# Identification of vulnerable urban areas in Accra, Ghana using census and remote sensing data

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# Preface

## *Author Contributions*

I, Robert MacTavish, am the primary author of both this thesis and the manuscript included. I conducted and wrote a literature review of slum classification techniques and research on child mortality differences between vulnerable and non-vulnerable urban areas. I also was responsible for the majority of the analytic work which included the Bayesian logistic regression models, descriptive statistics, and geographic information system (GIS) mapping. I wrote the manuscript included with contributions from others listed below.

Dr. Jill Baumgartner is an Associate Professor in the Department of Epidemiology, Biostatistics and Occupational Health and the Institute for Health and Social Policy at McGill University. She provided guidance and contributed to all aspects of the thesis including the conception of the research goals, data analysis, and communication of the main findings. Dr. Baumgartner extensively reviewed and edited several revisions of every chapter included in the thesis.

Dr. Alexandra M. Schmidt is a Professor in the Department of Epidemiology, Biostatistics and Occupational Health. Dr. Schmidt recommended the Bayesian logistic models used in the thesis, and both contributed to and revised the code used for the logistic models. Dr. Schmidt also reviewed and edited multiple revisions of all main chapters included in the thesis.

Dr. Honor Bixby is a Postdoctoral researcher in the Department of Epidemiology, Biostatistics and Occupational Health and the Institute for Health and Social Policy at McGill University. Dr. Bixby provided support and guidance during the analytical stages of the thesis and provided the estimates of child mortality at the neighbourhood-level.

Dr. Brian Robinson is an Associate Professor in the Department of Geography at McGill University. Dr. Robinson aided in the conception of the project and provided ongoing feedback during the entire duration of the thesis. Dr. Robinson also provided support while collecting remote sensing data such as the Digital Elevation Models (DEM).

Dr. Alicia Cavanaugh is a Postdoctoral Research at McGill University, and also provided feedback during the entire duration of the thesis. Dr. Cavanaugh helped run the statistical models on her computer, and helped revise and edit Chapters 1 and 2.

Dr. Majid Ezzati is a Professor of global environmental health at Imperial College London, and the Director of the Wellcome Trust-Imperial Centre for Global Health Research. Dr. Ezzati provided general guidance for the statistical analyses, and particularly suggested developing a prediction model to predict vulnerable urban areas across the entire Greater Accra Metropolitan Area (GAMA).

Dr. Samuel Agyei-Mensah is a Professor in the Department of Geography and Resource Development at the University of Ghana. Dr. Agyei-Mensah provided support for entry into Ghana, and provided general guidance during the early conception stages of the project.

Dr. Ayaga Bawah is an Associate Professor in the Department of Geography and Resource Development at the University of Ghana, and Research Affiliate at the University of Pennsylvania. Dr. Bawah provided general guidance during the early conception stages of the project and hosted me at the University of Ghana.

### *Thesis Organization*

My thesis consists of an Introduction in Chapter 1, explanation of terminology used in Chapter 2, research objectives in Chapter 3, literature review in Chapter 4, manuscript in Chapter 5, and overall discussion and conclusion in Chapter 6. My introduction provides context on the issue of growing vulnerable urban areas due to ongoing urbanization, introduces techniques to identify such areas and their limitations, and briefly summarizes child mortality differences between vulnerable and non-vulnerable urban areas as an application of vulnerable urban area identification. Chapter 2, focusing on terminology and definitional issues, provides an explanation on why I transitioned from the widely used term "slum" to the term "vulnerable urban area" for my thesis. Chapter 3 describes the motivation for my thesis and lists my specific research objectives. Chapter 4 is a literature review focused on vulnerable urban area identification methods, a description of the strengths and limitations of vulnerable urban area classification techniques, what vulnerable urban area classification techniques have been used in previous studies, and also provides a summary of child mortality research in vulnerable urban areas. Chapter 5 is a manuscript which evaluates the associations of housing, density, and environmental characteristics with vulnerable urban area classification in Accra, predicts vulnerable urban areas across the entire GAMA, and compares child mortality between urban vulnerable and non-vulnerable urban areas as an application of these models. Chapter 6 summarizes, discusses, and draws conclusions of the overall findings of the thesis paper and suggests directions of future research and policy.

## List of abbreviations

AMA: Accra Metropolitan Area
AMAUH: Accra Metropolitan Assembly and UN-Habitat
ANN: Artificial neural network
CBD: Central Business District
CI: Credible interval
CNN: Convolutional neural network
DEM: Digital elevation models
DHS: Demographic and Health Survey
EA: Enumeration area
EFA: Explanatory factor analysis
GAMA: Greater Accra Metropolitan Area
GIS: Geographic information system
GLCM: Grey-level concurrency matrix
GLSS: Ghana Living Standard Survey
GMI: Global Moran's I
GPS: Global Positioning System
GSS: Ghana Statistical Services
HR: Hazard ratio
ICAR: Intrinsic conditional auto-regressive
IMR: Infant mortality rate
IQR: Interquartile range
LISA: Local indicators of spatial association
LMIC: Low- and middle-income countries
MSE: Mean square error
NASA: National Aeronautics and Space Administration
NCSS: Nairobi Cross-sectional Slum Survey
NDVI: Normalized difference vegetation index
NFHS: National Family and Health Survey
NGO: Non-governmental organizations
NIR: Near-infrared
OBIA: Object-based image analyses
OR: Odds ratio
PMR: Postneonatal mortality
QES: Queen Elizabeth Scholarship
SD: Standard deviation
SRTM: Shuttle Radar Topography Mission
SSA: Sub-Saharan Africa
SSI: Slum severity index
TAMSUF: Tema Ashaiman Municipal Slum Upgrading Facility
U5MR: Under-5 mortality rate
UHS: Urban Health Survey
USGS: United States Geological Survey
UN: United Nations
UN-Habitat: United Nations Human Settlement Programme
V-I-S: Vegetation, impervious surface, bare soil
WAIC: Watanabe-Akaike Information Criterion
WHO: World Health Organization

# Abstract

*Background*: Countries in Sub-Saharan Africa are experiencing the most rapid rates of urbanization and urban growth globally. While urban populations, on average, have better access to health services and infrastructure than their rural counterparts, these averages can mask the large inequalities that exist within cities. Vulnerable urban areas in low- and middle-income countries (also known as slums and informal/squatter settlements) pose serious economic, social, and health risks for their populations. Cities must be able to identify, demark, and monitor these vulnerable urban areas to implement targeted policies and interventions that improve living conditions and health.

*Objectives*: I used a Bayesian logistic regression modelling approach to identify vulnerable enumeration areas (EAs; i.e., the smallest administrative unit) and their characteristics in the Greater Accra Metropolitan Area (GAMA) in Ghana. I then applied these results to compare child mortality between urban vulnerable and urban non-vulnerable neighbourhoods in the GAMA.

*Methods*: I obtained cross-sectional data on population housing and living conditions from the 2010 Ghana Census, a map of slums in the Accra Metropolitan Area (AMA) from a 2011 survey conducted by the city of Accra, and publicly available remote sensing imagery. Using these data, I built and evaluated models of the relationship between housing, density, and environmental attributes with the vulnerable urban area classification of 2,418 EAs in the AMA. The dependent variable was an AMA EA's slum classification by the city of Accra, and the predictor variables included housing and living conditions, population density, elevation, and vegetation abundance. The final model was used to predict EA vulnerability across all 4,611 urban EAs in the GAMA, the results of which were overlayed with neighbourhood child mortality from Bixby *et al.* (under review) to compare average child mortality between vulnerable and non-vulnerable urban areas in the GAMA.

*Results*: EA-level variables associated with a higher probability of being a vulnerable urban EA included the use of a public toilet facility for sanitation [OR: 3.51 (95% credible interval (CI): 1.55,7.53)] and greater population density [OR: 5.72 (95% CI: 3.85,8.65)], while variables inversely associated with the probability of being a vulnerable urban area included improved wall materials [OR: 0.11 (95% CI: 0.03,0.43)] and a satellite-derived measure for vegetation abundance [OR: 0.25 (95% CI: 0.16,0.39)]. Approximately 20% of EAs in the GAMA had a vulnerable urban area probability above 80%. Vulnerable urban neighbourhoods had a similar child mortality mean to urban non-vulnerable neighbourhoods [9.1% probability of dying before the age of 5 (sd=1.5%) versus 8.9%, (sd=1.5%), respectively].

*Discussion*: I conducted the first study to use a Bayesian logistic regression model to classify vulnerable urban areas in a low- and middle-income country (LMIC) setting, and expanded on previous studies by incorporating both survey and remote sensing data at high spatial resolution, and assessing the relationship between predictor variables and vulnerable urban area classification. The observed similarities in child mortality between vulnerable and non-vulnerable urban EAs may be attributed to improved health services in the GAMA including universal maternal health services. Future research should investigate other inequalities between vulnerable and non-vulnerable urban areas.

*Conclusion*: My analysis and high-spatial resolution identification of vulnerable urban areas in Accra can inform more targeted interventions and policies aimed at improving housing conditions, infrastructure, and access to urban services for the urban poor.

# Résumé

*Contexte* : Les pays d'Afrique subsaharienne connaissent les taux d'urbanisation et de croissance urbaine les plus rapides au monde. Si les populations urbaines ont, en moyenne, un meilleur accès aux services et infrastructures de santé que leurs homologues rurales, ces moyennes peuvent masquer les grandes inégalités qui existent au sein des villes. Les zones urbaines vulnérables des pays à faible et moyen revenu (également appelées bidonvilles, établissements informels ou colonies de squatters) présentent des risques économiques, sociaux et sanitaires pour leurs populations. Les villes doivent pouvoir identifier, délimiter et surveiller ces zones vulnérables afin de mettre en œuvre des politiques et des interventions ciblées qui améliorent les conditions de vie et de santé.

*Objectifs*: J'ai utilisé une approche de modélisation par régression logistique bayésienne pour identifier les zones de dénombrement vulnérables (ZD, c'est-à-dire la plus petite unité administrative), et leurs caractéristiques dans la grande region métropolitaine d'Accra (GRMA) au Ghana. J'ai ensuite appliqué ces résultats pour comparer la mortalité infantile entre les quartiers urbains vulnérables et les quartiers urbains non vulnérables de la GRMA.

*Méthodes*: J'ai obtenu des données transversales sur le logement et les conditions de vie de la population à partir du recensement de 2010 au Ghana, une carte des bidonvilles de la region métropolitaine d'Accra (RMA) provenant d'une enquête menée en 2011 par la ville d'Accra, et des images de télédétection accessibles au public. En utilisant ces données, j'ai construit et évalué des modèles de la relation entre le logement, la densité et les attributs environnementaux avec la classification des zones vulnérables de 2,418 ZDs dans la RMA. La variable dépendante était la classification des bidonvilles d'une ZD de la RMA par la ville d'Accra, et les variables prédictives comprenaient le logement et les conditions de vie, la densité de population, l'altitude et la végétation. Le modèle final a été utilisé pour prédire la

vulnérabilité des ZD dans les 4,611 ZD urbaines de la GRMA, dont les résultats ont été superposés à la mortalité infantile des quartiers de Bixby *et al.* (en cours de révision) pour comparer la mortalité infantile moyenne entre les zones vulnérables et non vulnérables de la GRMA.

*Résultats*: Les variables de niveau ZD associées à une plus grande probabilité d'être vulnérable comprenaient l'utilisation de toilettes publiques pour l'assainissement [rapport de cotes (RC): 3.51 (intervalle crédible (IC) de 95% : 1.55, 7.53)] et une plus grande densité de population [RC : 5.72 (IC de 95% : 3.85, 8.65)], tandis que les variables inversement associées à la probabilité d'être une zone vulnérable comprenaient des matériaux muraux améliorés [RC : 0.11 (95% IC : 0.03, 0.43)] et une mesure de l'abondance de la végétation dérivée d'un satellite [RC : 0.25 (95% IC : 0.16, 0.39)]. Environ 20 % des évaluations environnementales dans la région de GRMA avaient une probabilité de zone vulnérable supérieure à 0.80. Cinquante-quatre quartiers (13 % des quartiers de la région GRMA) étaient considérés comme des quartiers urbains vulnérables (c'est-à-dire que >50 % des ZD avaient une probabilité de vulnérabilité >0.5), et avaient une moyenne de mortalité infantile similaire à celle des quartiers urbains non vulnérables [9.1 % de probabilité de décès avant l'âge de 5 ans (écart-type (ét)=1.5 %) contre 8.9 %, (ét =1.5 %), respectivement].

*Discussion*: J'ai mené la première étude utilisant un modèle de régression logistique bayésien pour classer les zones urbaines vulnérables, développer les études précédentes en intégrant à la fois des données de recensement et d'enquête, et évaluer la relation entre les variables prédictives et la classification des zones vulnérables. Les similitudes observées en matière de mortalité infantile entre les zones urbaines vulnérables et non vulnérables peuvent être attribuées à l'amélioration des services de santé dans GRMA, y compris les services de santé maternelle universels, mais les recherches futures devraient examiner d'autres inégalités entre les zones vulnérables et non vulnérables.

*Conclusion*: Mon analyse et mon identification à haute résolution spatiale des régions vulnérables d'Accra peuvent permettre des interventions et des politiques plus ciblées, afin d’améliorer les conditions de logement, les infrastructures et l'accès aux services urbains pour les citadins les plus pauvres.

# Chapter 1: Introduction

## 1.1 Urbanization and the Growth of Slums in Sub-Saharan African Cities

Over half of the world's population currently lives in urban settlements (1), and estimates predict this number will increase to over two-thirds of the world's population by 2030 (2). Sub-Saharan Africa (SSA) has experienced the world's fastest urban population growth rates and is projected to increase from 294 million inhabitants in 2010 to 621 million in 2030 (3–5). Urban growth in SSA is mostly driven by the redistribution of populations within countries rather than migration between countries (2,6,7). Rural to urban domestic migration is most common, increasing the proportion of urban SSA inhabitants from 10.7% in 1950 to 30.8% in 2000 (7). Population resettlement from rural to urban areas is attributed to several pull factors including: the promise of greater economic opportunities; improved access to services such as health care and education; younger and more mobile populations immigrating into large cities with increased social stability and cultural diversity; and environmental push factors related to farm land degradation and natural disasters (2,5,6,8,9). Rapid urbanization stresses already inadequate urban infrastructure, and cities are unable to provide affordable and safe housing, roads and methods of transportation, and sufficient access to basic services (e.g., sanitation, clean water, refuse removal) for their growing populations. This particularly affects the poor and middle classes, forcing over a billion urban residents into what are most commonly referred to as "urban slums" (6,10–12). Slums are urban areas where a majority of residents live in inadequate housing conditions and disproportionately experience: adverse health outcomes with reduced health services and increased transmission of communicable diseases; social exclusion; poor environmental conditions; lower levels of education and literacy compared to other urban areas; unemployment and lack of economic opportunities; and gender inequality (11).

