixed low and medium  | 104                    |
| 3   | Kigamboni | Mjimwema  | Mjimwema        | 7413                        | 4.17                       | 1779.12                                       | Medium                | 91                     |
| 4   | Kigamboni | Mjimwema  | Kibugumo        | 4217                        | 8.91                       | 473.45                                        | Mixed low and medium  | 103                    |
| 5   | Kinondoni | Kawe      | Mbezi Beach 'B' | 16531                       | 4.40                       | 3755.40                                       | High                  | 105                    |
| 6   | Kinondoni | Magomeni  | Makuti 'A'      | 6826                        | 0.25                       | 27596.75                                      | Medium                | 100                    |
| 7   | Kinondoni | Kunduchi  | Ununio          | 7187                        | 4.35                       | 1650.46                                       | Mixed medium and high | 111                    |
| 8   | Kinondoni | Mikocheni | Regent Estate   | 2989                        | 1.08                       | 2775.82                                       | High                  | 73                     |
| 9   | Kinondoni | Msasani   | Masaki          | 7619                        | 3.98                       | 1913.10                                       | High                  | 134                    |
| 10  | Temeke    | Azimio    | Mji Mpya        | 9071                        | 0.35                       | 26153.12                                      | Mixed low and medium  | 91                     |
| 11  | Temeke    | Azimio    | Kichangani      | 8180                        | 0.20                       | 40350.63                                      | Low                   | 56                     |
| 12  | Ubungo    | Kimara    | Kimara Baruti   | 13269                       | 3.02                       | 4393.78                                       | Mixed medium and high | 110                    |
| 13  | Ubungo    | Manzese   | Mwembeni        | 9166                        | 0.25                       | 37016.40                                      | Low                   | 99                     |
| 14  | Ubungo    | Goba      | Goba            | 9471                        | 10.20                      | 928.37                                        | Mixed medium and high | 105                    |
| 15  | Ubungo    | Mburahati | Barafu          | 15912                       | 0.51                       | 31263.02                                      | Low                   | 116                    |

Appendix 3: Graphical representation of model performance indices and selection from Table 4.1, illustrating the distribution of key metrics for both Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM) performed.



# 5 CHAPTER FIVE

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## General Discussion and Conclusion

## **5.1 General Discussion and Conclusion**

Building on the empirical findings presented in previous chapters, this final chapter synthesizes the main results across spatial and socio-economic dimensions (Section 5.1 and 5.2), while also situating the Dar es Salaam case within the broader African urban context and global development frameworks (Sections 5.2 and 5.3). It critically reflects on methodological choices and challenges in spatial urban health research (Section 5.4). The following chapter further outlines key limitations and research gaps that warrant further exploration (Section 5.5) before concluding with a forward-looking vision of how to build more equitable, inclusive and healthy cities (Section 5.6). By drawing connections between local realities, national planning strategies and global health agendas, this chapter underscores the urgency of developing context-sensitive, interdisciplinary and community-engaged responses to urban health inequities in African cities undergoing rapid transformation.

## **5.2 Summary of the findings**

This study has provided important insights into how urban environments shape health disparities in Dar es Salaam through three interconnected dimensions, specifically neighbourhood heterogeneities of income and deprivation, environmental risks and consequent disease patterns. The findings of chapter two demonstrated that participatory community-based assessments of neighbourhood deprivation align closely with data-driven statistical approaches, validating local knowledge as a reliable tool for mapping urban inequalities. This convergence suggests that engaging residents in spatial analysis can enhance the accuracy of deprivation mapping, particularly in resource-constrained settings where formal data may be limited.

Linking the neighbourhood socioeconomic strata and health outcomes, specifically chronic respiratory diseases chapter three identified environmental and household-level factors,

including waterlogged terrain, overcrowding and poor waste management as key drivers of disease risk, while ventilation and cooling systems appeared protective. Notably, neighbourhood income does not directly predict respiratory illness, underscoring how poverty is a distal risk factor that operates through intermediary living conditions rather than as a direct proximal biological determinant. Similarly, the hypertension patterns examined in chapter four were strongly tied to environmental features, rather than economic status alone, with urban green vegetation cover showing a clear protective effect against high blood pressure. The marginal association between ambient temperature and hypertension suggests this relationship requires deeper investigation.

Across all findings, a consistent theme emerged: While income stratification identified vulnerable areas, health risks at fine geographical scales stemmed from environmental stressors like susceptibility to flood, inadequate green space and substandard housing. The results challenged purely economic explanations of urban health disparities, showing how spatial inequalities manifested through differential environmental exposures although poverty and deprivation were clear drivers of where people lived and how they lived. The study called for interventions addressing ecological determinants through infrastructure improvements, equitable green space distribution and community-engaged planning. By combining participatory and geospatial methods, the research reported herein provides a model for developing context-sensitive strategies to reduce place-based health inequities in cities of the Global South.

### **5.3 Integrated synthesis of spatial and health inequality findings across Dar es Salaam**

Overall, the study's findings highlighted the intricate relationship between spatial inequality, socio-economic deprivation and health disparities in Dar es Salaam. By integrating results from neighbourhood stratification, environmental risk factors and disease prevalence patterns, this synthesis highlights how urban geography and social inequities jointly shape population health.

The analysis demonstrates that health outcomes are not randomly distributed but instead cluster in specific areas, where residents are often highly exposed to environmental hazards (Msuya et al., 2025). These disparities reflect deeper structural inequities in urban development, where marginalized communities face compounded environmental and social vulnerabilities (Stephens, 2012; WHO, 2025). The following subsections discuss further these relationships in detail, examining the spatial concentration of health risks, the socio-economic mechanisms driving disparities and the policy failures that perpetuate them.

### **5.3.1 Spatial patterns of health disparities**

Health inequalities in Dar es Salaam follow distinct geographic patterns, with informal settlements emerging as consistent hotspots for health risk (Pasquini et al., 2020). The findings from this study challenge conventional assumptions about the primacy of socioeconomic factors in urban health disparities. Instead, they highlight how the built environment creates health risks that transcend economic boundaries. The study revealed that health disparities in Dar es Salaam were primarily driven by differential exposure to environmental hazards, independent of neighbourhood income levels. While environmental risks tended to cluster spatially, their health impacts were remarkably consistent, regardless of the economic characteristics of affected areas. This suggests that environmental exposure, rather than socioeconomic status, served as the primary proximal determinants of health outcomes. This is supported by the fact that even affluent areas with elevated risk of waterlogging were associated with high prevalence of respiratory conditions, while well off neighbourhoods with minimal vegetation cover also exhibited higher hypertension prevalence, of course once other household confounders been accounted for. This shows that environmental risk factors operated consistently across all communities, whether affluent or disadvantaged, indicating that the physical characteristics of the urban environment were more consequential for health than local income levels and other household characteristic.

### **5.3.2 Socioeconomic drivers of health outcomes**

While unhealthy environmental exposures like air pollution, inadequate sanitation, flooding and heat stress are well-established determinants of urban health, this study finds that socioeconomic conditions fundamentally shape how these risks are distributed, perceived and experienced across city neighbourhoods. In Dar es Salaam, where informal settlements dominate the urban fabric encompassing more than 70% of its settlements (Todd et al., 2019), these socioeconomic dimensions are neither secondary nor peripheral, they are central to understanding of how health disparities arose.

Key socioeconomic drivers, including education, employment status, housing quality and access to basic infrastructure and services, mediate both direct and indirect pathways to good or poor health (Allen et al., 2014; Lahelma et al., 2004). These factors often interact with environmental risks in mutually compounding ways. For example, low-income households may lack not only adequate shelter but also the financial and informational resources to avoid or respond to environmental exposures, such as flooding, heat stress or poor air quality (Gootzen, 2025). As such, socioeconomic disadvantage intensifies the health impacts of environmental stressors, while also limiting households' adaptive capacity.

The analysis revealed that the effects of certain socioeconomic conditions on household health outcomes were comparable in strength to direct environmental exposures. This confounding relationship shows that living in a structurally disadvantaged setting, characterized by overcrowding, poor waste disposal and poor housing can be just as harmful as exposure to environmental pollutants or urban heat. These findings in chapter three and four reinforce the idea that health outcomes in Dar es Salaam are not shaped by income levels alone, but by a complex interplay of spatial, infrastructural and social exclusion.