Some slums are administratively defined by governmental agencies to aid in urban planning and management, where the term "slum" describes often well-established neighbourhoods that historically had deprived conditions, experienced widespread poverty, and/or were oftentimes outside of governmental jurisdiction. More often, slum communities are difficult to administratively define due to their ambiguous and rapidly changing boundaries, and high degree of complexity and heterogeneity in their features (13). Slums experience varying degrees of deprivation (14,15), and even within the same city, can vary considerably in their size, history, public perception, economic opportunities, and socio-cultural characteristics (16,17). Perhaps the most commonly used definition of a slum is from the United Nations Human Settlement Programme (UN-Habitat), which defines slums as the most deprived areas in a city based on inadequate and unsafe housing and living conditions (11). However, this definition only considers household characteristics rather than environmental or social attributes, and may overestimate the abundance of slum households in LMICs. Moreover, the term "slum" has been criticized because it may stigmatize communities and can be used to justify inhumane forced evictions (18–20). New terminology is needed to conceptualize deprived areas in LMICs, and to locate areas where infrastructure development and social policy is required, without stigmatizing low-income families and communities.

### 1.2 Slum Identification Research in Low- and Middle-Income Country Cities

The development of methods that can differentiate between urban slum and non-slum areas is a necessary first step to: provide localized interventions; improve living conditions through infrastructure development and provision of services; and investigate the unique health, social, and economic challenges faced by populations living in slums. The main methodologies used to distinguish between urban slum and non-slum areas can be broadly classified as either remote-sensing based techniques (21–25) or survey-based approaches (24–30), although other methods such as field-based mapping or mixed-method techniques have also been used (31,32). A detailed review of these different methods is provided in *Chapter 4.4 Methodological Approaches to Slum Identification and Spatial Mapping*. Briefly, remote sensing techniques using widely available satellite imagery are generally more efficient; however, they cannot account for household characteristics and are not generalizable due to the heterogeneity of slums. As most health surveys and censuses in LMICs do not collect data on slum residency, a large portion of slum classification papers using survey data use the UN-Habitat's five criteria definition to quantify slum households (24–30,33,34). These data are available from censuses and from Demographic and Health Surveys (DHSs). The UN-Habitat additive slum index method has several limitations: it does not provide weights for variables based on the importance in predicting slum households; it relies on the subjective dichotomization of important predictors of household poverty; it does not investigate how each of the predictor variables is associated with slum classification; and it does not account for population density or environmental quality. A method of slum identification accounting for housing and environmental characteristics is needed to assess how the inadequate living conditions of slums contributes to poor health and wellbeing.

## 1.3 Social, Economic, and Environmental Determinants of Health and Wellbeing in Slums

Slums settlements are characterized by chronic poverty and socio-spatial exclusion, which puts them at greater risk of adverse health outcomes (11). The UN-Habitat classically defines a slum household as lacking: sufficient living space in a household (e.g., no more than three people share a sleeping space); durable housing materials; access to sufficient and safe drinking water at an affordable price; secure tenure; and access to improved sanitation, which is able to effectively separate excreta from human contact (11,15).

Slums expose their residents to a number of adverse social, economic, and environmental health risk factors that are known to increase the risk of poor health. Inequalities between urban slum and non-slum areas are related to social, environmental and economic risk factors such as: a lack of gender parity (35); decreased parental education (36); food insecurity (37,38); flooding which may propagate various illnesses such as malaria, cholera or dengue (39,40); decreased immunization rates (41,42); and deteriorating and unsafe housing conditions (14). Risk factors for poor health have been reported in urban slums in SSA, however there is relatively limited research comparing health among residents of urban slums versus non-slums in SSA as most censuses and health surveys do not distinguish between slum and non-slum areas (43,44). Differentiating health outcomes between urban slums and non-slums is important for policy efforts to ensure that people living in the poorest areas of a city do not experience inequitable health outcomes, and can help identify areas which may benefit from health interventions.

### 1.4 Child Mortality in Sub-Saharan African Cities and Slums

In 2015, the United Nations introduced the ambitious goal to end preventable deaths in children under 5 years old by 2030 in the Sustainable Development Goals (SDG-3) (45), with a quantifiable goal of reducing child mortality to 25 deaths per 1,000 live births. Child mortality rates have declined across nearly all countries over the past several decades (46,47), from 77.8 deaths to 42.5 deaths in children per 1,000 live births between the years 2000 and 2015 (3). However, this reduction in child mortality was heterogeneously distributed (47,48), with lower-income countries continuing to have relatively high levels of child mortality (48,49). For example, SSA has the highest child mortality rates (76 child deaths per 1,000 live births in 2019) compared to the global average (38 child deaths per 1,000 live births)

(50). As of 2015, SSA contained the ten countries with the highest child mortality rates worldwide, each having a child mortality rate over 90 deaths per 1,000 live births (47).

Children living in urban areas in SSA generally have lower child mortality rates compared with rural areas (51–53). In a study including 35 SSA countries, child mortality in rural areas was significantly higher than urban areas in 16 countries, while only 2 countries had significantly higher child mortality in urban areas (51). Yet aggregate data can mask the high inequality in child mortality that exists within urban settings, as the urban advantage may not apply to children living in urban slums. Multinational studies found higher child mortality rates in slum neighbourhoods compared with non-slum neighbourhoods in the same country, and the mortality rates were much closer to those seen in rural areas (26,27,54–57). An international study conducted in 45 LMICs reported 20% higher child mortality in urban slum neighbourhoods compared with non-slum areas (27). Yet the literature considering child mortality differences between slums and non-slums has several limitations: it is lacking in many large urban city centres; it is reliant on UN-Habitat's additive index to classify slums; the unit of analysis is often at the country-level rather than finer spatial scales; and child mortality is rarely mapped visually. Assessing differences in child mortality between identified slum and non-slum areas at fine spatial scales can identify areas of high risk and facilitate the implementation of more localized public health policies and programs to allow for more equitable health governance.

# Chapter 2: Defining and Conceptualizing Slums as "Vulnerable Urban Areas"

The term "slum" is pejorative and stigmatized in many settings. In this thesis, I transitioned away from the slum label, which often evokes negative connotations of people and communities, and instead employed the term "vulnerable urban area" which highlights the place and role of physical and social environments in low-income urban areas. Adapting Jankowska *et al.*'s (2012) definition of vulnerability, the manuscript in this thesis uses the term "vulnerable urban areas" to describe urban areas with physical, social, health, and demographic characteristics that make populations more vulnerable due to exposure to hazards or stressors (30).

The term "slum" is problematic as it often focuses on people and communities who live in low-income areas rather than highlighting the issue of substandard, inequitable, and unsafe living conditions (19). For example, young people living in Nima, a neighbourhood identified as a slum in Accra, reported finding it difficult to secure employment and achieve financial security because they reside in a "slum" neighbourhood (58). Use of the evocative term "slum", along with the politically-motivated goals of creating "slum-free" cities, may be misused in policy and result in unintended consequences including the forced eviction of vulnerable residents from their homes and communities (18–20). The label "slum" can also be subject to political rationales or may exclude other parts of a city, especially in newly emerging areas, which have similar conditions but are not recognized as slums, *per se*.

A number of alternative terms to "slum" have been proposed including "informal settlements", "squatter settlements", and "deprived areas" (30,59,60). These terms are often used interchangeably, but they are not synonymous and illustrate different aspects of living conditions and environments (30,59). Informal or squatter settlements refers to places where residents occupy the land and/or build structures illegally or outside of governmental regulation, and are among the most commonly used alternative terms to “slum”. While insecure tenure undoubtedly increases vulnerability, this classification does not fully encompass other conditions such as overcrowding, safe sanitation and drinking water, and housing durability (59). Informal settlements are not necessarily always low-income and, conversely, low-income neighbourhoods are not always informal. More recently, the alternative term “deprived area” was proposed by researchers to describe settlements where the urban poor live (61). Neighbourhood deprivation considers several factors including crime, health accessibility, water and sanitation, and public infrastructure (61); however, no formal and standardized definition of deprivation areas exists as it encompasses many factors such as crime rates which cannot be captured in available survey or remote sensing data. For these reasons, we employ the new term “vulnerable urban area” instead of other alternative terms used in past research.

In chapters of this thesis that are reporting on previous studies and papers, including *Chapter 1: Introduction* and *Chapter 4: Literature Review*, I use the terminology that was used by the authors of those studies, which was most commonly “slum”. In chapters related to my analysis, including *Chapter 3: Research Objectives*, *Chapter 5: Identifying vulnerable urban neighbourhoods in Accra, Ghana using census and remote sensing data*, and *Chapter 6: Discussion and Conclusions*, I instead use the term “vulnerable urban areas”.

# Chapter 3: Research Objectives

Since the 1950s, SSA has experienced the world's fastest urban population growth, and is expected to grow to 621 million inhabitants by 2030; however, the insufficient capital and resources of many SSA countries is driving urban populations into vulnerable urban areas which are characterized by poverty, overcrowding, the presence of multiple environmental hazards, insecure land and housing tenure, and a lack of access to services (3,11). An estimated one billion people globally, including 238 million residents of SSA, currently live in vulnerable urban areas (12,62), and this number is projected to increase to approximately three billion by 2050, including 1.2 billion residents in Africa (11,63–65). The growing populations in vulnerable urban areas pose concerns for accomplishing economic, social, and environmental equality in LMIC cities.

Spatially identifying and defining vulnerable urban areas enables policymakers, governments, and non-governmental organizations (NGOs) to quantify populations living in vulnerable urban areas and to implement more geographically targeted policies and interventions. Yet pre-existing demarcation of vulnerable urban area boundaries rarely exist, and previous studies aiming to identify vulnerable urban areas in cities did not account for both housing and neighbourhood characteristics that comprise them or quantify the relationship between important housing, density, and environmental characteristics with vulnerable urban area classification. In this thesis, I use spatially resolved census and remote sensing data to develop a Bayesian logistic regression model to identify and classify vulnerable urban areas in Accra, investigate the associations between housing and neighbourhood or environmental characteristics with vulnerability, and assess differences in child mortality between vulnerable and non-vulnerable neighbourhoods in GAMA as an application of the regression model. The specific objectives of my thesis are:

1. To develop Bayesian regression models of enumeration areas (EAs) for “vulnerable urban area” classification in the Accra Metropolitan Area (AMA), and to interpret associations with housing, density, and environmental predictor variables;
2. To apply our models developed in Objective 1 to predict the probability of all urban EAs in the GAMA as being a vulnerable urban area; and
3. To compare child mortality between neighbourhoods identified as vulnerable urban and non-vulnerable urban in the GAMA.

# Chapter 4: Literature Review

I conducted a scoping literature review to: (1) describe how slums emerge in a SSA and Ghanaian context; (2) examine the methods used to identify and distinguish urban slum versus non-slum areas; and (3) investigate literature on inequalities in child mortality between slum and non-slum areas. I used the following search engines to identify relevant peer-reviewed journal articles for my literature review: PubMed, Scopus, Google Scholar, and WorldCat Discovery. Search terms were used to search by article title, abstract, or keyword, and all articles used were published in English. From the search results, the papers reviewed were selected based on first scanning the title, and then reading the abstract to ensure they contained relevant information pertaining to either slum classification or child mortality in slums. In order to identify articles on slum classification techniques, I used the key search terms ("*slum*" or "*informal settlement*" or "*deprivation area*") and (*classification* or *identification* or *mapping* or *boundaries*). In total, these search criteria resulted in 854 studies identified in Scopus and 125 identified in PubMed. Articles with Accra, Ghana as the study location were prioritized in the literature review as it is the city of interest in my thesis. To identify research articles that investigated child mortality outcomes between slum and non-slum areas, I used the search terms (*slum* or *informal settlement*) and (*under-5 mortality* or *child mortality* or *neonatal mortality* or *infant mortality* or *under-5 deaths* or *U5MR* or *child deaths* or *infant deaths*). Scopus and PubMed identified 325 and 67 articles respectively. I identified an additional 5 research articles relevant to slum identification and 1 research article relevant to child mortality in slums by scanning the references in the selected papers.

### 4.1 Population Growth and Urbanization in Sub-Saharan Africa

The percentage of the global population living in urban areas has increased at an unprecedented rate, from 30% in 1950 to 55% in 2018, and is expected to further increase to 68% of the global population by 2050 (2,66,67). The absolute number of urban residents is growing at increasingly higher numbers, as the annual increase in urban residents changed from 57 million between 1990-2000 to 77 million between 2010-2015 (68). By 2050, the global urban population is expected to increase by 2.5 billion people, with 90% of this growth occurring in Asia and Africa (2). This growth is driven by a combination of factors including high fertility rates in cities, rural-to-urban and international migration, and rapid urban sprawl that transitions rural areas into peri-urban or urban settings (69). The perceived and often realized benefits of living in cities, including educational and employment opportunities, social benefits, accessible services, and cultural enrichment, are important drivers of these global trends.

In 1950 SSA was the least urbanized global region with under 15% of the total population living in urban areas (1), but the region's urban population rapidly increased during the post-independence phase period from 33 million in 1960 to 307 million in 2010 (70). At present, the urban growth rate is the highest urban growth rate globally at approximately 4.1% (70). The dominant migratory trend in SSA is the redistribution of populations from rural to urban settings within the same country, rather than migration between countries (2,6,7). Urban land cover in SSA is projected to grow 12-fold between 2000 and 2050 (71), as rural and peri-urban areas are integrated into cities. In SSA, the rapid urbanization and increasing urban population is alarming, as there remain concerns that the urban population growth rate in LMICs is outpacing the ability of these countries to provide adequate services and housing to all citizens (3,68).

### 4.2 Emergence of Urban Slums and their Development Over Time

The term “slum” has been used to describe communities living with insufficient housing conditions and poverty, and their presence has been documented for as long as large urban cities have existed (14,65). The earliest use of the term “slum” dates back to the 1800s in England, and typically described areas such as Jacob’s Island with outdated housing of poor quality, however authorities began identifying slums for concern of the propagation of infectious diseases (19,72). Slums are known to be heterogenous in their size, morphology, quality of living conditions, history, and culture (73,74). Urban slums emerge and grow for a variety of reasons, but their presence is most commonly a symptom of rapid urbanization paired with poor governance, inadequate urban infrastructure and services, and economic inequities disadvantaging the urban poor (65,75,76). Factors shown to contribute to slum emergence across many settings include: rapid rural to urban migration in search of better employment and educational opportunities; the suppression of entire communities by governments and businesses to capitalize on low-paid labour; unplanned migration into cities resulting from natural disasters, war, or forced displacement; the inability of cities to provide adequate affordable housing or to enforce planning regulations; a continued cycle of poverty where children born into slums lack the financial resources or connections to move out of them; and people remaining in established slums to remain in proximity to their family, livelihoods, and communities (14,65,75–78).

Globally, although the proportion of the urban population living in slums has decreased from 28% in 2000 to 23% in 2014, the absolute number of slum inhabitants still increased from 93 million to 200 million between 1990-2014 (2,11,14,79). Slums may exist as established communities which persist for decades experiencing perpetual cycles of intergenerational poverty and continue to grow in size. Established slums are often: large in size and have durable structures which makes slum upgrading difficult due to the high economic cost; experiencing rapid urban population growth paired with an unmet need for land and housing; and difficult to relocate because of the establishment of families, communities and livelihoods (65,78,80,81). Although there may be inadequate amenities in a slum, such as lack of drainage systems or formal urban planning, a majority of residents may still have tenure security (e.g., renting an owned property), making forced evictions or upgrading projects difficult (82). On the other hand, temporary slums may emerge and disappear relatively quickly, which could be due to: the development of migrant camps of temporary workers; small size slums with insecure tenure which are easier to upgrade or relocate; and temporary housing structures which are easily removed such as make-shift tents (80,83). Temporary slums have high temporal dynamics, such as slums in Bangalore which can virtually emerge and then disappear within 100 days (80), indicating that changes in temporary slums may occur in a matter of months or even weeks, compared to established slums which may persist for decades. Temporary slums are therefore more difficult to capture with cross-sectional survey data or satellite image analysis due to their small size and potentially short-lasting existence (83). With adequate financial support, cities may also successfully upgrade established slums, which could involve: rehousing where temporary structures such as shacks are demolished and replaced by new housing units, such as apartment buildings; re-siting, where slum residents are relocated to other areas of the city with low-income housing; and restructuring, where residents may remain in their homes, however the services and infrastructure surrounding their homes are upgraded, such as water and sanitation facilities (81,84).

#### *4.2.1 The emergence and growth of slums in Accra, Ghana*

The development of Accra as a large urban centre started in 1877 when the British colonial headquarters were moved from Cape Coast, Ghana to Accra due to the preference of largely uninhabited areas to protect Europeans from native diseases, and a recent earthquake in 1862 allowed colonizers to rebuild Accra (82). The colonization of Accra subsequently resulted in the influx of trading and higher economic power (82). This colonization also resulted in the demolishment of low-income areas to make way for a European-styled central business district (CBD), with traditional markets being relocated to the Makola market in a district termed "native town", a more impoverished area in Accra separated from the CBD. By 1924, a lack of urban planning and investment in the "native town" area resulted in unhealthy and congested living conditions for many Ghanaian citizens, and was geographically separated from the CBD in an attempt by the colonial government to give European immigrants a better quality of life than native Ghanaian citizens (82,85). This forced Ghanaian citizens into living in the "native town" district with poor housing conditions, inadequate health services and a lack of amenities relative to the higher-income CBD (Figure 1).

In the decades following the independence of Ghana in 1957, the CBD transitioned to a place where commercial and residential buildings were mixed, and the geographic boundaries between the traditional markets and the CBD began to disappear. The newly-established government attempted to develop Accra's public housing sector by constructing more low-income housing; however, the city's rapidly expanding urban population growth far outpaced their capacity for new housing contributions (82). The urban housing development was not uniformly distributed across the city, and resulted in both formally planned and high-income areas (e.g., Airport Residential Area and East Legon) and unplanned slum areas (e.g., Nima and Amui Djor) that were densely populated and characterized by inadequate housing, a high population density, and poor environmental conditions (58,86). Inequitable wages across Accra, high mortgage rates, and high cost of living left the majority of Ghanaian citizens in rental units of varying quality, many of which lacked basic infrastructure and services including roads, drainage systems, and sanitation facilities (82).

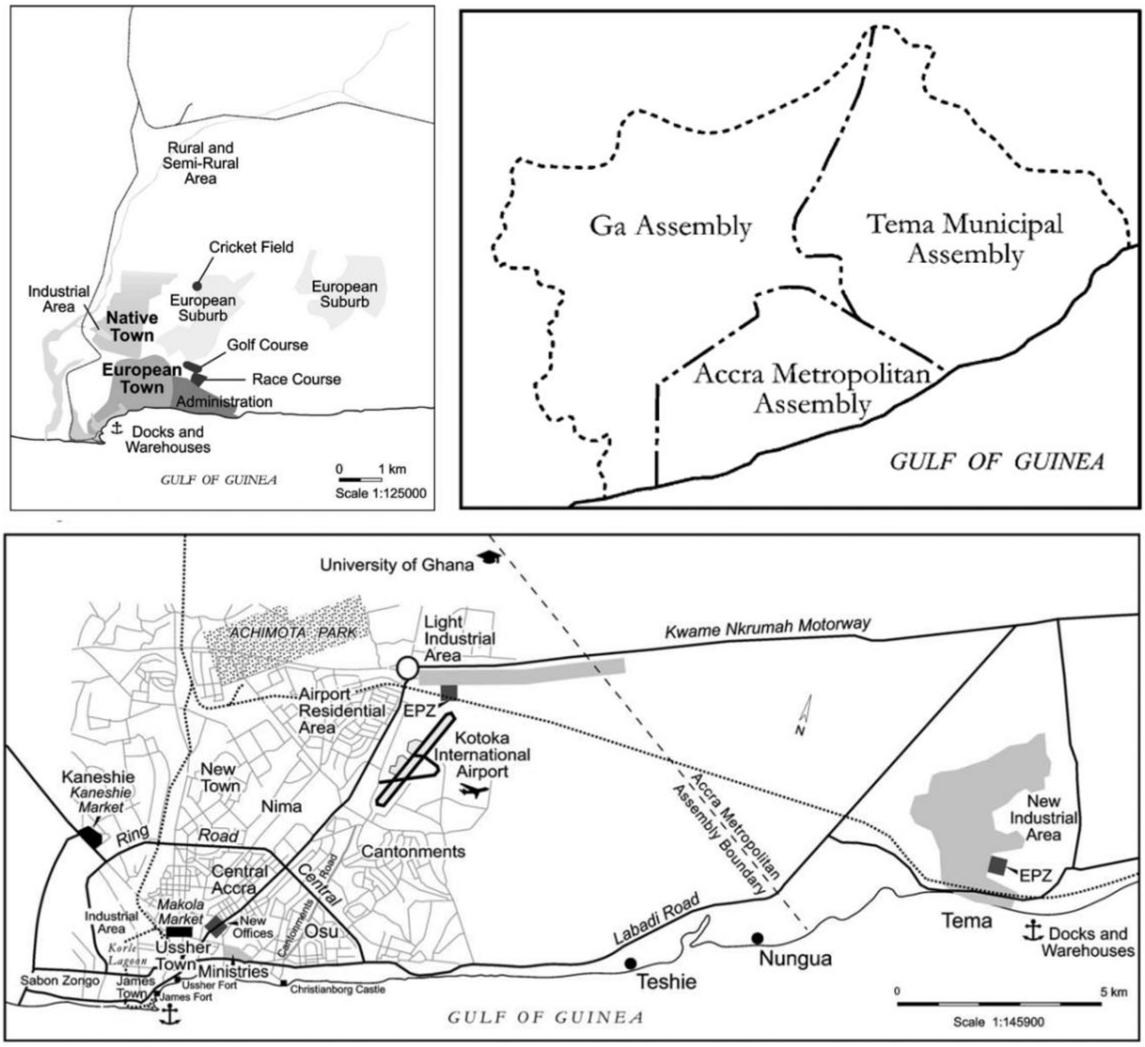


Figure 1: Map of colonial Central Accra (top left), the layout of the GAMA (top right), and modern Central Accra showing a portion of the AMA (bottom), as reported by Grant & Yankson (82). These figures were presented with permission from Elsevier ©.

The Government of Ghana has not formally mapped or reported the geographic distribution of slums across the entire country or for the GAMA region. Ghana's National Development Planning Commission reported that in 2001, nearly 5 million Ghanaian citizens lived in slums, and this number was expected to grow on average 1.83% annually; however, the method of slum identification was not reported (58,87). In Accra, slums are heterogenous in housing, population  density, and environmental conditions, have varying forms and degrees of vulnerability, and have arisen from unique conditions. For example, the well-established neighbourhood of Nima has densely-packed housing units that are mostly constructed of rusting corrugated iron sheets, and was developed without any formal urban planning (58). This slum rapidly developed between 1940 and 1960 with an influx of immigrants from Northern Ghana and West African countries seeking employment opportunities in Accra and settled in Nima because of its relatively low rents (58,88). Over time, the demography of Nima shifted from primarily recent immigrants, to a large proportion of its citizens who were born and raised in Nima. The Sodom and Gomorrah slum, also referred to as Old Fadama, emerged in the 1980s, and is an area where millions of discarded electronic products are dumped annually, and often illegally (89). Outside of electronics, this largely informal settlement is heavily polluted with other deposited garbage, human refuse and other waste products (90). This area is characterized as having inadequate access to safe drinking water, low employment with many informally employed citizens working by recycling discarded electronics, and is a lowland area prone to flooding (141,142). The Jamestown slum emerged in a neighbourhood with old colonial buildings, and was settled by the indigenous Ga population along with migrant groups from outside Accra (92). This community largely relies on fishing for employment, being a coastal area in Southern Accra (93). Although slums in Accra share certain characteristics such as being densely populated and having inadequate housing and neighbourhood infrastructure, many of these areas have unique emergence, cultures, and other characteristics defining their history. The UN-Habitat, in collaboration with the Ghana Statistical Services (GSS), estimated in 2011 that there were approximately 78 slum pockets and settlements within the AMA alone (94). The AMA region only accounts for 15.73% of the GAMA's geographical footprint (Figure 1), suggesting that the number of slum settlements in the GAMA is likely much greater.

### 4.3 Social, Economic, and Environmental Conditions in Slums

People living in slums often face a lack of infrastructure and services including waste collection systems, electricity, adequate lighting in public spaces, drainage, and formally planned roads and footpaths (14,74). A common characteristic of slum households is that they lack secure tenure, with many slum dwellers occupying land outside government regulations, putting them at risk of forced evictions and resettlement (11,14). Housing in slums is also inadequate, and homes are often built using nondurable materials unable to withstand climatic conditions (11,14). Houses are generally overcrowded where single room units are oftentimes shared with multiple inhabitants (11,14). Households in slums often lack access to improved drinking water protected from contamination by faecal matter or other pollutants (11). Drinking contaminated water may increase the incidence of illnesses such as typhoid, cholera, or other diarrheal illnesses (95–100). It was reported that during a cholera outbreak in Kenya’s slums, drinking untreated water significantly increased the odds of cholera [adjusted OR 6.5 (95% CI 2.3-18.8)] (101). It is imperative for households to have improved sources of drinking water, as unsafe drinking water may also increase the risk of illnesses due to inorganic pollutants such as lead or arsenic, and from organic pollutants such as pesticides (102). The sanitation facilities of slums are also often unimproved and unable to effectively separate human waste from human contact (11). In the slums of Addis Ababa, children living in households with unsafe sanitation facilities had a significantly increased odds of diarrheal illnesses, including sharing a sanitation facility with 6 or more households [adjusted OR: 4.7 (95% CI: 2.4,9.4)] versus not sharing or sharing with under 6 households, and having a shared sanitation facility within 15 meters of one’s home [adjusted OR: 6.6 (95% CI: 2.5,17.0)] (96).

The environmental conditions of areas surrounding slums are often poor and potentially dangerous. For example, slums may be built in areas in close proximity to industrial sites or dumping grounds for waste disposal, polluting the environment (14). The Sodom and Gomorrah slum in Accra receives millions of discarded electronic products every year (89), and already has heavily polluted lands from deposited garbage, human refuse and other waste products (90). The unplanned nature of slums and lack of urban infrastructure further contributes to these environmental risks. Slums in Kumasi, Ghana, lack formal rubbish collection or disposal systems, which leads to the illegal dumping of waste into the Aboabo River (103,104). In many settings, including Accra, slums are situated in lower elevated areas and are at a higher risk of frequent flooding which contributes to water pollution, contamination or destruction of food sources, and an increased risk of communicable diseases such as malaria and cholera (105,106). Slums are reported to have a lower abundance of vegetation and biodiversity (107,108), which may contribute to poor health (109) and a decline in other benefits provided by green spaces such as social cohesion and safe play spaces for children (110).

Poverty is often deemed a cause of slum emergence and growth rather than an inherent characteristic (14), and persists in slums as residents lack the financial resources or employment opportunities to relocate or improve their living conditions (78). Unemployment and underemployment tend to be high among slum populations, and jobs that do exist tend to be underpaid informal jobs (11). In Accra, slum residents reported difficulty in finding employment due to the lack of employment opportunities and the stigmatization they faced being from an area considered a “slum” (58). Slums are also described as poverty traps, where inhabitants are trapped in intergenerational cycles of poverty due to lack of formal home ownership, high rent premiums in big cities, poor governance, and lack of interest in investment in these areas (78). In a survey of over 1,000 slum residents in Bangalore, India, roughly 75% of survey respondents earned a monthly income of INR 4,000 (55 USD), Bangalore’s poverty line, or less (111,112). In the same study, an average of 91% of respondents' monthly income was spent on basic necessities such as food and rent, not leaving sufficient funds for services like education or health care (111). In Accra, Engstrom *et al.* found through regression analysis that poverty was significantly associated with higher slum index scores ($p<0.001$) (32). Studies in Kenya and India also reported lower rates of school attendance and lower levels of educational attainment in slums versus non-slums (29,113). In Kenya, school enrolment rates in slums were comparable to those of children living in rural areas, where education rates are, on average, much lower than in cities (29).

Residents of slums often face social inequalities when compared to other urban settings. Slum residents often face social exclusion due to poverty or being composed of segregated or vulnerable groups such as ethnic minorities, displaced populations, or immigrants (14). Social exclusion is a risk factor for high levels of crime in slum areas (114). Gender inequality has been identified with several studies in Nairobi's slums showing that men had better employment or educational opportunities and improved health outcomes compared with women (115–117). Studies in Bangladesh, Kenya, and SSA found that gender-based violence was more common in slums than other urban areas (118–120). In the Kibera slum in Nairobi, one of the largest slums in the world, 85% of women reported having experienced physical violence in their lifetime compared with 39% of women in Nairobi's general population (119).

### 4.4 Methodological Approaches to Slum Identification and Spatial Mapping

There is no universal definition of "slum" or a standard method used by cities to delineate slum boundaries across space and time even though improving the health and wellbeing of those living in slums is a global health priority (61,121). Goal 11.1 of the Sustainable Development Goals (SDG) necessitated that by 2030, all populations must have access to adequate, safe and affordable housing and basic services, which includes the upgrading of existing slums (122). Tracking global progress in meeting this goal is impeded by measurement challenges in identifying existing and emerging slums in most LMIC cities. More specifically, slum identification is limited by the coarse and inconsistent definition of slums across and even within cities, and the lack of standardized methods to identify urban slums using available housing and environmental data. In the absence of systematic ways to identify existing or emerging slums, most global cities are unable to implement effective policy to improve the lives of people living in urban slums.

Historically, four methods have been used by researchers and governments to systematically identify urban slum neighbourhoods, namely field-based mapping, machine-learning classification based on satellite imagery, human interpretation of slums using satellite imagery, and survey-based mapping. This section critically assesses these approaches and describes their implementation in previous assessments.