Participatory deprivation mapping played a critical role in validating this insight. Residents consistently identified infrastructural deficits, service deprivation and daily lived experiences of marginalization, rather than only monetary poverty, as defining features of neighbourhood disadvantage. These community perspectives not only aligned with data-driven spatial analyses but also brought attention to important local nuances that conventional metrics often overlook. In doing so, they underscore the value of participatory, community-engaged approaches in identifying the true contours of urban inequality.

#### **5.4 Intra-urban health disparities in African cities**

Intra-urban health disparities are a defining feature of rapidly growing African cities, where spatial, socioeconomic and infrastructural inequalities intersect to produce highly uneven health outcomes (Kilroy, 2012; Nijman & Wei). The case of Dar es Salaam illustrates a broader continental trend as urban populations expand and health risks increasingly concentrate in underserved urban neighbourhoods especially in informal settlements that exist outside the reach of formal planning and service delivery (Pasquini et al., 2020). Across cities such as Lagos, Nairobi, Accra and Kinshasa, health disparities mirror patterns observed in Dar es Salaam, with environmental hazards clustering in low-income areas, while access to healthcare, green space, clean water and waste management remains limited or at least uneven (Sverdlik, 2011; Zerbo et al., 2020). These conditions are compounded by weak governance, limited fiscal capacity and the persistence of colonial-era urban planning legacies that reinforce exclusionary spatial structures (Raveendranathan, 2025).

Importantly, intra-urban health inequalities in African cities are not simply by-products of poverty but are produced and sustained by structural processes, including land tenure insecurity, discriminatory planning practices and underinvestment in basic infrastructure (Dachaga & de Vries, 2022; Factor et al., 2013). The result is a form of urban fragmentation where proximity to services and exposure to environmental risk vary drastically even within



meters with even two dwellings sharing a common wall having different very disease exposure profiles (Msuya et al., 2025) as presented in chapter four. This study contributes to growing evidence that urban health disparities in Africa are deeply spatialized and structurally embedded (Friel et al., 2011; Grant, 2010; Ichoku et al., 2013).

#### **5.4.1 Regional urbanization trends and health risks**

Sub-Saharan Africa is undergoing an unprecedented wave of urbanization, with its cities projected to absorb the world's fastest-growing urban populations over the next three decades (UN-Habitat, 2020). This rapid transformation is accompanied by widespread informal housing growth, infrastructural strain and emerging urban health burdens that increasingly mirror and, in some cases, exceed those of rural areas (Levira & Todd, 2017). A defining feature of African urbanization is its informality, with the majority of urban residents live in unplanned, underserved settlements that are characterized by poor housing quality, inadequate sanitation and minimal access to formal healthcare (Orkpeh & Adedire, 2024; Zerbo et al., 2020). In cities like Dar es Salaam, the majority of the population lives in informal settlements (Todd et al., 2019). This pattern is echoed across other urban centres, Accra, Addis Ababa and Kampala, where rapid natural population growth and rural to urban migration outpaces the capacity of governments to plan, regulate and deliver services (Kamana et al., 2024).

As a result, urban residents face a dual burden of disease. On one hand, communicable diseases such as cholera, malaria and tuberculosis remain prevalent due to environmental contamination, poor hygiene and water insecurity (Bhanye & Bhanye, 2024; Goswami, 2024). On the other hand, lifestyle-related non-communicable diseases (NCDs) like hypertension, diabetes and respiratory conditions are rising due to urban stressors such as air pollution, sedentary living, poor diets and mental health stress as shown in the current study. These emerging health burdens are often unequally distributed, with marginalized communities

facing the highest exposure and least access to prevention or care (Di Cesare et al., 2013; Quinn & Kumar, 2014).

Moreover, climate change and environmental degradation intensify these risks, particularly for low-income households living in flood-prone zones (chapter 3) or in heat islands with little vegetation cover (chapter 4). Urban health outcomes are thus not only shaped by individual behaviours or incomes, but by broader structural conditions rooted in the pace and form of urban growth (Galea & Vlahov, 2005; Thomson et al.; Vlahov et al., 2007).

#### **5.4.2 Scaling local solutions to national policies: how Tanzania and indeed other African countries can adopt Lesson learned in Dar es salaam.**

The findings from Dar es Salaam presented herein offer valuable insights for scaling local, community-driven approaches to mapping health inequities (chapter 2) into broader urban policy frameworks across Tanzania and other African countries. While many of the health risks identified in Dar es Salaam are context-specific, the mechanisms through which they emerge, such as informality, household characteristics and environmental exposures are widely shared across African cities. This opens opportunities for policy transfer, adaptation and national upscaling of effective local practices.

One key lesson is the value of participatory methods in spatial health assessment. The use of community-based deprivation mapping proved not only accurate in identifying nuances to local health risks which are easily obscured in national demographic statistics but also effective in engaging residents as co-producers of knowledge (chapter 2 and Msuya et al., 2025). Institutionalizing such approaches at the national level within Tanzania's urban planning and health surveillance frameworks could improve targeting, accountability and responsiveness, particularly in informal settlements where formal data systems are weakest.

Another lesson is that environmental conditions, not just income, drive urban health disparities. Findings showed that risks such as waterlogging, overcrowding, poor waste management and lack of green infrastructure significantly influence respiratory and cardiovascular health outcomes. These exposures often transcend income levels and are deeply tied to the physical characteristics of neighbourhoods with wealthy households and generally well-off locals often badly affected. The lesson to be learned here is that urban health policy must prioritize environmental infrastructure, such as drainage systems, green spaces and housing quality, rather than relying solely on income-based targeting of health interventions.

In addition, health inequalities are spatially produced and require place-based responses. Patterns of respiratory illness and hypertension were found to cluster in areas with specific environmental stressors, highlighting the spatial embeddedness of health risks. This underscores the need for urban health strategies that are geographically targeted and ecologically informed. The lesson is that addressing disease burdens in cities like Dar es Salaam demands not only health system improvements but also spatial planning that mitigates environmental risks and promotes healthier urban ecosystems.

## **5.5 Global policy implications of the local findings through international frameworks**

The health disparities and spatial inequalities uncovered in Dar es Salaam do not occur in isolation; they are deeply embedded within broader urban and global development dynamics. As African cities grow, local health challenges increasingly intersect with global policy frameworks aimed at promoting sustainable, equitable and healthy urban development (Abejirinde et al., 2022; Grant et al., 2017; Ramirez-Rubio et al., 2019; Vearey et al., 2019). The findings from Dar es Salaam reveal significant barriers to achieving SDG 3 (Good Health and Well-being) and SDG 11 (Sustainable Cities and Communities). While both goals are explicitly linked to improving urban health and living conditions, progress remains uneven, particularly in informal settlements (Todd et al., 2019). The study showed that environmental

exposures, such as indoor air pollution with fungal spores and lack of green space, are core determinants of health, yet they are often overlooked in national SDG3 monitoring frameworks, which tend to prioritize formal health service delivery (Jönsson & Bexell, 2021).

Goal 3's targets, such as reducing mortality from non-communicable diseases and improving environmental health, are directly threatened by the spatial and socioeconomic inequalities documented in this study and other (Oh et al., 2023). Likewise, Goal 11's ambition to make cities "inclusive, safe, resilient and sustainable" remains aspirational in contexts like Dar es Salaam, where informal settlements are structurally and systematically excluded from urban planning and infrastructure investment (Nkengla-Asi et al., 2024). The lesson is clear, as shown in the current study, achieving the SDGs will require greater integration of environmental, spatial and participatory dimensions into health and urban development planning, based on disaggregated, locally relevant data that reflects the lived experiences of marginalized urban residents yet the fine scales that matter most.

## **5.6 Methodological advances and challenges in urban health research**

Urban health research in African contexts is increasingly marked by the need for innovative, context-sensitive and interdisciplinary methods capable of capturing the complexity of health outcomes shaped by spatial, social and environmental factors (Appiah & Grimm, 2025; WHO, 2016). The current study in Dar es Salaam demonstrated both the potential and the limitations of current methodologies, particularly in contexts of informality, data scarcity and rapid urban transformation. The following subsections reflect on key methodological contributions and obstacles encountered during the research process several of which were successfully overcome.

### **5.6.1 Innovations in spatial health mapping, GIS, remote sensing or mixed methods approaches.**

One of the study's key methodological advances was the integration of Geographic Information Systems (GIS), remote sensing data and participatory mapping to assess intra-urban health disparities. GIS technologies allowed for high-resolution spatial analysis of environmental risk factors, such as waterlogging areas, vegetation coverage and land use patterns, which enabled the study to link environmental features directly to health outcomes, crucially they allowed nuanced querying beyond the beyond the level of neighbourhood to scales fine enough to see features that could not be easily captured by the source of data available in most tropical urban contexts.

Remote sensing provided additional insights into urban morphology, informal expansion and green space distribution that may not be possible to get from conventional health surveys. These spatial datasets were combined with household survey data to uncover associations between location, environmental exposures and disease risks such as respiratory illness and hypertension.

A particularly innovative component of the study was the use of community-generated data through participatory deprivation mapping at a neighbourhood level. These mixed methods approach not only enhanced the validity of spatial stratification but also introduced locally relevant indicators such as lived experience, perceived poverty and intra neighbourhood gaps that are often invisible in standardized datasets (Msuya et al., 2025). These innovations underscore the growing potential of spatial tools to inform urban health research, especially when embedded in participatory frameworks. However, their effectiveness depends on data quality, technical capacity and institutional uptake challenges further discussed below.

### **5.6.2 Data scarcity and proxy indicators in measuring informal urban health.**

Conducting urban health research in cities like Dar es Salaam is often constrained by data scarcity, particularly in informal settlements where formal surveys, census data and administrative records are patchy, outdated or non-existent. This data vacuum makes it difficult to conduct accurate health surveillance, track inequalities or monitor progress on urban health indicators (Harpham & Few, 2002; Oh et al., 2023). To address this, the study relied on household level data and proxy environmental indicators (TWI, NDVI and LST) as indirect measures of health risks. While these proxies are useful for capturing environmental determinants, they lack clinical precision and can obscure important nuances in health conditions or access to care.

Additionally, health data from hospitals are often aggregated at administrative or facility levels, which masks intra-urban disparities and underrepresents populations in informal areas where access to formal healthcare is limited or inconsistent due to level pass in attempt to seek better-equipped facilities elsewhere (Green, 2000; Ibrahim, 2011). As a result, researchers must triangulate multiple data sources, household surveys, environmental assessments, participatory mapping and health facility data to approximately represent the full picture.

The use of proxy indicators and alternative data sources is a pragmatic response to data gaps, but it also introduces measurement error, comparability challenges and questions of validity. Future research must invest in scalable, locally adapted data generation systems, including community-led health monitoring through community health workers (CHW) who are now established almost across every street in Dar es Salaam (Geldsetzer et al., 2019) and mobile-based platforms, that can bridge this persistent gap between urban health realities and the data infrastructure available to measure them.

### **5.6.3 Interdisciplinary challenges in melding qualitative context with quantitative spatial analysis.**

Urban health research sits at the intersection of public health, geography, civil engineering, architecture, urban planning and the social sciences (Boarnet & Takahashi, 2005; Corburn, 2004; Freudenberg et al., 2009). This interdisciplinarity is a strength, but it also presents major methodological challenges relating to when integrating qualitative insights with quantitative spatial analysis. In this study, combining geospatial data with community narratives revealed important complementarities. While spatial analysis helped visualize disease clustering and environmental exposures, qualitative inputs from participatory mapping and household interviews enriched interpretation, added nuance and grounded the analysis in lived experience. For example, spatial analysis, in this study initially classified certain areas as dry and low risk. However, ground-truthing and geovalidation revealed hidden signatures of surface water such as stagnant ponds or abandoned houses due to flooding that helped explain the unexpected presence of CRD cases in those locations.

On the one hand, qualitative data are context-rich but often non-generalizable while, on the other, quantitative data are scalable but risk abstraction (Emon, 2024). Integrating them requires deliberate methodological design, flexibility in analytical frameworks and sometimes a willingness to accept partial convergence or even apparent contradiction. This interdisciplinary integration also presents challenges in research collaboration, as disciplinary norms, languages and expectations vary widely (Okafor et al., 2025; Vladova et al., 2025). Urban health research must continue to foster cross-sectoral teams, develop hybrid methods and build analytical tools that respect both statistical rigor and inclusive nuanced that often subjective community knowledge that is sometimes difficult to define clearly. Ultimately, the study's methodological contribution lies in demonstrating that no single approach is sufficient for understanding complex urban health dynamics. A layered, iterative and reflexive approach

is necessary complex in rapidly evolving cities like Dar es Salaam, where informal growth, infrastructural inequality and health vulnerability are deeply intertwined.

### **5.7 Study limitations and directions for future research**

While this study presented important findings regarding the spatial and socio-environmental drivers of health disparities in Dar es Salaam, several limitations must be acknowledged, that may need to be addressed by future research. A key constraint was the absence of individual-level health data, which limited the ability to assess personal risk factors or disaggregate health outcomes by age, gender or occupation. As a result, the analysis relied on household-level data, that, while useful for capturing broader living conditions and infrastructural deficits, may obscure intra-household variations in exposure or health status. More granular data would allow for a deeper understanding of vulnerability within households and improve the targeting of interventions.

In addition, the study faced broader data availability challenges, including gaps in recent census coverage, missing variables related to informal housing typologies and reliance on proxy indicators for environmental and infrastructural exposures. Temporal biases also emerged, as satellite imagery and remote sensing tools used for environmental assessment captured only snapshots in time that overlapped with the period of data collection, potentially overlooking seasonal dynamics and fluctuating risk conditions.

Another limitation lies in the generalizability of the findings. While Dar es Salaam serves as a valuable reference for other large, rapidly urbanizing African cities, its urban governance model, ecological context and infrastructure systems differ from those of smaller cities and towns. Applying these findings to different urban contexts will require careful adaptation, particularly in areas where the forms of informality, climate risks or service provision models



differ significantly. Future comparative research across cities of different sizes, regions and governance contexts would help refine the applicability of spatial health approaches.

Finally, this study points to emerging frontiers in urban health research, particularly the need to explore how climate change intersects with spatial inequality and public health outcomes (Chapter 4). As climate-related hazards, such as flooding, extreme heat and disease outbreaks become more frequent and severe, urban health systems will be increasingly tested, especially in marginalized communities. There is an urgent need for longitudinal studies and community-led monitoring that can track changes over time and assess resilience strategies from the ground up. Integrating climate data, health indicators and socio-spatial variables into a unified analytical framework will be crucial for understanding how cities can build equitable, adaptive and health-promoting systems in an era of climatic and demographic transformation.

## **5.8 Toward equitable cities: concluding reflections**

This study has shown that health disparities in Dar es Salaam are not incidental or haphazardly distributed but are spatially patterned, environmentally mediated, predictable and structurally defined. Drawing on three core dimensions namely neighbourhood deprivation, environmental risks and disease patterns, the research revealed how spatial inequalities shape both the choices people can make such as residential location, and the likely health outcomes they would eventually experience as a result. These patterns challenge dominant narratives that rely solely on income or individual behaviour to explain urban health disparities. Instead, they point to the decisive role of place, infrastructure and ecological exposure in mediating access to health and well-being.

A critical insight from this study concerns the role of data aggregation and spatial scale in shaping how urban health inequalities are often understood and misrepresented. Much of the existing urban health data in Dar es Salaam is collected and reported at highly aggregated

administrative levels, such as wards or districts, which obscures the micro-scale spatial variations that exist between and within neighbourhoods (Msuya et al., 2025). This level of aggregation can mask pockets of vulnerability, especially in informal settlements where health risks are concentrated but invisible in coarse scale datasets. By contrast, this study's use of household-level data and high-resolution spatial analysis allowed for a more nuanced understanding of intra-urban health disparities, capturing localized environmental conditions such as stagnant water, heat exposure and waste accumulation, that are rarely evident in conventional health reporting. The findings underscore the need for urban health data systems to operate at finer spatial scales and to integrate participatory, community-generated inputs, particularly in rapidly changing, data-scarce environments. Without this shift, policy responses risk being too broad, too delayed or misaligned with the actual geography of need.