*4.4.1 Community mapping of slums*

Community mapping generally involves the demarcation of neighbourhood boundaries and creation of geographical units with shared social and physical characteristics based on the input of different community stakeholders including residents, non-government organizations (NGOs), government officials, and researchers (31,61,123). Community maps can be fine-tuned with survey data collected on household characteristics such as tenure security (124,125). Studies in Kenya, Namibia, India, and the Philippines used a variety of data sources to identify slum settlements including integration of GIS applications, paper maps, and mobile Global Positioning System (GPS) units or applications (125-129).

Participatory approaches like community mapping have a number of advantages compared with other commonly used methods including remote sensing techniques. They utilize local spatial knowledge of community members about neighbourhood boundaries and can be updated over time (123,127). Collaborations between governments, NGOs, and community leaders can create opportunities for community members to become more involved in local decision-making and slum upgrading programs (124–127). Community-based field mapping also avoids some degree of the misclassification of slum boundaries that can result from remote sensing methods, which are less effective in differentiating between adjacent slums or identifying regions with distinct building materials in the absence of local knowledge (126).

Notable limitations of field-based mapping exercises are that they are expensive, time-intensive, and logistically-challenging to implement, particularly over large geographic areas like cities (61,126). This method of mapping also technically requires a standard definition of slum settlement that can be communicated to all mapping participants. Even with standard definitions, different mapping volunteers may have different conclusions about slum boundaries based on subjective opinion. A study in India found that the integration of GPS technology was difficult for some older community members to comprehend, highlighting the need for adequate training of GIS or GPS technology (126).

#### *4.4.2 Census or Survey-Based Slum Classification Approach*

The application of survey and census data on household characteristics to identify and map slum areas has primarily relied on UN-Habitat's definition of a slum household (24,26,27,30,32–34,128,129), which is a household lacking one or more of the following five features (11):

1. Sufficient living space in a household, meaning no more than three people sharing a sleeping space.
2. Household must be durable and be protected from climatic conditions.

3. Household must be able to easily access a sufficient amount of safe drinking water at an affordable price and within a reasonable effort.
4. Household tenure must be secure to prevent forced evictions.
5. Household must have access to improved sanitation, either in the form of a private toilet able to effectively separate excreta from human contact or a public toilet shared by a reasonable number of people.

Studies in Ghana, Mexico, India, and several multinational studies used a simple slum index from 0-5 based on how many of the five features were lacking (24–27,30,33,128). The slum index is additive, and each variable is therefore weighted equally (e.g., having unsafe drinking water is weighted the same as having unimproved housing materials). Typically, the results at the household-level are aggregated to the neighbourhood-, area-, or survey cluster-level by taking the mean household score for the given geographic scale (25–27,32,33,46,55,128,130).

Gathering household data through surveys or censuses can better capture health-relevant household characteristics including drinking water source, type of sanitation facilities and home ownership. Standardized definitions also allow for greater comparability of results across cities or regions (61,128). Survey-based slum classification using administrative data, such as through censuses or DHSs, is often less expensive than other mapping methods including remote sensing or community mapping methods, whereas primary data collection for slum identification would still be time- and resource-intensive (131).

The slum criteria used by UN-Habitat are also very sensitive, such that most LMIC households meet at least one criteria and are defined as a slum household (26), leading to a likely overestimation of the prevalence of people living in slums (25). In a real-world setting, it is also unlikely that each of the five criteria contribute equally to an area being considered a slum. Using an additive index, the relation between the five criteria and slum classification cannot be assessed. The slum criteria are also exclusively based on household characteristics, and do not reflect neighbourhood or social characteristics, which could miss many important attributes of slums such as population density or environmental conditions. Although the slum index may quantify the number of people who live in slum or deprived conditions, it is difficult to use this method to distinguish between slum and non-slums as there is no requirement of spatial contiguity in this method (25).

Studies that used surveys or census data for slum classification are summarized in Table 1. In past research a slum index score was calculated at the EA-level in Ghana (24,32,130), neighbourhood-level in Ghana (51), and country-level through multinational studies including several LMICs (35,132,133). In the slum classification studies identified during the literature review, all nine used the UN-Habitat criteria to define a slum (Table 1), and seven used an additive slum index score (24–27,30,33,128). Three of these studies, including one in Mexico and two multinational studies, used only four of the five UN-Habitat criteria in their slum index score because DHS data sources did not collect information on tenure security (26,33,34), and an additional global study using DHS data by Kyu *et al.* only used three of the five criteria as the authors also decided not to include number of household members sharing a bedroom as a proxy for overcrowding because co-sleeping with babies or children is a societal norm in some countries regardless of socioeconomic status (27).

Historically, neighbourhoods are dichotomously classified as slums or non-slums; however, the use of aggregated neighbourhood-level slum index scores provides a continuous measure, and slums with higher slum index scores have a higher degree of deprivation (25,30,128). Other recent studies shifted to the use of thresholds to categorize neighbourhoods as either slums or non-slums (24–27,33). The distinction of neighbourhoods as slums or non-slums may help identify which neighbourhoods are the most deprived.

Studies using a dichotomous classification of slum versus non-slum neighbourhoods have adopted different methods to distinguish between slum and non-slum households and neighbourhoods. Researchers identified households as slum households if they lacked at least one (25,26,33,128), two (25–27,33), three (25), or four (25) of UN-Habitat's criteria. The methods to dichotomize the slum index score at the neighbourhood-level included labeling the 10 analytical regions with the highest slum index score as the 10 worst slums (24), and labelling households as being within slum neighbourhoods if the majority of the neighbourhood's households were identified as slum households (25–27,33).

Two studies in Accra, Ghana that are particularly relevant to this thesis evaluated the use of additive slum index scores against remote sensing methods to assess whether the two methods were comparable (24,25). Weeks *et al.* first used a regression analysis to assess whether remote sensing features including Ridd's V-I-S model and a texture variability index could predict the variability of the slum index in Accra, Ghana, reporting a $R^2$ of 0.38 and adjusted $R^2$ of 0.42 after accounting for spatial autocorrelation (24). Slum areas in Accra were predicted to have a low abundance of vegetation, high levels of impervious surface and bare soil, and little texture variability due to the similarity of building materials used and densely packed buildings. Engstrom *et al.* compared a remote sensing method using several spatial, structural, and contextual features to map slum areas in Accra against the use of a slum index score (25). Through a simple linear regression analysis, there was a moderate correlation between slum index and percent neighbourhood classified as slum using remote sensing ($r^2$= 0.45, adjusted $r^2$=0.44), however, this correlation further increased after adjusting for population density at the neighbourhood-level ($r^2$=0.78, adjusted $r^2$=0.78) (25). The authors additionally compared the remote sensing technique with dichotomous slum definitions where areas were defined as slums if the majority of households met at least one, two, three or four of the UN-Habitat criteria, and found that the highest agreement was between the remote sensing technique and when areas were defined as slums when the majority of households met at least four of the UN-Habitat criteria (overall agreement of 74.7% and Cohen's Kappa coefficient of 0.49 indicating moderate agreement) (25).

More recently, two studies adapted the UN-Habitat criteria to classify slums based on a random forest machine-learning technique (32) and explanatory factor analysis technique which allowed the four UN-Habitat criteria used to be weighted differently (34). In the machine-learning technique, Engstrom *et al.* used the two additional explanatory variables population density and elevation in constructing a slum index score because slums are typically overcrowded areas, and slums in Accra are often developed in low-elevation areas that may be susceptible to natural hazards such as flooding (32). This method also allowed all variables relevant to the UN-Habitat slum definition to be separate explanatory variables in the slum index model without needing to define what constituted an improved drinking water source, sanitation facility, tenure, building material or household size. The authors discovered the mean slum index score among official slum EAs was 0.764, while the mean slum index outside these EAs was 0.331, although further validation techniques were not implemented (32). In 2020, Roy *et al.* developed a Slum Severity Index (SSI) using explanatory factor analysis (EFA) and four of the UN-Habitat criteria to study household deprivation in Mexico City between 1990-2010 (34). In the EFA, factor loadings were included as weights, which prevented the use of arbitrary and equal weights such as in the additive slum index score. The SSI calculated was validated against grey-level concurrency matrix (GLCM) variance derived from high-resolution satellite imagery, and the calculated Pearson correlation coefficient indicated a negative correlation between SSI and GLCM variance ($r= -0.67$, $p<0.05$) (34), which was in agreement with past research as low GLCM variance is typically calculated in densely-packed slums (32,107,131).

*4.4.3 Machine Learning Classification of Slums Using Satellite Imagery*

A large portion of slum identification work has relied on remote sensing techniques to rapidly and automatedly map slums based on the unique textural, morphological, spectral or structural properties of these areas. For example, a number of indices were used to delineate boundaries of urban slums including: (i) a GLCM method, in which slum areas tended to have low GLCM variance indicating that buildings in slums are too densely-packed and small to clearly contrast them from the surrounding environment (32,107,131); (ii) normalized difference vegetation index (NDVI), as slums tended to have a low proportion of vegetation (107,131); and (iii) the vegetation, impervious surface, bare soil (V-I-S) model, which found that slum areas tended to have a lower proportion of vegetation and a higher proportion of bare soil or impervious surfaces (24,134,135). Machine-learning methods, which include the convolutional neural network (CNN) or artificial neural network (ANN) methods, trained networks using identified slums in satellite imagery to assess the presence of slums in a new set of images (136,137).

Machine-learning methods are commonly used due to the widespread coverage and availability of satellite imagery and the ability to conduct these analyses remotely (136). Machine learning methods predict slums based on neighbourhood or environmental characteristics, including features such as NDVI, elevation, and spectral or textural features for the specified geographical units. The inclusion of neighbourhood or environmental features may be missed in survey-based mapping because surveys typically include information solely on housing characteristics. Machine learning methods are generally thought to have greater accuracy than survey-based methods using the UN-Habitat definition of slums, such as in Accra where remote sensing classification had greater agreement with a government slum map (25). Compared with field-based or community slum mapping methods, these machine learning methods typically produce slum maps much faster, and have larger spatial coverage (61,131).

There are numerous known limitations of machine-learning approaches. Object-based image analyses (OBIA) often rely on very high resolution satellite imagery data, which can be expensive, computationally intensive to process, and require technical capabilities and specialized software programs (61,131,136,138). Many satellite images do not capture areas with high temporal, radiometric, spectral, and spatial resolution, such that researchers have to prioritize one type of resolution for their analysis. In previous slum identification studies, images with high spatial resolution were often favoured in order to easily identify objects and buildings, which limited the resolution of the other image dimensions (139). There are also issues with the generalizability of results using methods such as OBIA since slums in different cities and even within the same city may have very different textural or spectral features (136–138,140,141). Certain textural attributes may also appear too similar such as textures from paved roads and concrete rooftops, which could lead to the misclassification of land uses (107). Finally, while image-based methods utilize neighbourhood and environmental quality characteristics, many of these techniques fail to account for many health-relevant household characteristics that are less visible in satellite images, including drinking water source, fuel or stove type, type of sanitation facilities, and tenure type and level of security.

#### *4.4.4 Manual Interpretation of Slums Using Satellite Imagery*

Satellite images can also be manually assessed to delineate slum boundaries, although this requires a prior definition of the features that constitute a slum to avoid high degrees of subjectivity (61). For example, researchers visually assessed morphological attributes such as settlement density, building arrangement, and building construction materials to construct maps of slum settlements in Bangladesh and Brazil (142,143).

These methods have many of the same benefits as machine-learning techniques, including that the analyses can be done more efficiently compared with large-scale surveys or field-mapping and they can be updated over time. Additionally, these methods allow for the integration of local knowledge into the identification process which can help identify slums across a city that are heterogenous in textural and spectral attributes (144).

An important limitation of this approach, as identified in previous studies, is its low internal validity since the delineation of slum boundaries can vary due to unclear boundaries of slums in satellite images, and mapping inconsistencies when using different interpreters (144,145). Interpreters should have local knowledge of the area they are mapping to avoid misclassification. Area classification can also be difficult as slums may not always have distinct morphological features (143). Other limitations are similar to those described for machine-learning methods, including the cost of high-resolution images, the labour- and computationally-intensive nature of larger-scale projects, and the inability to capture important household or social features.

## 4.5 Infant and Child Mortality in Low- and Middle-Income Countries and Slums

### *4.5.1 Infant and child mortality in low- and middle-income countries*

Globally, child mortality rates have declined considerably over the past several decades, from 91 deaths per 1,000 live births (90% uncertainty interval [UI]: 89,92) in 1990 to 43 deaths per 1,000 live births (90% UI: 41,46) in 2015 (146). Yet these reductions in child mortality are not equally distributed across countries as child mortality rates in SSA remained high at 76 deaths per 1,000 live births in 2017 (147), despite considerable child mortality reductions with an annual rate of reduction in SSA of 3.2% between 1990 and 2017, including a 61.0% reduction in Ghana (148). In 2015, child mortality rates were highest in West and Central Africa at 99 deaths per 1,000 live births (90% UI: 88,114), which is nearly 15 times higher than high-income countries at 7 deaths per 1,000 live births (90% UI: 6,8) (146). Inequitable child mortality rates exist in Sub-Saharan Africa between the poor and wealthy, as higher child mortality rates in Sub-Saharan Africa have been associated with several socioeconomic status variables including: lower income per capita or household wealth (147,149,150); lower percent of population living in urban areas (149); higher illiteracy levels and lower maternal education (149,150); higher number of children (151); lack of safe sanitation (150); lack of safe drinking water (150); and single parent households (152).

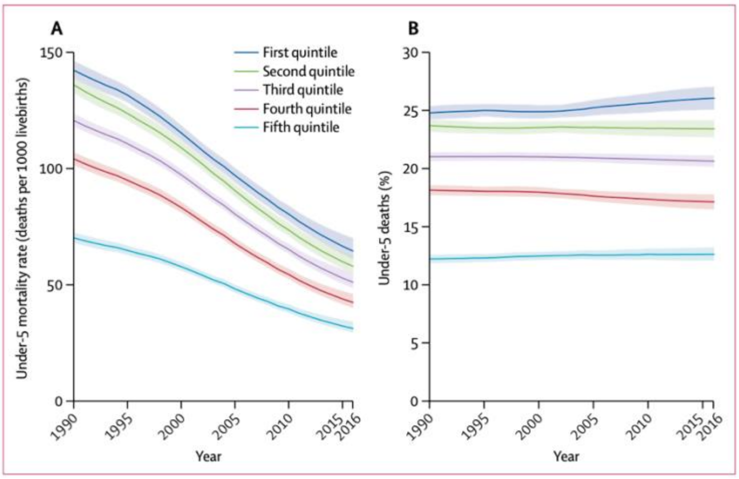


Figure 2: Child mortality differences from 1990-2016 between wealth quintiles for all LMICs, as reported by Chao *et al.* (153). This figure was presented with permission from Elsevier ©. Panel A shows the under-5 mortality rate over time per wealth quintile, while panel B shows the percentage of under-5 deaths per wealth quintile. The first quintile represents the poorest quintile, while the fifth quintile represents the richest quintile.