By triangulating geospatial tools with participatory deprivation mapping, the study demonstrated how neighbourhood stratification closely aligns with both perceived and measurable health risks. The strongest predictors of respiratory and cardiovascular conditions were not income levels but environmental and household features such as indoor air pollution, lack of green space and overcrowding. These findings support a growing body of evidence that calls for shifting urban policy from economic targeting alone toward place-based and ecologically informed strategies (Balvanera et al., 2017; Bentley & Pugalis, 2014; Matti et al., 2025).

The study also highlighted how urban residents, particularly in informal settlements, hold valuable knowledge about the spatial distribution of deprivation. When engaged meaningfully, this knowledge can serve as a powerful planning tool. Moving forward, efforts to build equitable cities must prioritize community-generated data, enhance the granularity of spatial planning and embed health considerations into everyday urban development.

Considering these findings, three priorities emerge for future urban development. First, equity must be spatialized, with health-promoting infrastructure and services planned according to micro-level variations in risk and vulnerability. Second, policy levers must address structural conditions, including land tenure reform, the upgrading of neglected neighbourhoods and the decentralization of health care to underserved areas. Third, achieving urban health equity requires interdisciplinary collaboration and community co-production of knowledge, where planners, public health professionals and residents work as partners in shaping resilient, just and healthy urban futures.

The spatial stratification of cities like Dar es Salaam will continue to influence health outcomes as urbanization accelerates. This study calls for a new urban health agenda, one that moves beyond treating symptoms and begins to transform the spatial and ecological conditions that cause them. Building equitable cities is ultimately a question of justice, inclusion and shared responsibility.

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# Supporting Materials

## Published chapters

**Msuya, I.,** Boudou, M., Levira, F., Moshi, I., O'Dwyer, J., & Killeen, G. (2025). Stratifying urban neighbourhoods by income: Comparison of a subjective participatory approach and an objective statistical analysis of deprivation indicators in Dar es Salaam, Tanzania. *Environment and Planning B: Urban Analytics and City Science*, 23998083251334686.

# Stratifying urban neighbourhoods by income: Comparison of a subjective participatory approach and an objective statistical analysis of deprivation indicators in Dar es Salaam, Tanzania

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## Abstract

Mapping out geographic heterogeneities across urban neighbourhoods can inform urban planning and intervention targeting. Despite their subjectivity, intuitive participatory stratification approaches (PSAs) are becoming increasingly popular because of their affordability and practicality. In contrast, more objective statistical approaches, like latent profile analysis (LPA), typically require rich survey data and advanced capacities that are often lacking in low- and middle-income countries. This study therefore assessed these two distinct approaches, to compare their effectiveness, applicability, and complementarity for identifying geoeconomic heterogeneities of urban neighbourhoods in a typical contemporary African city. This study assessed a PSA to stratify neighbourhoods across the Tanzania city of Dar es Salaam in terms of income, by comparing it with a complementary LPA of national census data to stratify them in terms of deprivation. A consultative community-based workshop was used for the PSA, while 15 selected deprivation indicators from

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Data Availability Statement included at the end of the article



the census data were used to profile them using LPA. While the PSA allocated neighbourhoods to five income strata, six clear deprivation strata could be distinguished by LPA. A strong positive correlation was observed between the stratum identified by the LPA and that obtained through the PSA ( $\rho = 0.739$ ,  $p < .0001$ ). Furthermore, paired comparison of the two sets of correlation coefficients between each deprivation indicator and the stratum assigned by each stratification approach revealed no difference ( $V = 33$ ,  $p\text{-value} = .1354$ ), confirming that the two approaches yielded very similar patterns of stratification. Also, the two approaches yielded broadly comparable cartographic pictures of the city, depicting similar spatial distribution of wealth and poverty. Overall, this evidence indicates that subjective community knowledge and lived experience may be invaluable for understanding built environment and for mapping out pockets of poverty and affluence at fine scales with minimum resources.

### Keywords

Participatory mapping, neighbourhood stratification, income inequality, latent profile analysis, deprivation indicators

## Introduction

More than half of the world's population now lives in towns and cities ([United-Nations, 2016](#)). While Africa and eastern and southern Asia have been urbanized most rapidly, the pace of urbanization in these regions is expected to slow over the coming decade ([UN-Habitat, 2020](#)). Meanwhile, limited government investment in urban planning has contributed to more extensive and overcrowded informal settlements, where approximately 47% of the world's 4.3 billion urban dwellers live ([UN-Habitat, 2020](#)). In Tanzania, for instance, it has been estimated that more than 75% of settlements have been informally developed ([Magina et al., 2020](#)). Indeed, Dar es Salaam is the largest city in Tanzania, where >75% of the population live in informal settlements with highly heterogeneous wealth distribution ([Rasmussen, 2013](#)).

Several historical studies on the early development of what is now the old city centre of Dar es Salaam have rationalized the distribution of settlement patterns in terms of colonial planning processes, which were heavily influenced by residential segregation policies. During the colonial era, the city was planned in a way that segregated people by race and income, with affluent neighbourhoods located near the city centre and along the Indian Ocean (Europeans and Indians) and the less affluent near and around the city centre (black Africans, referred to in that era as natives) ([Brennan and Burton, 2007](#)). The evident pattern in the city demonstrates that a significant portion of its development has unfolded through informal processes ([Msuya et al., 2021](#)). Informal settlements tend to be situated either within formal areas or near them, aligning with the contextual reality of the city's historical evolution. This historical development trajectory has contributed to an uneven distribution of neighbourhood attributes in terms of income and affluence, a disparity that persists today. However, despite the inclination to attribute these disparities solely to colonial influences, a more thorough investigation challenges this prevailing narrative. Contrary to the common assumption that the current state of Dar es Salaam, beyond the old city, is a direct result of colonial planning ([Brennan, 2007](#)), in fact, it emerged from limited planning, especially during the city's rapid expansion from the 1970s onward ([Brennan and Burton, 2007](#)).

While both formal and informal settlements co-exist side-by-side in cities, they exhibit varying neighbourhood characteristics, constantly evolving at very fine scales. This results in a myriad of



spatial, socio-demographic, economic, and cultural diversities coexisting within relatively small, but nevertheless, very heterogeneous geographic areas. This vibrant evolutionary process is particularly dynamic in unplanned, informal settlements, catalysing different types of disparities, such as health inequality, social division, exclusion, and segregation, which are typically assessed in terms of income inequality or socioeconomic deprivation (Odoi et al., 2005). Despite the conceptual differences in how income and deprivation are, respectively, used to assess the two-sided coin of wealth and poverty (Supplemental Box S2), either may be readily applied to surveying the distribution of inequalities across urban areas.

For the first time within the context of internationally agreed development goals, the 2030 Agenda aims to reduce inequality based on income (UN, 2020b). While efforts are being made to bridge the gap between rich and poor (Apel, 2020; Cingano, 2014), there is still insufficient investment in methodologies for socioeconomic profiling of urban neighbourhoods (2020). In response to that methodological need, this study sets out to evaluate a subjective participatory stratification approach (PSA) to classifying neighbourhoods across the Tanzanian city of Dar es Salaam in terms of income, by comparing it with an objective latent profile analysis (LPA) of deprivation based on national census data, see Supplemental Box 2, summary of the relevant evidence base and methodological considerations that informed the formulation of the study design.

## Methods

### *Geographical context and study data*

Dar es Salaam is the largest city in Tanzania, located on the Indian Ocean coast (Supplemental Figure 1). The city had a population of approximately 4.4 million in 2012 but currently has approximately 5.4 million inhabitants, distributed across an administrative area that has remained constant at 1590 km<sup>2</sup> (URT and NBS, 2022). It is also the port in Tanzania, contributing substantially to the national economy and served as a government administrative centre before de facto relocation to the official capital, Dodoma, was practically implemented in 2016 (Todd et al., 2019).

The study reported herein used Tanzania's 2012 Population and Housing Census (PHC) data from the National Bureau of Statistics of Tanzania (NBS) to generate variables which were considered likely to represent deprivation in the study context (Supplemental Table 1). The data is presented via administrative units, starting from regions down to districts, wards (*kata*) and neighbourhoods (*mitaa*, literally translated as *streets* but actually means a larger, formalized administrative area with defined boundaries, rather than just a road and structures built along it). The data from PHC primarily consisted of socio-demographic information such as gender, age, disability, marital status, citizenship, place of residence, education status, migration patterns, economic activities, fertility rates, general mortality rates, and enrolment in social security programs. Other data include household with members who are living in diaspora, food and cash crops cultivation, and information about asset ownership and housing conditions. The current study used data aggregated at the neighbourhood level (Supplemental Figure 1(C)), the finest scale freely available to the public upon request for research purposes to derive deprivation indicators based relevant variables in the PHC (Supplemental Table 1). The dataset included 452 neighbourhoods from three districts that comprised Dar es Salaam at the time (Supplemental Figure 1(A)).

Neighbourhoods in Dar es Salaam city are unevenly distributed, with Kinondoni District having the highest number of neighbourhoods, while Ilala has the lowest number of neighbourhoods (Supplemental Table 2). In terms of population, Kinondoni also has the highest share of residents living in this district, while Ilala is the least. However, from a historical perspective, Ilala stands as the most well-established district, comprising neighbourhoods with a rich legacy that dates back

over a century. On the other hand, most parts of Temeke were relatively new and were experiencing rapid growth and development at the time.

### Study design

A mixed method approach was adopted, based on considerations of the relevant methodological literature ([Supplemental Box S2](#)). Overall, this study sought to assess a subjective participatory stratification approach (PSA) to classifying neighbourhoods in terms of income level by comparing it with an objective statistical approach using latent profile analysis (LPA), to stratify neighbourhoods in terms of deprivation based on socioeconomic data from the 2012 PHC in the Tanzania city of Dar es Salaam. While the income which is referred by the PSA is inherently subjective and based on the lived experiences and knowledge of the city's residents, the LPA of deprivation strata in quantitative terms is a more objective socioeconomic metric derived from formal ways of living standards, conditions, and education at the neighbourhood level ([Dirksen et al., 2022](#)).

### Participatory stratification approach (PSA)

The PSA involved active participation of community members and professionals in the stratification of Dar es Salaam neighbourhoods into different income strata. This 1-day workshop, carried out on Friday, 22<sup>nd</sup> March 2019, from 09:00 a.m. to 17:00 p.m. at Ifakara Health Institute offices in Mikocheni, Dar es Salaam, involved 50 people, specifically five residents from each district recommended by the neighbourhood leaders, two town planners from each district, three community development officers from each district ([Supplemental Table 2](#)), five practicing town planners from the private sector, two urban and regional planning lecturers from Ardhi University, and 13 Ifakara Health Institute scientists working in urban projects in Dar es Salaam. The task started by collectively agreeing on the number of income strata to which the city's neighbourhoods should be assigned. Then, each of the 452 neighbourhoods were assigned to a respective stratum by each individual participant, following which a consensus was established through group discussion to collectively agree on the stratum it was finally assigned to ([Supplemental Figure 4](#)). Although the task fundamentally relied on the participants' knowledge and lived experience of the city, some other complementary sources of information, such as satellite images, were also used to facilitate the process of informed debate and consensus building.

### Latent profile analysis (LPA)

Deprivation profiles were identified as latent (unobserved) variables, inferred from patterns in the observed socioeconomic indicators within the neighbourhood-level PHC data. These profiles were distinguished by analysing the relationships among relevant variables to uncover underlying groupings. The first step of the LPA was the identification of the most appropriate recorded variables. Based on the data and context, 15 variables in the PHC data that were intuitively expected to be closely associated with deprivation were identified. These included education indicators such as *proportion completed any school level*, *proportion educated to university level*, *proportion educated to secondary level*, literacy and language proficiency; *proportion of literate*, *proportion of English literacy*, economic factors; *proportion of potentially economically active individuals*, *proportion enrolled in social security*, *proportion household with members in diaspora*, social and legal indicators; *proportion with registered birth certificate*, demographic factors; *average household size*, *proportion of female*, *proportion of single head households*, and health and mortality statistics; *proportion with disability*, *proportion of death caused by diseases*, and *crude death rate*. Different indicators from the census data were used to derive these variables

(Supplemental Table 1) for participating respondents or households, aggregated at neighbourhood level. To provide a standardized way to compare different quantities while allowing for more accurate and meaningful comparisons between variables in predicting outcomes or estimate probabilities, almost all variables were transformed into proportions, except for household size and crude death rate which were presented in their actual metrics units.

Descriptive statistics of the selected variables can be found in Figure S5 in the Supplementary Material, which shows prior expected general distribution of income and poverty across three study districts at the time, which are consistent with the actual existing situation in the city.

Depending on the nature of data, different six LPA models structures can be used which range from simple to complex, determined by how variance and covariance are treated and whether relationships between variables are considered, thus affecting model parsimony and complexity (Rosenberg et al., 2018). In model selection process, Pearson's rank correlation test was employed to quantify the level of correlation to inform optional specification of model assumption and maximize model performance. In addition, the correlations between variables can help with the interpretation of the resulting latent profiles, as such, if two variables exhibit high level of correlation it can suggest that these two variables may be driving the occurrence of profile and provide insights into the nature of the profile. Broadly speaking, a correlation coefficient  $\rho \geq +/ - 0.4$  and  $p$  value  $\leq .05$  was considered as an indication of strong correlation (Gogtay and Thatte, 2017). The Pearson's rank correlation analysis revealed that a significant correlation existed among 10 out of the 15 variables ( $p \leq .05$ ) (Supplemental Figures 2 and 3). Hence, from the six tidyLPA model structures proposed by Rosenberg et al., 2019, model structure six with varying variances and covariances was selected. It is the most complex model, so while it allows for the estimation of variances and covariances across profiles without constraints, potentially providing a deeper understanding of the relationships between the variables, it is also less parsimonious.

The LPA modelling was performed using R version 4.2.0 and RStudio version 2023.03.0 + 386 with the *tidyLPA* package. *tidyLPA* acts as an interface to the *mclust* package and provides the functionalities to estimate the commonly specified models used in the analysis, with different parameters depending on model complexity according to the structural forms developed by (Rosenberg et al., 2018). Seven criteria were used for best fit model selection (Supplemental Table S3), specifically the Log-Likelihood (LogLik), Akaike Information Criterion (AIC), Difference in AIC values ( $\Delta$ AIC), Consistent Akaike Information Criterion (CLC), Kullback-Leibler Information Criterion (KIC), Sample-Size Adjusted Bayesian Information Criterion (SABIC), and Entropy (Average Uncertainty or Randomness in Latent Class Assignments). Across the existing LPA literature, it has been widely reported that selection of the best fit model with the most informative number of distinct profiles remains a challenging task (Tein et al., 2013). Correspondingly, to validate the model optimization based on the fit statistics, an analytic hierarchy process (AHP), as proposed by (Akogul and Erisoglu, 2017) which helps in determining the correct number of profiles in a model based clustering was used.

Two approaches were used to interpret and assign meaning to each profile from the selected best fit model in relation to deprivation. Firstly, the distribution of the variables was plotted against every profile in a dot and violin plot. Secondly, using z score or scaled mean of each variable on each profile. While median centre data around the second quartiles or 50% quantiles, z score means centre data around zero because the scaling involves standardizing each observed variable to have mean of zero and standard deviation of one ( $\mu = 0$ ,  $\sigma = 1$ ) (DeVore, 2017). In the context of LPA, scaled means are often reported as part of the model output along with other fit statistics. Often, scaled means may have negative value due to scaling even though latent variable has only positive values; however, this does not necessarily indicate that the underlying construct is negative (Little et al., 2006). This helps in comparing the relative positions of the means across variables with different

scales or variances, as well as for interpreting the magnitude and direction of the differences between the means of different profiles.

In LPA, after numbering profiles by ranking them according to their order of score, it is always a task to the investigators to interpret and assign their intuitive meaning (Ferguson et al., 2020). The ranked deprivation profiles were then each interpreted and assigned to name ranked deprivation stratum. The LPA deprivation strata were then compared to the results from the PSA using a non-parametric statistical correlation test (Spearman's rank correlation test), to assess the strength and direction of the relationship between the ranked strata from the two approaches. Further analyses were performed to cross-validate the PSA income strata by plotting values using violin and dot plot for the same PHC variables broken down by PSA stratum. To test statistical significance difference between the two approaches, a Wilcoxon signed-rank test was applied to compare the Spearman's correlation coefficients ( $\rho$ ) obtained for each of these variables compared to either PSA or LPA.