A multinational study of 28 SSA countries concluded that between 1980-2010, 74-78% of variation in child mortality was attributed to within-country differences rather than national factors (154). There remains considerable heterogeneity of child mortality rates within LMICs, with the poorest populations experiencing higher child mortality rates than the wealthy in India, Kenya, Bangladesh, and multinational studies (54-58,171,173,174,177,178). While the absolute child mortality rates declined most in the poorest people in LMICs, the relative difference in child mortality rates between the richest and poorest did not significantly change (153,157). In a 2018 study by Chao *et al.*, it was concluded that the absolute difference in child mortality rates between the poorest and richest quintiles within LMICs decreased from 72 deaths per 1,000 live births (90% UI: 68,77) in 1990 to 33 deaths per 1,000 live births (90% UI: 30,38) in 2016 (Figure 2,12). However, the ratio of child mortality rates between the poorest and richest quintiles changed very little over time (2.03 in 1990 versus 2.06 in 2016) (Figure 2,12).

*4.5.2 Previous literature on child mortality in slums*

Since slums generally exist as neighbourhoods with perpetual poverty and potentially life-threatening living conditions, it is plausible that these areas have higher child mortality rates than city averages. Strong empirical evidence associates wealth and socioeconomic status with child mortality (146,153,163,155–162); however, relatively few studies examine differences in child mortality between slum and non-slums (Table 2).

There were multiple ecological studies reviewed investigating differences in child mortality between slums and non-slums using LMICs as the units of analysis, and concluded that there is an association between urban slum prevalence and child mortality rates (35,132,133). In a 2009 global study involving 99 LMICs, a bivariate correlation analysis between urban slum prevalence at the country-level and child mortality rates reported a Pearson correlation of 0.386 ($p<0.001$) when adjusted for both GDP per capita and urban population growth (35). Past studies have also studied the association between living in slums and child mortality at the neighbourhood-level, and concluded that living in urban slums increased neighbourhood child mortality rates (26,27). In a 2013 study including 45 LMICs, Kyu *et al.* concluded that living in slums compared to non-slums increased the risk of child mortality at the neighbourhood-level with an adjusted OR of 1.20 (95% CI: 1.07,1.35) (27). Evidence of an association between urban slum residency and child mortality has not been ascertained at the individual- or household-level, although two studies conducted warrant future research (27,164). Kyu *et al.* concluded that living in slums compared to non-slums increased the risk of child mortality at the individual-level, however not significantly (adjusted OR:1.07 (95% CI: 0.97,1.19)) (27).

Most of the child mortality studies reviewed relied on additive slum scores based on UN-Habitat's five criteria (26,27,33,35,132) to define slums, which could result in the misclassification of place of residence as previously discussed. All of the studies classified areas as slums based on census data or previously defined slum areas by surveys, rather than using remote sensing, manual interpretation of satellite-imagery or field-based methods of mapping. Although two reports did rely on previously published surveys which distinguished between slums and non-slums (133,164), many surveys and censuses do not include this information, particularly in SSA. Several studies also used countries as the units of analysis when studying mortality (35,132,133), or included data from DHSs from multiple LMICs (26,27,33). Although DHS are nationally-representative, these studies were not able to assess the spatial distribution of slums in the context of a specific country or city as not all EAs are sampled during DHS waves (165). This makes it difficult to assess where public health interventions should be targeted within a country as the geographical locations of slums in these studies cannot be ascertained. Several of the papers examined only used crude mortality rate calculations (33,133), or aimed to examine child mortality in urban slums and non-slums relative to rural areas rather than examining child mortality inequalities within urban centres directly (26,164).

### *4.5.3 Child Mortality Research in Ghana*

Ghana has experienced a decline in child mortality across all districts over the past several decades, and between 2000 and 2010, child mortality rates decreased from a median of 99 deaths to 70 deaths per 1,000 live births (166,167). It was reported that child mortality is not equitable across regions, as the more impoverished Northern region had the lowest odds of child survival [adjusted OR: 0.26 (95% CI: 0.13,0.50)] in 2010 compared to the Western region (168,169). Southern Ghana, with more resources and economic activity, had the lowest child mortality rates in 2010 at 75 deaths per 1,000 live births (170,171). Studies reported that many household characteristics were significantly associated with child mortality in Ghana (168,172–174), including mothers having no intention to use contraception lowering the odds of survival [adjusted OR: 0.56 (95% CI: 0.37,0.82)] compared to using modern methods, and female child sex increasing the odds of child survival [adjusted OR: 1.31 (95% CI 1.01,1.72)] (168). No previous research has mapped child mortality at a finer geographic scale in Ghana than the district-level, which makes it difficult to propose targeted health interventions for at-risk communities. There has also not been any research investigating relative inequalities in mortality outcomes between urban slums and non-slums in Ghana. To meet the SDG-3 in child mortality, inequalities in child mortality outcomes across Ghana related to socioeconomic status must be investigated at a fine scale in order to guide localized future health programs.

## 4.6 Conclusions

My literature review identified that the majority of published slum identification studies using survey data used an additive slum index score derived from the UN-Habitat definition of a slum (Table 1). This slum identification method has a number of limitations including that it does not weight explanatory variables, it relies solely on housing characteristics, and does not account for spatial contiguity. A smaller number of studies adapted the UN-Habitat definition of slums to develop methods that weight the explanatory variables differently when calculating a slum index score, but there remains a need for slum identification research that incorporates survey and remote sensing data, identifies slums using a method that examines the relationship between explanatory variables and slum classification, and considers possible latent structures not accounted for by the available covariates (e.g., spatially structured random effects), so that slum populations can be identified and their health outcomes assessed.

**Table 1: Survey-based slum classification or identification studies conducted in a low- and middle-income country settings**

| Author (Year of publication) | Location and Units of Analysis | Data Source | Method(s) | Finding(s) |
|---|---|---|---|---|
| Weeks *et al.* 2007 (24) | Accra, Ghana; EA-level, analytical regions created using areal aggregation technique | 10% sample of Ghana 2000 Census, DigitalGlobe Quickbird satellite imagery | • Census-based 5-score additive slum index based on UN-Habitat's slum criteria<br>• Satellite imagery-based Ridd's vegetation, impervious surface, bare soil (V-I-S) model<br>• Linear regression analysis between slum index (dependent) and independent variables from remote sensing data | • Variability in slum index score can be predicted by % vegetation (Adjusted $R^2$=0.38)<br>• % Vegetation predicts individual criteria better, such as proportion with no toilet or sewer (Adjusted $R^2$=0.67)<br>• Slum index classification missed some well-known slum areas |
| Jankowska *et al.* 2011 (30) | Accra, Ghana; EA-level | 10% sample of 2000 Census, elevation data from Ghana Department of Lands and Surveys | • Census-derived slum index score based on UN-Habitat's five criteria<br>• OLS regression to assess if EA-level slum index score could predict vulnerability measures (physical hazards, socio-economic factors, demographics and health) | • Slum index score significantly predicted three vulnerability measures ($p<0.001$), excluding health<br>• Relationship between vulnerability and slum index score varied by slum neighbourhoods, indicating slums are heterogeneous |
| Günther & Harttgen 2012 (33) | Sub-Saharan Africa (18 countries); Individual-level | 18 Demographic and Health Surveys (DHS) | • Additive slum score based on four of five UN-Habitat criteria, excluding tenure<br>• Participants identified as slum dwellers based on three definitions: Household met at least one slum indicator; household met at least two slum indicators; or household is in cluster with over 50% slum households (>1 slum indicator)<br>• Compared child mortality rates between urban slum and non-slum participants at country-wide level | • Using the less strict first slum definition, 70% of participants are classified as slum dwellers<br>• Using the stricter approach, 28% of the population was identified as slum dwellers<br>• According to the third cluster-based definition, 76% of population were classified as urban slum dwellers |
| Kyu *et al.* 2013 (27) | Global Study (45 low- or middle-income countries); | 45 DHS | • Defined slum household as lacking at least two of three UN-Habitat slum criteria: Improved water, improved sanitation, and structural quality | • 12% of neighbourhoods across 45 countries were considered slum neighbourhoods |

| | | | | |
|---|---|---|---|---|
| | Neighbourhood-level | | • Defined as slum neighbourhood if EA or cluster had over 50% slum households | |
| Fink *et al.* 2014 (26) | Global Study (73 low- or middle-income countries); Neighbourhood-level (using DHS sample clusters as neighbourhood definitions) | 191 DHS | • Additive slum score based on four of five criteria, excluding tenure<br>• Neighbourhoods classified as slum if >75% of its households met at least two slum criteria (with less conservative models for robustness checks) | • With most restrictive cut-off, 20% neighbourhoods in LMICs classified as slums<br>• Less restrictive definition (slum if >75% of households meet at least one slum indicator) resulted in 60% of neighbourhoods being considered slums<br>• Some wealthier neighbourhoods were likely identified as slums (misclassification) |
| Patel *et al.* 2014 (128) | Mumbai and Kolkata, India; Household-level | India's National Family and Health Survey (NFHS) | • Slum severity index (SSI) calculated based on the UN-Habitat five criteria<br>• Households identified as slum households if deprived of at least one of five criteria<br>• Grouped households by type of deprivation (i.e. sanitation deprived) | • 730,000 households and 320,000 households in Mumbai and Kolkata respectively, previously identified as non-slum in India's Census, identified as slum households<br>• 81.7% and 64.1% of households classified as slum households in Mumbai and Kolkata respectively (higher than census which classified 52.5% of Mumbai and 29.0% of Kolkata as slum households) |
| Engstrom *et al.* 2015 (25) | Accra, Ghana; Neighbourhood-level | 10% sample from Ghana's 2000 Census, map provided by AMAUH, Quickbird Satellite imagery | • Census-derived slum index score based on UN-Habitat's five criteria<br>• Found proportion of slum, non-slum and non-settlement per neighbourhood based on remote sensing. Random forest classifier was used, with remote sensing predictors (e.g. Pantex, NDVI, and GLCM)<br>• Calculated correlation between slum index score and remote sensing method | • Remote sensing technique had 92% agreement with AMAUN map for classifying slums, with overall agreement of 94.3% (Kappa= 0.91)<br>• Comparing remote sensing map with slum index maps, highest agreement when slum neighbourhoods defined as having average slum index score of 4 (overall agreement 74.7%, kappa=0.49) |

| | | | | |
|---|---|---|---|---|
| | | | • Linear regression model between slum index and random forest classifier | • Moderate correlation between slum index and remote sensing (r=0.67, adjusted $r^2$ = 0.44, p=0.00)<br>• After multiplying slum index by population density, correlation increased (r=0.88, adjusted $r^2$ = 0.78, p=0.00) |
| Engstrom *et al*. 2017 (32) | Accra, Ghana; EA-level | Ghana's 2010 Census, Ghana Living Standards Survey Round 6 (GLSS6), Quickbird-2 multispectral imagery | • Machine-learning random forest method to estimate slum index, using same variables from UN-Habitat definition with additional variables elevation and population density<br>• Trained model using six well-known slum regions and twelve wealthy regions<br>• Small area estimation methods (175) to estimate poverty levels in Accra | • Elevation and population density identified as two most important predictors of slum index<br>• EAs classified as slums by AMAUN map had higher mean slum index score through random forest technique than non-slum EAs (0.764 and 0.331 respectively)<br>• Poverty rates higher in EAs with high slum index scores (>0.75) compared to EAs with lower slum index scores (<0.75) |
| Roy *et al.* 2020 (34) | Mexico City, Mexico; Block-level | Mexico 1990, 2000, and 2010 Census from INEGI; WorldView-2 satellite images | • Used four of UN-Habitat criteria, barring secure tenure, to measure SSI<br>• Used explanatory factor analysis to determine SSI between 0 and 1, and validated SSI using satellite imagery-based GLCM | • Negative Pearson correlation between SSI and GLCM (r=-0.67, p< 0.05), as slums typically have lower GLCM variance (107) |

**Table 2. Review of the Association of Urban Slum Residence and Neonatal, Infant or Child Mortality**

| Author (Year of publication) | Location and Units of Analysis | Slum Classification Method | Study Design and Statistical Analysis | Results | Covariates |
|---|---|---|---|---|---|
| Rice & Rice 2009 (35) | Global Study (99 LMICs); Country-level | Slum household defined as lacking at least one of four UN-Habitat criteria (excluded tenure). Calculated national urban slum prevalence as % of slum households | Cross-sectional; Bivariate and partial correlation (Pearson r) between urban slum prevalence and both infant and child mortality rates | Range of Pearson r for infant mortality: 0.39-0.42; Range of Pearson r for child mortality: 0.39-0.52 | GDP per capita and urban population growth between 1990 and 2003 |
| Jorgenson & Rice 2010 (132) | Global Study (80 LMICs); Country-level | Percent of the total country's population living in a slum household using UN-Habitat database (slum household if it lacks one or more of five criteria) | Cross-Sectional: First-difference model to assess how country's % population living in slum is associated with IMR and U5MR; OLS regression models for association between % population living in slum and both IMR and U5MR | first-difference model coefficient for IMR: 0.210 (std.error =0.054, p <0.01); first-difference model coefficient for U5MR: 0.242 (std. error=0.061, p<0.01); OLS regression IMR coefficient: 0.141 (std.error =0.047, p <0.01); OLS regression U5MR coefficient: 0.145 (std. error=0.051, p<0.01) | GDP per capita, fertility rate, exports as a % total GDP, health expenditures per capita, % secondary education enrollment |
| Günther & Harttgen 2012 (33) | Sub-Saharan Africa (18 countries); Individual-level | DHS participants identified as slum dwellers based on three definitions: Household met at least one of four slum indicators; household met at least two slum indicators; or household located in cluster where >50% of households met at least one slum indicator | Cross-sectional; Calculated crude U5MRs separately for slums vs non-slums and aggregated at country-level | First definition U5MR: 110.5 deaths per 1,000 children in slums, and 67.0 deaths per 1,000 children in non-slums; Second definition U5MR: 122.7 deaths per 1,000 children in slums and 66.3 deaths per 1,000 children in non-slums; Third definition U5MR: 112.8 deaths per 1,000 children in slums and 67.1 deaths per 1,000 children in non-slums | None |
| Kyu *et al.* 2013 (27) | Global Study (45 LMICs); Individual-level (child) and | Defined as slum household if lacking at least two of three indicators: Improved water, improved sanitation, or structural quality of buildings; | Cross-sectional; Multilevel logistic regression with three levels: children nested within survey clusters (or | Slum IMR OR at neighbourhood-level: 1.30 [95% CI 1.17-1.45] compared to non-slums; Slum IMR adjusted OR at neighbourhood -level: 1.20 [1.07-1.35]; | GDP per capita, DHS Wealth Index, antenatal care, maternal height, |

| | | | | | |
|---|---|---|---|---|---|
| | neighbourhood-level | Neighbourhood was considered slum if DHS survey cluster had at least 50% slum households | neighbourhoods), nested within countries | Slum IMR OR adjusted with interaction term at neighbourhood-level: 1.34 [1.15-1.57];<br>Slum IMR at child-level: 1.25 [1.14-1.37];<br>Slum IMR adjusted OR at child -level: 1.07 [0.97-1.19];<br>Slum IMR OR adjusted with interaction term at child-level: 1.07 [0.97-1.19]; | place of delivery, breastfeeding |
| Fink *et al.* 2014 (26) | Global Study (73 LMICs); Neighbourhood-level (DHS sample clusters) | Slum neighbourhood if >75% of households met at least two of the four slum criteria | Cross-sectional;<br>Cox proportional hazard model to assess association between living in slum and neonatal mortality, postneonatal mortality (PMR) and child mortality | City slums NMR adjusted hazard ratio (HR) with rural reference: 0.647 (std. error 0.0924)<br>Non-slums NMR adjusted HR: 0.694 (0.0461);<br>City slums adjusted PMR HR: 0.758 (0.135);<br>Non-slums adjusted PMR HR: 0.891 (0.0678);<br>City slums adjusted U5MR HR: 0.896 (0.171);<br>Non-slums adjusted U5MR HR: 0.678 (0.0671) | Child characteristics (sex, twin/non-twin, preceding birth interval, birth order), maternal education, household asset indicator, affordable health services, distance to health services |
| Ezeh *et al.* 2017 (133) | Bangladesh and Kenya;<br>Country-level | Used surveys which distinguish between slum and non-slum areas | Cross-sectional;<br>Compared crude U5MRs;<br>Used Urban Health Survey (UHS) from 2006-2013, Nairobi Cross-sectional Slum Survey (NCSS) from 2000-, and DHS from 2003-2014 to calculate U5MR for both countries. | Bangladesh slum U5MR: 80.7 deaths per 1,000 live births in 2006 and 57 deaths per 1,000 live births in 2013;<br>Bangladesh urban U5MR: 63 deaths per 1,000 live births in 2007 and 37 deaths per 1,000 live births in 2014;<br>Kenya slum U5MR: 151 deaths per 1,000 live births in 2000 and 79.8 deaths per 1,000 live births in 2012;<br>Kenya urban U5MR: 93 deaths per 1,000 live births in 2003 and 57 deaths per 1,000 live births in 2014 | None |
| Pörtner & Su 2017 (164) | India;<br>Individual-level (child) | First method: 2001 Census classification of slum (by state/local government, housing and slum boards, or compact area with >300 people or >70 households, and complying with Gupta *et al.* slum definition | Cross-Sectional;<br>Estimate association between area of residence and U5MR incorporating individual, household and area (state-level) characteristics; | Slum adjusted female U5MR HR: 0.31 (std. error 0.13);<br>Non-slum adjusted female U5MR HR: 0.55 (0.12);<br>Slum adjusted male U5MR HR: 1.25 (0.34);<br>Non-slum adjusted male U5MR HR: 0.90 (0.16) | Child gender, child age, paternal and maternal education, maternal height, household head religion, household wealth, area wealth, |

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| | | which includes lacking drinking water and living in unhygienic environment (176);<br>Second method: Local field assessment using definition by Gupta *et al.* (176) | Present results separately by sex | | area health environment |

# Chapter 5. Identifying vulnerable urban neighbourhoods in Accra, Ghana using census and remote sensing data

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## Abstract

Identifying vulnerable communities in cities can facilitate more targeted interventions and policies to ensure equitable health services, improve housing and infrastructure conditions, and reduce economic and social inequality. However, few governmental agencies in low- and middle-income countries (LMICs) are able to demark vulnerable urban area boundaries, and limited work has been conducted using available census and remote sensing data to identify such areas. We leveraged cross-sectional housing data from the 2010 Ghana Census, slum classification data from the Accra Metropolitan Assembly and UN-Habitat (AMAUH), and remote sensing imagery from the United States Geological Survey (USGS) and National Aeronautics and Space Administration (NASA) to introduce Bayesian logistic regression models to identify vulnerable urban areas in Accra, Ghana. Using these models, we assessed the associations of housing, density, and environmental attributes with vulnerable urban area classification of EAs in the Accra Metropolitan Area (AMA). We applied the final model to predict the probability of urban EAs across the entire Greater Accra Metropolitan Area (GAMA) as being vulnerable, and compared child mortality among urban vulnerable, urban non-vulnerable, and rural neighbourhoods in the GAMA. The variables significantly associated with the probability of an EA being vulnerable included the use of public toilet facilities [OR: 3.51 (95% credible interval (CI): 1.55,7.53)], population density [OR: 5.72 (95% CI: 3.85,8.65)], use of improved wall materials [OR: 0.11 (95% CI: 0.03,0.43)], and vegetation abundance [OR: 0.25 (95% CI: 0.16,0.39)]. Nearly one-fifth of EAs in the GAMA, corresponding to 752,367 people, had a vulnerable urban area probability above 80%, however the mean child mortality in urban vulnerable neighbourhoods was similar to non-vulnerable neighbourhoods [9.1% probability of dying before the age of 5 (sd=1.5%) versus 8.9%, (sd=1.45%), respectively]. Our method for identifying vulnerable urban areas in a LMIC setting improved on past identification techniques by accounting for

housing, density, and environmental characteristics, assessing the relationship between predictor variables and vulnerable urban area classification, and providing weights for the predictor variables when predicting vulnerability. This modeling approach could be used in future studies to identify geographic clusters of vulnerable urban areas where interventions are warranted to improve housing and environmental conditions. Future research could use more recent data to investigate the temporal trends of vulnerable urban area development in Accra, and utilize the spatial distribution of urban vulnerability in the GAMA to investigate other potential inequalities between vulnerable and non-vulnerable urban areas.

## 5.1 Introduction

Low-income vulnerable urban areas, often referred to as "slums", are the most deprived areas of cities in low- and middle-income countries (LMICs). Despite the growing prevalence of middle-classes across LMICs including many in Sub-Saharan Africa (SSA) (178–181), rapid urban population growth in LMICs has exceeded the capacity of cities to provide sufficient employment, affordable housing, and access to services for their growing populations (67,180). In SSA, although the proportion of urban residents living in vulnerable urban areas decreased from 70% to 56% between 1990 and 2014, the absolute number of people more than doubled from 93 million to 200 million during the same period (2,11,79). People living in vulnerable urban areas share many spatially-determined risks including insecure tenure, unsafe living and environmental conditions, high population density, and limited involvement in governance (11). These conditions may subsequently increase the risk of adverse health outcomes across the life course (97-103,182–198). While urban areas have better health on average than rural areas, the large inequalities between vulnerable and non-vulnerable urban areas may diminish the health advantages of urban living for many (27,33,35,132,133).

Identifying and disaggregating slums allows for the identification of unique urban-related needs that are specific to their populations and for the prioritization of areas for interventions or infrastructure upgrading. Yet this has proven challenging for LMIC cities which are often data sparse and rapidly changing. Censuses and other multinational data collection activities do not track the characteristics of populations living in vulnerable urban areas. Instead, vulnerable urban areas are often masked in aggregate statistics, hidden within census tract, neighbourhood, and collective urban metrics (61,185). Measures of poverty alone are usually inadequate proxies for health in vulnerable urban areas, as they tend to ignore the neighbourhood effects of shared physical and social environments (95,133). The most commonly used method to identify vulnerable urban areas using survey data involves an additive household slum index score based on household features defined by the UN-Habitat related to vulnerable urban areas, namely lacking adequate access to safe drinking water, improved sanitation facilities, durable housing conditions able to weather climatic conditions, sufficient living space, and secure tenure to prevent forced evictions (25–27,30,33,128,135). When creating an additive index score, several limitations exist: all the predictor variables are weighted equally; each of the criteria relies on dichotomous definitions for whether that criteria is met or not, which depends on subjective opinion; density or environmental characteristics are not included; and the association between the predictor variables and slum classification cannot be assessed. Even the use of the term "slum" can be problematic. It is often used to emphasize the seriousness of environmental and social problems in these neighbourhoods, but people living in these areas identified as slums may face stigmatization and be at a greater risk of forced evictions from their homes or communities (59–61). In this study, we therefore use the term "vulnerable urban area" rather than slum to emphasize that the physical environment and social conditions of these neighbourhoods prevent their populations from living decently and thriving (30).

In SSA cities, understanding inequalities in vulnerable urban areas has become a policy priority for international organizations and municipalities to ensure equity in living conditions and access to services across cities (61). However, few studies in SSA identify vulnerable urban areas in high spatial-resolution to assess inequalities (43). Our study leveraged administrative and remote sensing data to model and map predicted vulnerable urban area metrics across the Greater Accra Metropolitan Area (GAMA). Specifically, the objectives of this study were to (1) develop Bayesian logistic regression models of "vulnerable urban area" classification and interpret the associations with housing, density, and environmental predictor variables, (2) characterize the spatial patterns of the predicted probabilities of an area being vulnerable for the GAMA, and (3) apply the prediction model to investigate potential inequalities in child mortality between vulnerable urban areas and the rest of urban GAMA. This study was conducted within the larger Pathways to Equitable Healthy Cities project (http://equitablehealthycities.org).

## 5.2 Study Location

Our study was conducted in the GAMA, the most densely populated region in Ghana, and the country's political, economic, and administrative capital (estimated population in 2010 and 2020: 4.0 million and 5.1 million) (186,187). This large metropolitan area comprises 22 districts that are divided into 406 neighbourhoods, which are further subdivided into 4,611 urban EAs and 408 rural EAs. Urban EAs in the GAMA have a median land size of 0.05 km$^2$ and population of 689 [Interquartile Range (IQR): 486,940]. At GAMA's urban core is the Accra Metropolitan Area (AMA) (estimated population in 2010 and 2020: 1.6 million and 2.1 million) which compromises ~52% of urban EAs in the GAMA (188). GAMA has continued to experience rapid population growth over the past decade, with a population growth rate of 3.5% per year, and is projected to more than double in population by 2040 (186). This rapid growth has contributed to large and increasing inequalities in housing, incomes, and exposure to crowding and environmental pollutants across the GAMA (31,82).

## 5.3 Methods

### 5.3.1 Modelling approach

We used a series of Bayesian logistic regression models to predict vulnerable urban areas in the GAMA based on housing, density, and environmental characteristics. The regression model with the best fit was used to quantify the relationship between housing, density, and environmental characteristics with vulnerable urban area classification in the AMA. We subsequently used the regression model with the best predictive power to identify vulnerable urban areas across the entire GAMA.

### 5.3.2 Data

#### *5.3.2.1 Field survey-based slum data for the AMA*

We obtained a spatial map of slum versus non-slum classification for the AMA from a field survey conducted in 2011 by the Accra Metropolitan Assembly and UN-Habitat (AMAUH) (145, **Figure A1**). In brief, the AMAUH study mapped urban slums in AMA using a combination of aerial photography, the number of persons versus number of dwellings derived from the 2000 Ghanaian Census, income levels based on the city's income classification scheme, and interviews with members of the city's assembly and AMA residents (94). The final map identified 78 slum settlements and pockets within AMA In 2017, the AMAUH slum map was georeferenced by Engstrom *et al*. with urban EAs in AMA from the 2010 census (32). We therefore classified EAs as "vulnerable urban areas" if their centroid fell within the boundaries of a slum settlement or pocket on the AMAUH map, using the same classification system as Engstrom *et al.* (32).

*5.3.2.2 Housing characteristics and population density*

We obtained data on housing characteristics using a 10% random sample of the most recently available (2010) Ghanaian Census (186). Independent variables selected for the regression model were derived from census questions related to the UN-Habitat's five criteria to be considered a slum household, including: drinking water source; type of sanitation facility; ownership of dwelling; type of dwelling (e.g., compound house or separate house); type of housing materials for roof, floor, and wall; household size; and number of bedrooms in the home (see list of **Table A1**). We assessed housing density by dividing the household size by the number of bedrooms per household, and then estimated average housing density for each EA. For categorical variables, a dummy variable was created to dichotomize the category with the most household observations within the AMA versus other categories combined, and was expressed as the percentage of households in each EA.

The number of individuals per EA and the EA area in $km^2$ were included in shapefiles of the GAMA received from the Geographic Information System (GIS) team of the GSS. Population density at the EA-level was estimated by dividing the number of individuals per EA by the total area (number of people per $km^2$).

*5.3.2.3 Environmental quality*

We obtained data on flood risk and greenness to characterize environmental quality. We assessed risk of flooding for each EA using Digital Elevation Model (DEM) data from the National Aeronautics and Space Administration (NASA) (https://lpdaac.usgs.gov/products/nasadem_hgtv001/). The DEM data was calculated through NASA's Shuttle Radar

Topography Mission (SRTM), which used two interferometric radar images taken at slightly different angles at the same time to measure surface elevation using the difference between these two radar signals (189). Raster data were extracted using QGIS version 3.16.0, and zonal statistics were used to determine the mean elevation for each EA and for the 5km buffer surrounding the EA. For each EA we calculated the ratio of mean elevation of the EA to the mean elevation of the surrounding 5km buffer, to account for northern GAMA EAs being naturally located at higher elevations.

Greenness was assessed using the normalized difference vegetation index (NDVI), which quantifies the abundance of vegetation by measuring the difference between near-infrared (NIR) wavelengths, which vegetation reflects, and red wavelengths, which vegetation absorbs (range: -1.0 to 1.0). Landsat-8 satellite imagery were obtained for 2013-2016 from the United States Geological Survey (USGS) EarthExplorer for southern Ghana (190). Landsat-7 data prior to 2013 were unavailable due to satellite scanline errors. We obtained raster data including the fourth and fifth spectral bands, representing red light and NIR light respectively. Satellite images from the dates December 6, 2015 and January 7, 2016 were selected, since they were the two earliest satellite images available with minimal cloud cover (<10%). NDVI was calculated in QGIS using equation 1:

**Equation 1:** $$NDVI = \frac{(NIR-RED)}{(NIR+RED)}$$

where NIR are pixel values of NIR light and RED are pixel values of red light. Zonal statistics were used to calculate mean NDVI scores for each EA.

*5.3.2.4 Estimates of child mortality*

We obtained neighbourhood estimates of child mortality for GAMA in 2010 from Bixby *et al.* (citation forthcoming). Detailed information on the methods for small-area estimation of child mortality is provided elsewhere (191,192). Briefly, the census collects information on maternal age, number of children ever born, and number of children surviving for each woman censused. These age and summary birth history data can be used to estimate child mortality using established demographic methods (192). Bixby *et al.* obtained population data for the full Ghana 2010 Census (accessed in December 2019 at the Ghana Statistical Services) to estimate child mortality rates for each neighbourhood in GAMA using the indirect maternal age cohort method (191,192).