Additionally, using the ranked results from the two approaches, neighbourhood income and deprivation strata from PSA and LPA, respectively, were mapped using ArcGIS Pro 3.1.2, to understand and compare stratification of the city neighbourhoods by the two approaches in terms of comparative spatial distribution. In spatial comparative analysis, ground truthing evidence of the existing conditions in the selected neighbourhoods, specifically, housing density and quality of buildings, using in situ ground photographs and satellite images, was used to provide further descriptive insights into the meaning of the results.

## Results

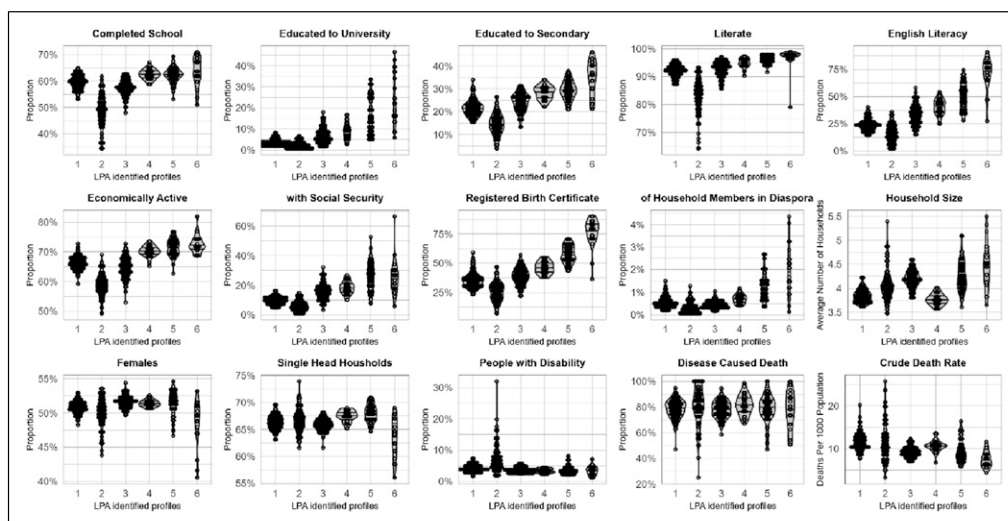
### *Latent profile identification*

The best fit profile model identified by LPA of the census data was with 6-profiles: The goodness of fit consistently decreased as the number of profiles modelled increased, while entropy increased with a 98% classification quality reached for this final optimal 6-profile model that was the last one to converge (Supplemental Table S3). These model optimization results were confirmed using the AHP approach (Akogul and Erisoglu, 2017), which also indicated that the model with 6 profiles was optimal based on the fit statistics in Supplemental Table S3. The results, therefore, suggested that six clear deprivation strata could be identified based on census data, as compared to the five income strata obtained from the participatory stratification approach.

### *Interpreting the underlying meaning of identified latent profiles*

From the dot and violin plots in Figure 1, the value distributions of the most important individual indicators of deprivation show that ranking the numbered LPA profiles based on these same variables, yields an order of 2, 1, 3, 4, 5, and 6 for the profile numbers assigned by the LPA best fit model (Supplemental Table 3). Correspondingly, these were, respectively, assigned the following stratum names; *Highly Deprived*, *Deprived*, *Moderately Deprived*, *Moderately Affluent*, *Affluent*, and *Highly Affluent* (Table 1). To further examine and query these profile assignments based on variable value distributions, a calculated scaled mean for each variable was used (Supplemental Figure 6), consistent with other LPA studies that assigned interpreted profile meanings (Mathew and Doorenbos, 2022; Pastor et al., 2007; Voisin et al., 2018; Yalçın et al., 2021). These scaled means for each variable within each stratum confirmed the same apparent profile order (Table 1) for most variables, as ranked from the most deprived to the most affluent (Supplemental Figure 6).

Based on the interpretation of the LPA identified profiles (Supplemental Figure 6), six assigned deprivation strata could be resolved from the census data (Table 1). On the other hand, however, the results from participatory stratification approach revealed five income classes (Table 2) with *low*



**Figure 1.** Violin and dot plot showing the distribution of values for 15 potential indicators of deprivation recorded by the 2012 national census, broken down across the six profiles distinguished by LPA analysis (Supplemental Table 3). Horizontal lines within the violin plot represent the first, second, and third quartiles, or the 25%, 50% (median), and 75% quantiles. The units for most of these variables are proportions of participating respondents or households, aggregated at neighbourhood level, the only two exceptions being household size and crude death rate.

**Table 1.** Latent profile analysis (LPA) assigned profiles numbers with investigator assigned ranked deprivation stratum names. Based on interpretation of Figure 1 and Supplemental Figure 6, with the number and proportion of neighbourhoods attributed to each stratum.

| Profile number | Assigned profile name              | No. of neighbourhoods (n) | %  |
|----------------|------------------------------------|---------------------------|----|
| 2              | Highly deprived neighbourhoods     | 98                        | 22 |
| 1              | Deprived neighbourhoods            | 117                       | 26 |
| 3              | Moderately deprived neighbourhoods | 115                       | 25 |
| 4              | Moderately affluent neighbourhoods | 33                        | 7  |
| 5              | Affluent neighbourhoods            | 66                        | 15 |
| 6              | Highly affluent neighbourhoods     | 23                        | 5  |

**Table 2.** Neighbourhood income classes obtained from participatory stratification approach (PSA), with the number and proportion of neighbourhoods attributed to each stratum.

| Class number | Assigned classes name       | No. of neighbourhoods (n) | %  |
|--------------|-----------------------------|---------------------------|----|
| 5            | Low income                  | 19                        | 4  |
| 4            | Mixed low and medium income | 88                        | 19 |
| 3            | Medium income               | 199                       | 44 |
| 2            | Mixed medium and high       | 102                       | 23 |
| 1            | High income                 | 44                        | 10 |

*income stratum* accounting for a remarkably low percentage of neighbourhoods while the *medium income stratum* had the highest.

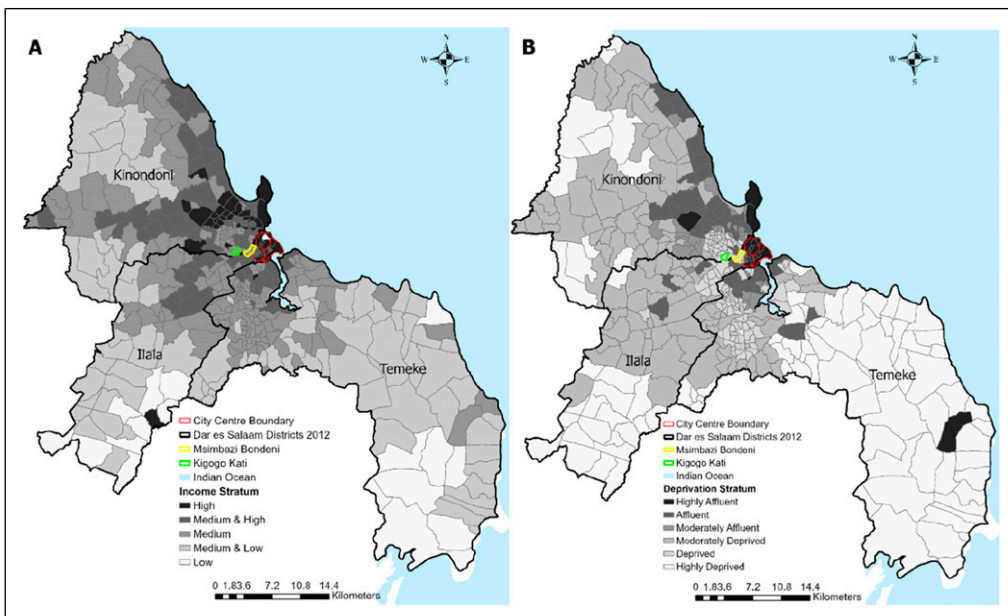
### Comparison of PSA with LPA of the census data

The results of the spearman rank correlation test shows that there is a strong positive correlation ( $\rho = 0.739$ ,  $S = 4,015,865$ ,  $p < .001$ ) between the stratum identified by the LPA of census data and the results of the PSA (Supplemental Figure 7).

The same variables used to stratify the neighbourhoods by LPA yielded distribution of values that were just as consistent with their income stratum as determined by the PSA (Supplemental Figure 8) as they were with their deprivation stratum as determined by the LPA (Figure 1 and Supplemental Figure 8).

Further analysis of Spearman's rank correlation tests between each variable from the census data and stratum rank as determined by each of the two different stratification approaches can be seen in Supplemental Figure S7 in the Supplementary Material. A Wilcoxon signed-rank test to compare these two sets of correlation coefficients in a paired manner revealed no difference between the two approaches ( $V = 33$ ,  $p\text{-value} = .1354$ ), indicating that the two approaches yielded very similar patterns of stratification.

Overall, the two stratification approaches yielded relatively similar cartographic pictures of wealth and poverty distribution across the city (Figure 2). High income, highly affluent neighbourhoods are mainly located in or around the city centre and along the coast to the north, while low income, deprived neighbourhoods are generally distributed along the outskirts of the city. The distribution pattern of the medium income stratum, as determined by PSA, corresponds well with the moderately deprived and moderately affluent strata identified by LPA. Focussing on the city



**Figure 2.** The spatial distribution of income and deprivation strata across Dar es Salaam city neighbourhoods. Panel A: Income strata obtained from the participatory stratification approach (PSA) (Table 2). Panel B: deprivation strata generated from a statistical latent profile analysis (LPA) (Table 1) of population census data.



centre and areas immediately around it, the results reveal patches of low income and deprived neighbourhoods located near high income and highly affluent neighbourhoods, forming a pocket of poverty running from central Ilala into Temeke District. However, in the western direction, this pocket of deprived, medium income neighbourhoods is enclosed by moderately deprived, mixed medium and high income neighbourhoods.

The overall distribution, on the other hand, shows that most of the neighbourhoods classified by PSA as medium income in [Figure 2\(a\)](#), such as Msimbazi Bondeni and Kigogo Kati, have been classified as deprived neighbourhoods by LPA in [Figure 2\(b\)](#). Many of these neighbourhoods are found in the same pocket of deprived neighbourhoods described above that cuts across all three districts but mostly sits in northern Temeke.

Looking at the heterogeneous settlement patterns of these neighbourhoods sheds light on how they were classified differently by the two different methods ([Supplemental Figure 9 and 10](#)). For example, the varying density and quality of the buildings in Kigogo Kati illustrated in [Supplemental Figure 9](#) shows that, while participants in the PSA stratification process considered the mixed housing qualities and density that are clearly visible in panel A to be a reasonable basis for classifying it as medium income, LPA averaged out the diversity existing at fine scale within the neighbourhood and consequently classified it simply as being deprived.

Additionally, while the example in [Supplemental Figure 5](#) outlines the spatial distribution of different building qualities within the same neighbourhood, similar variability is clearly noticeable within some other neighbourhoods. For example, [Supplemental Figure 10](#) illustrates part of the Msimbazi Bondeni neighbourhood, where two housing blocks with obviously different building qualities are found in the same neighbourhood, which has been classified as medium income by PSA but deprived by LPA. Moreover, these two blocks with obviously different mean housing density and quality lie at opposite sides of a steep topographic incline ([Supplemental Figure 10 A and B](#)), with the denser informal settlements with generally smaller, poor quality housing being found in the flood-prone valley to the north of it, while the carefully constructed apartment blocks and planned housing developments ([Supplemental Figure 10 D and E](#)) were all found approximately 20 m uphill to the south. Indeed, as one walks southward along the transect depicted in [Supplemental Figure 10 A and B](#), from the valley up the hill onward along a relatively flat plateau, a clearly noticeable shift is observed in building quality with elevation ([Supplemental Figure 10, panel D and E](#)).

Although there are some differences between the two approaches in the distribution patterns of income and deprivation across neighbourhoods, with very few being classified as purely low income by PSA ([Table 2](#)), the geographic distribution of poverty displayed by the two approaches ([Table 1](#) and [Table 2](#)) nevertheless follow a similar pattern ([Figure 2](#)).

## Discussion

This study contributes to a growing area of research demonstrating similarities and differences in the results obtained through quite different methodological approaches to neighbourhood stratification. The use of LPA has provided valuable insights into the classification of neighbourhoods, particularly in the assessment of deprivation profiles. The results demonstrate LPA's ability to identify statistically distinct discrete neighbourhood deprivation profiles using socioeconomic data, while highlighting its limitation in missing out the complex realities existing at a finer spatial scale within neighbourhoods. This, however, is just one facet of the broader challenge posed by profiling deprivation using aggregated data at the level of the neighbourhoods in which people live, especially in diversified cities like Dar es Salaam. Furthermore, through cross-validation of the two approaches, both statistically and spatially, the results of the PSA yielded very similar patterns of heterogeneity as the LPA, in terms of the distributions of variable values and neighbourhood

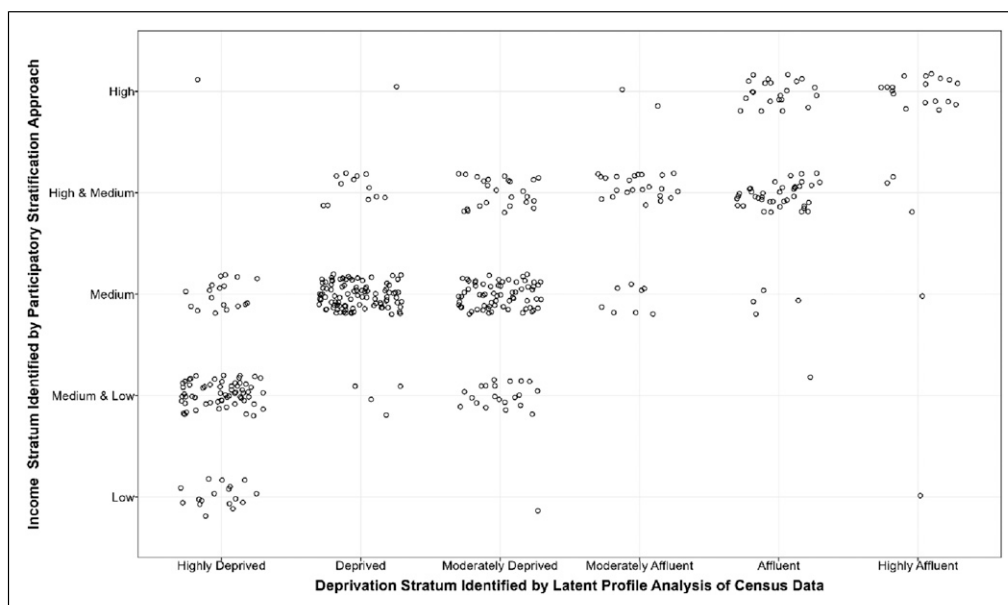
classifications, respectively. Furthermore, PSA proved capable of elucidating several otherwise hidden factors relying on perceived and lived understanding of poverty, which were missed by LPA for understandable reasons ([Supplemental Figure 9 and 10](#)). Akin to many participatory approaches ([Cook, 2018](#); [Emmel, 2008](#); [Israel et al., 2005](#); [Lung-Amam and Dawkins, 2020](#); [Meenar, 2017](#); [Vaughn and Jacquez, 2020](#); [Wallerstein, 2020](#)) relying on the subjective perspectives of contributing participants, the PSA developed in this study, proved to be cost-effective and user-friendly. In contrast, while statistical analyses of formally collected data, such as the LPA approach described herein, have the advantage of being objective, they are also time-consuming, data-intensive and require advanced analytical skills.

Nevertheless, the subjectivity of participatory approaches has been confirmed by the numbers of neighbourhoods attributed to each income stratum. While PSA classified only 4% of the city's neighbourhoods as typically low income ([Table 2](#)), LPA classified 22% as highly deprived neighbourhoods ([Table 1](#)). On the other hand, PSA classified 44% of the city's neighbourhoods as medium income, indicating a bias away from extreme classification assignments. The surprisingly low frequency with which neighbourhoods were classified as low income by PSA participants implies the subjectivity of the approach, as even some small pockets of better housing in a neighbourhood known to be generally very poor often prompted participants to classify it as medium income.