### 5.3.3 Statistical Analysis

*5.3.3.1 Model building and evaluation*

We used a Bayesian logistic regression approach to model urban EA vulnerability as a function of independent variables encompassing housing, density, and environmental quality in the GAMA (**Table A2**). This technique enabled us to (i) interpret the mean associations of EA vulnerability with selected predictor variables, and (ii) predict EA vulnerability for urban areas outside of the core AMA (i.e., the region where the AMAUH slum study was conducted). The dependent variable was the dichotomous classification of EAs in AMA as slum or not based on the AMAUH map (referred to in our analysis as "vulnerable urban area") (94). The 11 predictor variables captured eight household characteristics related to UN-Habitat's definition of a slum, and three environmental characteristics previously used to characterize vulnerable urban areas in Accra (11,25,32,195,**Table A2**). In order to ensure there was no multicollinearity present, only one predictor variable was derived from each categorical census question to ensure that predictor variables included in the model could not be predicted solely from one or more of the other predictor variables. Additionally, we evaluated for potential multicollinearity through a correlation matrix, scatter plots between all the predictor variables, and a chi-square test of independence between binary predictor variables. No collinearity was detected through these tests. We also assessed whether the addition of random effects at the neighbourhood-level improved the model fit and its predictive performance.

The first fitted regression model, equation 2, did not include neighbourhood random effects.

**Equation 2:**
$$Y_i \sim Bernoulli(p_i)$$
$$logit(p_i) = \alpha + \beta X_i$$

The fitted model was a Bernoulli distribution with parameter $p_i$ representing the probability of being a vulnerable urban area for the $i^{th}$ EA; a dependent variable $Y_i$ categorized as 1 if the EA was classified as a "slum" in the AMAUH slum map and 0 otherwise; $X_i$ was a vector of 11 independent variables at the EA-level; β was an 11-dimensional vector of coefficients capturing the linear relationship between each of the independent covariates and the logit of the probability of being a vulnerable urban area; and the constant $\alpha$ was the intercept which captures the overall probability when all covariates are simultaneously equal to zero. We assigned to the coefficients $\alpha$ and β independent normal distributions with mean zero and standard deviation 0.98. The specification $\beta_k \sim N(0,0.98^2)$ corresponds to a 95% odds ratios interval of $\exp(\pm 1.96 \times 0.98)$ which is equal to [0.15,6.8], a range of odds ratio probabilities that are reasonable for a Bayesian generalized linear mixed models with a binary outcome as recommended by Wakefield in 2013 (193).

The subsequent second and third regression models used a second fitted model, equation 3, and included neighbourhood-level random effects.

**Equation 3:**
$$Y_{ij} \sim Bernoulli(p_{ij})$$
$$logit(p_{ij}) = \alpha + \beta X_{ij} + V_j$$

In this case (model 2), the fitted model assumes a Bernoulli distribution for the outcome with parameter $p_{ij}$ representing the probability of being a vulnerable urban area for the $i^{th}$ EA in the $j^{th}$ neighbourhood; and $V_i$ was the EA random effect at the neighbourhood level. In this model, $V_i$ was an unstructured EA random effect, where the model was fitted to the data assuming that the neighbourhood random effects were independent, *a priori*. The prior for the $V_i$ follows independent zero mean normal distributions, with a weakly-informative half-cauchy prior for the standard deviation (194). In the third model (model 3) we additionally assumed *a priori* that the $V_i$ EA random effects followed an intrinsic conditional auto-regressive (ICAR) prior distribution, which imposed a prior spatial structure to the random effects (195). In this model, EAs located in adjacent neighbourhoods tend to adjust similarly after accounting for the covariates.

For all three fitted regression models, sampling from the resultant posterior distribution was conducted using Markov chain Monte Carlo (MCMC) methods, with 20,000 iterations and 2,000 burn-ins. The fitted models were run using Nimble (196), a hierarchical statistical modeling package on R (196). We configured an automated factor slice sampler for $\alpha$ and β, which samples more efficiently than alternative MCMC sampling algorithms (197). Trace plots, segment plots, and histograms of the posterior distributions of the coefficients were evaluated to ascertain convergence. Our model outputs included the posterior distribution of the probabilities of EAs being vulnerable urban areas and the mean summary of the posterior distribution of the model coefficients, which can be interpreted as odds ratios (OR) (198).

*5.3.3.2 Model Selection*

We undertook a model selection process to first identify a parsimonious and generalizable model that maximized model fit to assess the associations between the independent variables and vulnerable EA classification. We selected our final model based on the best fit using Watanabe-Akaike Information Criterion (WAIC) which is the generalized version of the Akaike Information Criterion that estimates prediction error while considering model simplicity to prevent overfitting (199,200). The ORs of each independent variable were reported with 95% posterior credible intervals to evaluate which variables were associated with a higher or lower odds of an EA being vulnerable.

A second model selection process was conducted to select a generalizable model with the best predictive performance for vulnerability in the GAMA. We evaluated the fit of models 1 and 2 with cross-validation of 2.5%, 3.7%, 5.0%, 6.2%, 7.5%, 8.7%, 10% random samples of the EAs in the AMA. Briefly, these EAs were excluded from the fitted models prior to fitting. Each respective model was then used to predict the vulnerable urban area probability scores of the excluded EAs. We did not evaluate model 3 with spatially structured random effects because we assumed a conditional autoregressive prior distribution for the random effects, which results in an improper distribution of the neighbourhood random effects that were not in the sample. The posterior distributions of the predicted vulnerable urban area probabilities were assessed, and the predicted probabilities of these EAs were compared to their fitted probability values. In each of the cross-validation comparisons, the mean square error (MSE) values and 95% posterior credible intervals were assessed as indicators of predictive performance. We also tested whether model assumptions were upheld using diagnostic plots of the predictive posterior distributions.

#### *5.3.3.3 Predicted EA vulnerability in the GAMA*

After selecting our final model for prediction, we generated the predictions of EA-level vulnerable urban area probabilities for all EAs in the GAMA. The predictions were restricted to EAs categorized as urban in the 2010 Ghana Census so that we did not predict out of sample. We spatially overlayed the predicted probabilities onto the map of urban EAs across GAMA, and summarized the percentage of the urban population living in EAs that fell into different bins of vulnerable urban area probabilities in the GAMA (0-20%, 20-40%, 40-

60%, 60-80%, and 80-100%). For clusters of three or more EAs identified as having a high vulnerable urban area probability (i.e., >0.80), we used Google Earth Pro version 7.3.3.7786 to retrieve satellite images from 2010, the same year of the census data. Visual characteristics of these areas were identified, including vegetation abundance, roads, building materials, nearby services, and building density.

*5.3.3.4 Local indicators of spatial association (LISA) analysis*

We spatially mapped the summary means of the posterior distributions of the independent variables across the AMA, and clusters of low and high values were identified for each independent variable using the local indicators of spatial association (LISA) technique. We applied Moran's I, an indicator of spatial autocorrelation, to each of the 11 independent variables at the EA-level to assess similarities in each EA's values to neighbouring EAs (201). LISA was then applied to the independent variables to detect the presence of significant clustering ($p<0.001$) (202). We identified clusters of high or low values for each of the 11 predictor variables in neighbourhoods which had low (e.g., <0.2) or high (e.g., >0.8) vulnerable urban area probabilities.

*5.3.3.5 Application of the model to estimate inequalities in child mortality*

We identified census vulnerable neighbourhoods where at least 50% of EAs had a high probability of being a vulnerable urban area (>0.80). While most neighbourhoods included only urban EAs (n=398), 8 neighbourhoods had both rural and urban EAs. In these cases, the neighbourhoods were classified as urban if over half their EAs were classified as urban. We compared the mean child mortality between vulnerable urban areas, other urban neighbourhoods, and rural neighbourhoods in the GAMA.

As a sensitivity analysis, we compared child mortality inequalities by place of residency (i.e., urban vulnerable) with varying cut-offs for neighbourhood vulnerability to ensure that inequalities in child mortality were not due to the choice of threshold. Multiple thresholds were used to distinguish vulnerable urban neighbourhoods, including being considered a vulnerable neighbourhood if: at least 50% of EAs had a probability of being a vulnerable urban area of 0.80 or higher; over 50% of its EAs had a vulnerable urban area probability of 0.50 or higher; and at least 80% of its EAs had a vulnerable urban area probability of 0.80 or higher.

The statistical analysis and spatial mapping were conducted in RStudio version 1.2.5042. The raster data extraction and preparation of density and environmental quality predictor variables was conducted in QGIS version 3.16.0. Satellite images of notable areas of high or low vulnerability probabilities were retrieved and visually assessed using Google Earth Pro version 7.3.3.7786.

## 5.4 Results

### *5.4.1 Descriptive statistics of housing, density, and environmental characteristics*

Compared with rural and other urban areas in the GAMA, EAs identified as slums by AMAUH had a higher proportion of households that lived in dwellings owned by others outside of the family, obtained drinking water from an outdoor piped network, relied on public toilets for sanitation, lived in compounds rather than individual units, and had cement or concrete flooring (**Table 3**). There were also differences in overcrowding, population density, and environmental characteristics related to place of residency in Accra. Population density at the EA-level was higher in slums than non-slums as expected. Additionally, the average person to bedroom ratio was slightly higher in urban slums than non-slums. Both vegetation abundance and elevation measures were higher in non-slums than slums.

**Table 3. Housing, density, and environmental characteristics in urban slum, urban non-slum, and rural households in the GAMA. Classification based on the AMAUH map.**

| | Place of residency in AMAUH classification | | |
|---|---|---|---|
| | **Urban Slum** | **Urban Non-slum** | **Rural** |
| **Total number of households** | 24,793 | 68,376 | 5,132 |
| **Ownership of dwelling** | | | |
| Other private individual | 11,148 (45.0%) | 28,482 (41.7%) | 1,795 (35.0%) |
| Household member | 9,276 (37.4%) | 26,293 (38.5%) | 2,420 (47.2%) |
| Relative | 3,294 (13.3%) | 7,884 (11.5%) | 598 (11.7%) |
| Other | 1,075 (4.3%) | 5,717 (8.4%) | 319 (6.2%) |
| **Drinking water source** | | | |
| Outdoor pipe | 8,570 (34.6%) | 18,293 (26.8%) | 894 (17.4%) |
| Sachet water | 6,716 (27.1%) | 19,513 (28.5%) | 2,273 (44.3%) |
| Indoor pipe | 5,922 (23.9%) | 20,266 (29.6%) | 443 (8.6%) |
| Public tap | 3,023 (12.2%) | 5,370 (7.9%) | 241 (4.7%) |
| Bore-hole or tube-well | 77 (0.3%) | 873 (1.3%) | 535 (10.4%) |
| Other | 485 (2.0%) | 4,061 (5.9%) | 746 (14,5%) |
| **Sanitation facility** | | | |
| Public toilet | 13,904 (56.1%) | 19,269 (28.2%) | 726 (14.1%) |
| Flush toilet | 4,205 (17.0%) | 26,337 (38.5%) | 1,178 (23.0%) |
| Pit latrine (improved) | 3,563 (14.4%) | 9,789 (14.3%) | 729 (14.2%) |
| Bucket/pan | 1,476 (6.0%) | 842 (1.2%) | 9 (0.2%) |
| Pit latrine (unimproved) | 1,070 (4.3%) | 7,153 (10.5%) | 1,448 (28.2%) |
| No facility | 466 (1.9%) | 4,595 (6.7%) | 1,016 (19.8%) |
| Other | 109 (0.4%) | 391 (0.6%) | 26 (0.5%) |
| **Dwelling type** | | | |
| Compound house (rooms) | 19,559 (78.9%) | 35,110 (51.3%) | 1885 (36.7%) |
| Improvised (i.e. kiosk) | 1,503 (6.1%) | 4,154 (6.1%) | 289 (5.6%) |
| Semi-detached house | 1,292 (5.2%) | 6,553 (9.6%) | 400 (7.8%) |
| Separate house | 1,253 (5.1%) | 13,116 (19.2%) | 1,764 (34.4%) |
| Flat/Apartment | 678 (2.7%) | 5,517 (8.1%) | 177 (3.4%) |
| Other | 508 (2.0%) | 3,936 (5.7%) | 617 (12.0%) |
| **Wall materials** | | | |
| Cement/Concrete | 19,608 (79.1%) | 58,304 (85.3%) | 3929 (76.6%) |
| Wood | 3,146 (12.7%) | 6,787 (10.0%) | 341 (6.6%) |
| Mud bricks/Earth | 913 (3.7%) | 773 (1.1%) | 641 (12.5%) |
| Other | 1,126(4.5%) | 2,512 (3.7%) | 221 (4.3%) |
| **Roof Material** | | | |
| Metal sheets | 13,541 (54.6%) | 32,252 (47.2%) | 3,127 (60.9%) |
| Slate/Asbestos | 9,801 (39.5%) | 30,304 (44.3%) | 1,232 (24.0%) |
| Cement/Concrete | 634 (2.6%) | 3,018 (4.4%) | 177 (3.4%) |
| Other | 817 (3.3%) | 2,802 (4.1%) | 596 (11.6%) |

| | | | |
|---|---|---|---|
| **Floor Material** | | | |
| Cement/Concrete | 21,518 (86.8%) | 53,058 (77.6%) | 3,955 (77.1%) |
| Wood | 1,154 (4.7%) | 2,471 (3.6%) | 210 (4.1%) |
| Mud/earth | 928 (3.7%) | 3,544 (5.2%) | 332 (6.5%) |
| Ceramic/Marble/Granite | 412 (1.7%) | 3,262 (4.8%) | 266 (5.2%) |
| Vinyl tiles | 284 (1.1%) | 2,260 (3.3%) | 155 (3.0%) |
| Terrazzo Flooring | 259 (1.0%) | 3,023 (4.4%) | 166 (3.2%) |
| Other | 238 (1.0%) | 758 (1.1%) | 48 (0.9%) |
| **Total number of EAs** | 983 | 3,628 | 408 |
| **Log Population Density** | | | |
| Mean ± SD | 10.6 ± 0.6 | 9.1 ± 1.2 | 6.8 ± 1.4 |
| Median [IQR] | 10.5 [10.2-11.0] | 9.2 [8.4-10.0] | 7.0 [6.0-7.8] |
| **NDVI** | | | |
| Mean ± SD | 0.065 ± 0.014 | 0.097 ± 0.025 | 0.155 ± 0.043 |
| Median [IQR] | 0.065 [0.054-0.075] | 0.097 [0.079-0.115] | 0.148 [0.127-0.185] |
| **Elevation** | | | |
| Mean ± SD | 1.00 ± 0.42 | 1.11 ± 0.49 | 0.86 ± 0.25 |
| Median [IQR] | 0.99 [0.68-1.29] | 1.04 [0.78-1.39] | 0.87 [0.72-1.01] |
| **People: Bedroom ratio** | | | |
| Mean ± SD | 2.75 ± 0.65 | 2.49 ± 0.61 | 2.62 ± 0.72 |
| Median [IQR] | 2.67 [2.37-3.02] | 2.45 [2.09-2.83] | 2.60 [2.20-3.00] |

### *5.4.2 Model performance*

We chose the model with independent neighbourhood random effects to assess the associations between the independent variables and vulnerable urban area classification because it had the smallest WAIC score. Including a spatially structured random effect by applying an ICAR prior to the neighbourhood random effects did not improve the model fit.