Furthermore, these PSA results seem incompatible with those of previous studies indicating that large African cities scattered all across the continent accommodate large deprived populations ([Kuffer, 2020](#); [Thomson et al., 2020](#)). Additionally, the observation that PSA classified some of the neighbourhoods as medium income while LPA classified them as deprived, requires consideration of the fundamentally different strengths and weakness of these two complementary approaches. A possible explanation for this apparent bias of PSA towards moderate stratum assignment may well lie in the diversity existing at fine scales within neighbourhoods. Such fine-scale heterogeneities can easily be missed by the objective statistical approaches but captured, and perhaps subjectively over-represented, by the qualitative understanding of the city obtained through the lived experiences of the PSA participants, wherein even very small differences in housing quality and infrastructures within neighbourhoods were considered in the stratification. For example, the small blocks of high-quality, low density housing that are highlighted in yellow bordered panels in [Supplemental Figures 5 and 11](#) resulted in these neighbourhoods being classified as medium income, despite being well known as poor neighbourhoods ([Supplemental Figure 9 and 10](#)). Also, the confirmatory stage of the consensus building process in the PSA workshop, resulted in participants providing supplementary justification for their initial income stratum assignment, taking into consideration additional factors that varied across coarser scales than income per se, such as physical accessibility, closeness to the valley, road condition, roof age, and building density. These intuitive considerations, and ability of the PSA to accommodate them in a flexible manner, differentiate the fine-scale lens of PSA from the coarser analysis of the LPA, which unavoidably blurs such heterogeneities within neighbourhoods.

Such mixed contexts at fine scales might also help explain some of the more puzzling outliers in [Figure 3](#), because the nuanced, intuitive and holistic basis of the PSA could result in it being subjectively influenced by the most obvious features and characteristics of a neighbourhood in a disproportionate manner, whereas the LPA relies on an objective representation of the area as a whole. Nevertheless, the two approaches yielded nearly statistically equivalent results, even though extensively surveyed semi-quantitative indicators of deprivation were used for the objective LPA, whereas intuitive qualitative knowledge of much smaller numbers of participants were solicited for the more subjective PSA. This study therefore provides an illustrative example of how these two alternative approaches can be applied to complement and cross-validate each other and in various scenarios with different application requirements for stratification ([Weller et al., 2020](#)).





**Figure 3.** Jitter plot showing the relationship between the neighbourhood classification obtained through the participatory stratification approach (PSA), and through statistical latent profile analysis (LPA) stratification based on national census data.

This study contributes to the growing area of research by demonstrating methodological similarity and differences existing in neighbourhood stratification. It complements the existing literature on economic inequality and urban segregation (Babere and Chingwele, 2018; Babere and Chingwele, 2018; Musterd, 2020; Smiley, 2007; Smiley, 2013; Todd et al., 2019; Vaughan and Arbaci, 2011; Villaça, 2011), which relies for the most part on statistical analysis of empirical data. Furthermore, it suggests that this more subjective participatory approach, which exploits community knowledge of the location, lived experiences and local expertise, could be used in the future without any such data-intensive statistical approaches to validate it. Overall, this study provides clear evidence that cost-effective PSA methodologies could have a variety of practical applications, such as services planning and local tailoring of urban interventions.

While this research reassuringly presents neighbourhood-level income and deprivation profiles, respectively, assessed through a subjective PSA and an objective LPA of formal socioeconomic data, some important study limitations are worth mentioning. For example, the certainty of the findings may be somewhat limited by the fact that, at the time of this study, there were no more recent census data available than those from the 2012 PHC, so the results obtained with the two methods cannot be considered exactly contemporaneous. Similarly, the retrospective post hoc examination of heterogeneities within neighbourhoods (Supplemental Figure 9 and 10) relies on images of contemporary Dar es Salaam, which has obviously changed somewhat since the time that the PSA was conducted and the PHC data used for LPA were collected.

Moreover, the absence of data relating to variables like employment, household incomes, neighbourhood incomes, property ownership, and living conditions (including housing, water, and electricity) restricted our ability to establish a conclusive relationship between income and living standards on one hand and deprivation on the other. These factors are traditionally utilized as indicators for assessing deprivation across various geographical and poverty dimensions.

Consequently, future studies should explore alternative poverty indicators and incorporate updated data when accessible.

Additionally, the study used area-based data aggregated at neighbourhood level, which was the finest administrative scale made available to the investigators, so the stark heterogeneities that clearly exist within individual neighbourhoods ([Supplemental Figure 9 and 10](#)), are obviously blurred around the neighbourhood average income by the LPA and cause underrepresentation of the lowest income neighbourhoods by PSA ([Figure 3](#)). Correspondingly, further research is needed to similarly compare subjective PSAs with objective statistical stratification based on formal survey data at finer scales, which in the context of Dar es Salaam, for example, could relate to 10 cell unit housing clusters. Other avenues for future research can also include studies on how the built environment influences income and deprivation, and how the physical geography of the landscapes those human settlements are built upon affects patterns of income, access to services, health and wellbeing among residents.

## Conclusion

The purpose of this study was to evaluate a PSA to stratifying neighbourhoods across the Tanzanian city of Dar es Salaam in terms of income, by comparing with LPA of deprivation based on national census data. The findings revealed the potential of both LPA and PSA methods and set a precedent for their further application as complementary approaches to neighbourhood classification. With reference to PSA, this study highlights ample room for advancing our understanding of the complex relationships between poverty, location, and socio-spatial dynamics in urban settings. To achieve a more comprehensive perspective, we recommend moving beyond reliance on relatively coarse geographic units for aggregating large-scale datasets. Instead, we propose adopting a finer-grained approach that can capture previously overlooked social, economic, physical, and environmental factors at the very fine scales they can vary across. Overall, such participatory methodologies may be valuable, not only for policy makers, but also for urban planning practitioners and researchers who seek a deeper understanding of the diverse dynamics occurring within towns and cities across various scales. These findings confirm that subjective PSA methodologies offer more affordable and practical alternatives to conventional objective statistical analyses of formal survey data, with which to obtain detailed geographic information to inform planning and intervention targeting in towns and cities all across low and middle-income countries.

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## Author contributions

The statistical analysis was conducted by IM. IM and GFK collaborated on the first draft, synthesizing research results with IM's input to create a thorough story. FL and IRM participated in the data collection process for the study. MB and JO enhanced the draft manuscript with edits and inputs. GFK and FL also contributed to the study conceptualization with IM.

## Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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## Ethical statement

### *Ethical approval*

Ethical clearance for the study, a component of the Sustainable Cities project at Ifakara Health Institute (IHI), was granted by the Institutional Review Board of the Ifakara Health Institute (IHI/IRB/NO.: 26-2018) and the Medical Research Coordinating Committee at the National Institute for Medical Research in Tanzania (NIMR/HQ/R.8a/Vol. IX/2954). Verbal consent, in accordance with the approved protocols, was obtained from all human participants.

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## Data availability statement

The data supporting the findings of this study are openly available in GCRF Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods: Household Survey and Neighbourhood Focus Group Data from Seven Asian and African Countries, 2021–2022 at <https://doi.org/10.5255/UKDA-SN-855998> (Wang et al., 2023). However, census data can be accessed upon request through <https://www.nbs.go.tz/tnada/index.php/home>.

## Supplemental Material

Supplemental material for this article is available online.

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**Gerry Killeen** is an ecologist and epidemiologist who has spent over 18 years living in east Africa, working on the behavioural ecology of mosquitoes and biologically rational approaches to more effective control of vector borne parasites like malaria and lymphatic filariasis, as well as arboviruses like Dengue, Zika and Chikungunya. Gerry's previous work on malaria vectors has helped shape global policies on coverage targets and target product profiles for insecticide treated nets and established implementation models for larval source management with environmentally friendly biological insecticides. Gerry's work on the host preferences and feeding behaviours of malaria vector mosquitoes has influenced ongoing global research investment priorities and his recent move to UCC through an AXA Research Chair Award extends that work to examine how community-based wildlife conservation creates both obstacles and opportunities for enhanced malaria vector control in Africa. Closer to home, undergraduate research projects Gerry supervises include the influence of captivity on vocal territorial advertising by Asiatic lions at Fota Wildlife Park and risks of avian pathogen importation into Ireland through migratory birds.