We selected the model without random effects to predict vulnerable urban areas in the GAMA because: (1) it consistently had lower MSE values during cross validation (**Table A3**); (2) the posterior distribution of the neighbourhood random effects was proportional to its prior distribution, resulting in predictive posterior distributions of the probabilities that were almost uniformly distributed in (0,1) (**Figure A2**); and (3) the posterior distributions of the vulnerable urban area probabilities in the model with independent neighbourhood random effects were imprecise with wide 95% posterior credible intervals (**Figure A3**). The posterior distributions of the probabilities from Model 1 were more precise as the distributions of vulnerable urban area probabilities were more concentrated around the posterior means (**Figure A3**).

### *5.4.3 Associations of housing, density, and environmental predictors with vulnerable urban area classification*

The probability of an EA being a vulnerable urban area was higher with greater population density, greater household crowding, a higher proportion of households using public toilets for sanitation, and a higher proportion of households living in a compound dwelling (**Figure 1**). Variables associated with a lower odds of an EA being vulnerable included higher NDVI (a measure of vegetation), higher elevation relative to neighbouring EAs, a higher proportion of households with piped drinking water, and a higher proportion of households with cement walls. Neither housing tenure nor roof materials were associated with vulnerability. The associations between the independent variables and vulnerable urban area classification for the model without neighbourhood random effects and for the model with spatially-structured random effects are presented in **Figures A4 and A5**, respectively.

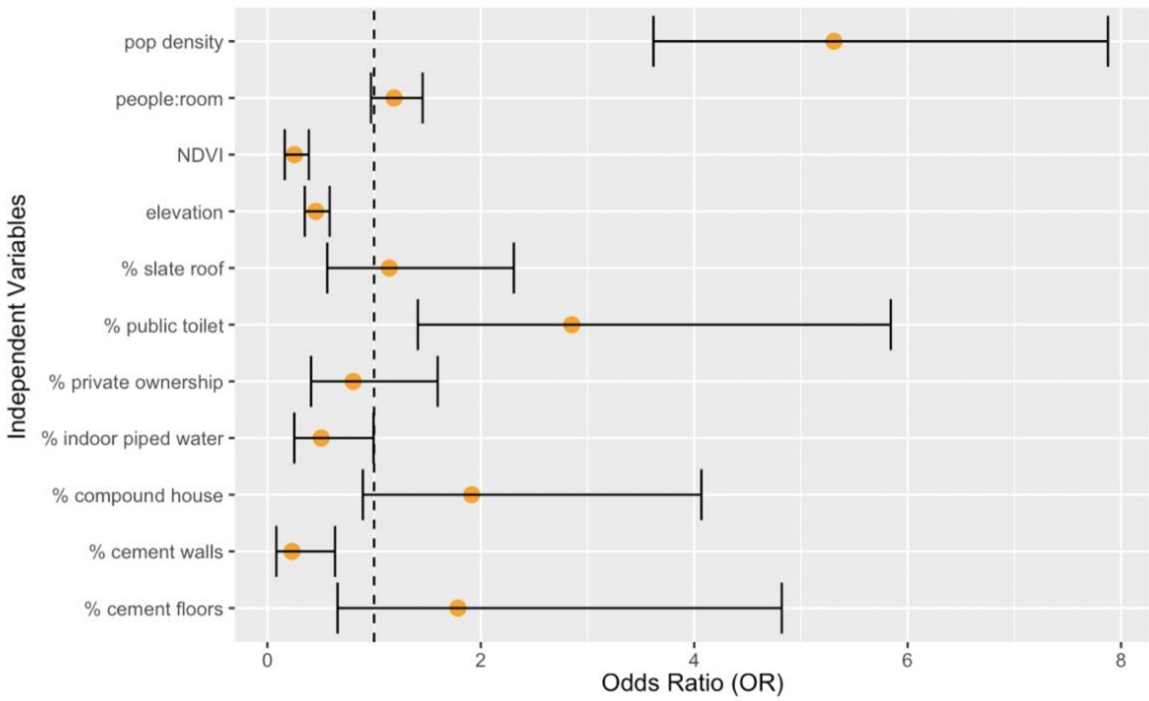

Figure 1: Posterior summary of the odds ratio (OR) (orange solid circles: mean and line segments: 95% posterior credible intervals) illustrating the associations of vulnerable urban area classification with housing, density, and environmental characteristics in the Accra Metropolitan Area, using a Bayesian logistic regression model with independent neighbourhood-level random effects.

*5.4.4 Spatial patterns of vulnerable urban areas and housing, density, and environmental characteristics in the AMA*

In the LISA cluster analysis, elevation was significantly clustered (Global Moran's I [GMI]=0.86, p<0.001) (**Figure 2**), particularly along the banks of the Odaw River in South-Western AMA (**Figure A9**). Vegetation abundance also had clustering (GMI=0.84, p<0.001), with many identified vulnerable EAs having low vegetation abundance including the long-established vulnerable neighbourhoods of Chorkor, Nima and Sodom and Gomorrah. The percentage of households that rely on public toilets for sanitation was clustered in the AMA (GMI=0.59, p<0.001), and tended to be localized in the low-income coastal neighbourhoods including South Teshie, Jamestown, and Gbegbeyisie, but were also clustered in several inland neighbourhoods including Sabon Zongo and Sodom and Gomorrah. Population density had high value clusters (GMI=0.57, p<0.001) within several vulnerable urban areas including Sabon Zongo and Nima. We also observed a number of clusters with low population density in neighbourhoods with low vulnerable urban area probabilities (<0.2) including East Legon and the Airport Residential Area.

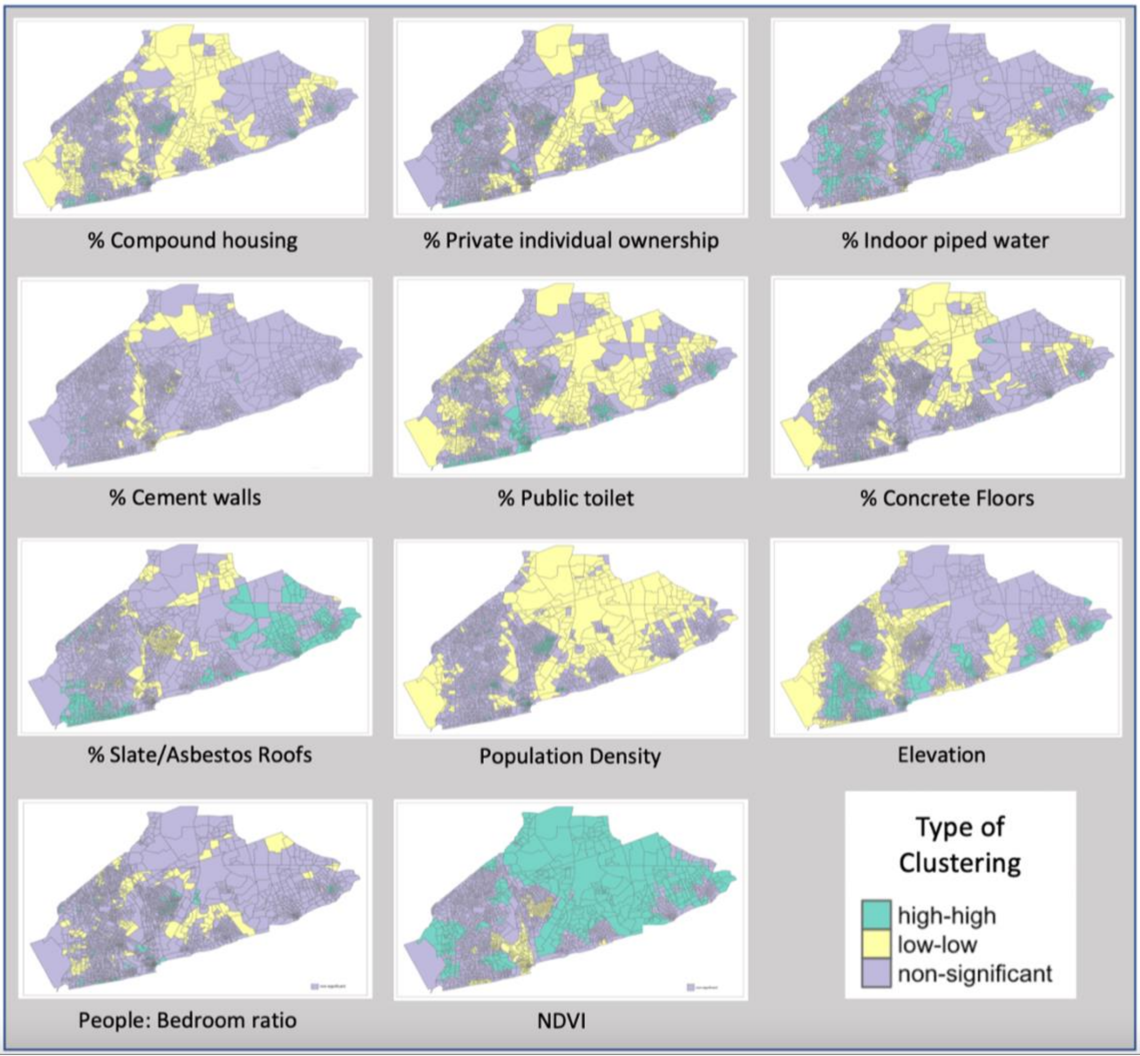


Figure 2: Spatial clustering of housing, density, and environmental quality attributes for enumeration areas (EAs) in the Accra Metropolitan Area (AMA). Results from a LISA spatial autocorrelation test. Turquoise shading indicates statistically significant clusters of high values (p<0.05), yellow shading indicates statistically significant clusters of low values (p<0.05), and purple shading indicates no observed spatial correlation (p>0.05). Each of the eleven independent variables demonstrated significant clustering (p<0.001).

*5.4.5 Urban population exposed to living in vulnerable urban areas in the GAMA*

Nearly one in five urban EAs in the AMA had a high probability of being a vulnerable urban area (**Figure 3**). Several well-established vulnerable urban areas had a high vulnerable urban area probability in our model including the coastal neighbourhoods Chorkor, Jamestown, and La, as well as in-land vulnerable urban areas including Russia, Nima, and Sodom and Gomorrah (**Figure 3**). Multiple EAs with low vulnerable urban area probabilities fell within areas identified as slum pockets and settlements in the AMAUH map, where other clusters with high vulnerable urban area probabilities, such as in South Teshie, were in areas previously not identified as slums by AMAUH (**Figure 4**). EAs with high vulnerable urban area probabilities were dispersed across the entire AMA, but were more prominent in western AMA and along the coast.

The median vulnerable urban area probability calculated at the EA-level in the GAMA was 34% (IQR: 10%-73%). Nearly one in five GAMA residents (~750,000 people) lived in EAs with a high probability of being a vulnerable urban area, and an additional one in seven GAMA residents (~500,000 people) lived in urban EAs with a moderately-high probability of being vulnerable between 0.6-0.8 (**Figure A10**). The majority of the population lived in EAs with a low (<0.50) probability of being a vulnerable urban area. Neighbourhoods with high urban vulnerable probabilities tended to be dispersed across the entire GAMA (**Figure 5**).

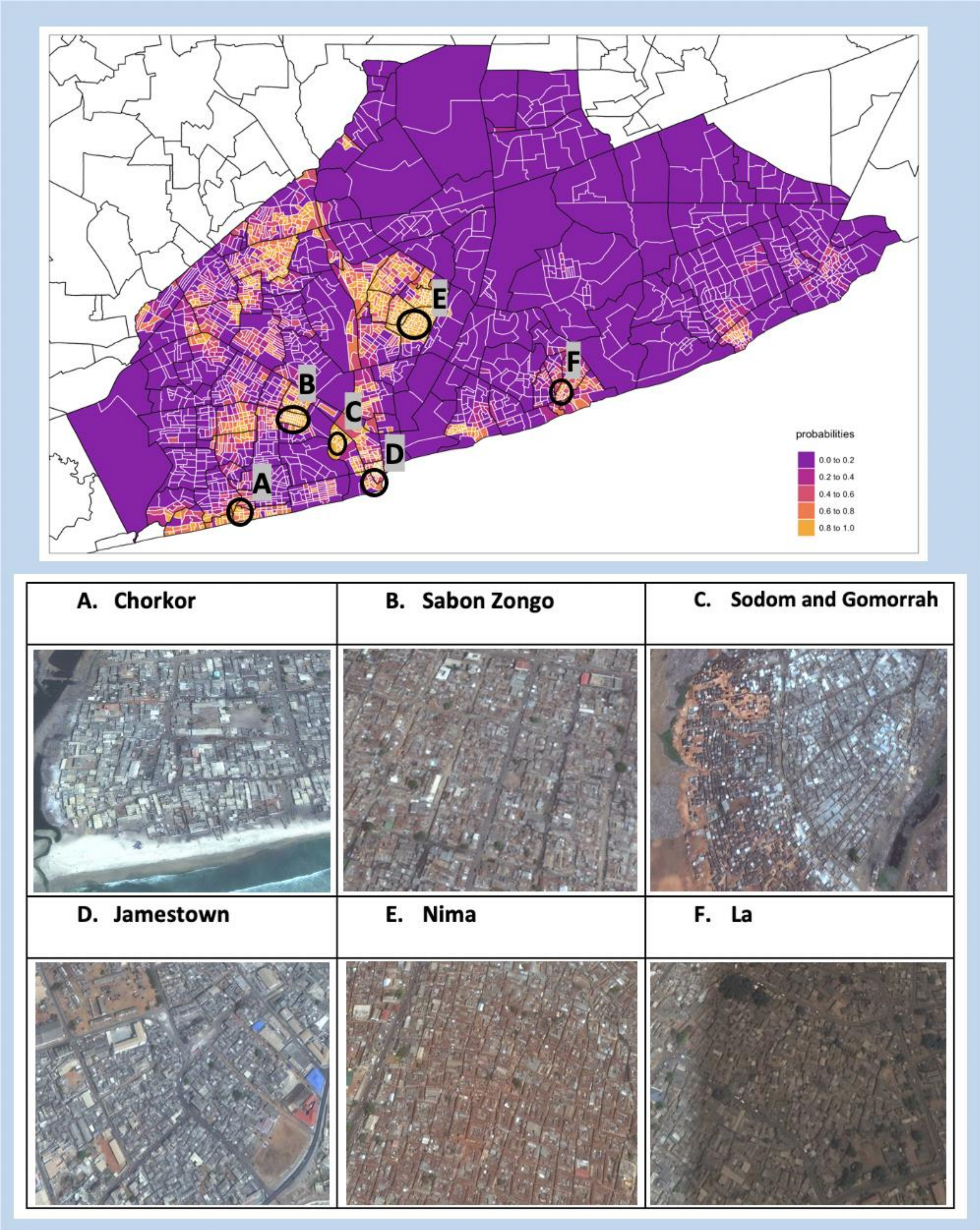


Figure 3: Prediction of vulnerable urban areas in the AMA. Areas identified are neighbourhoods that had clusters of high vulnerable urban EA probabilities and were classified as slums by the AMAUH slum map. Maps Data: Google, ©2009-2021 CNES/ Astrium, Maxar Technologies

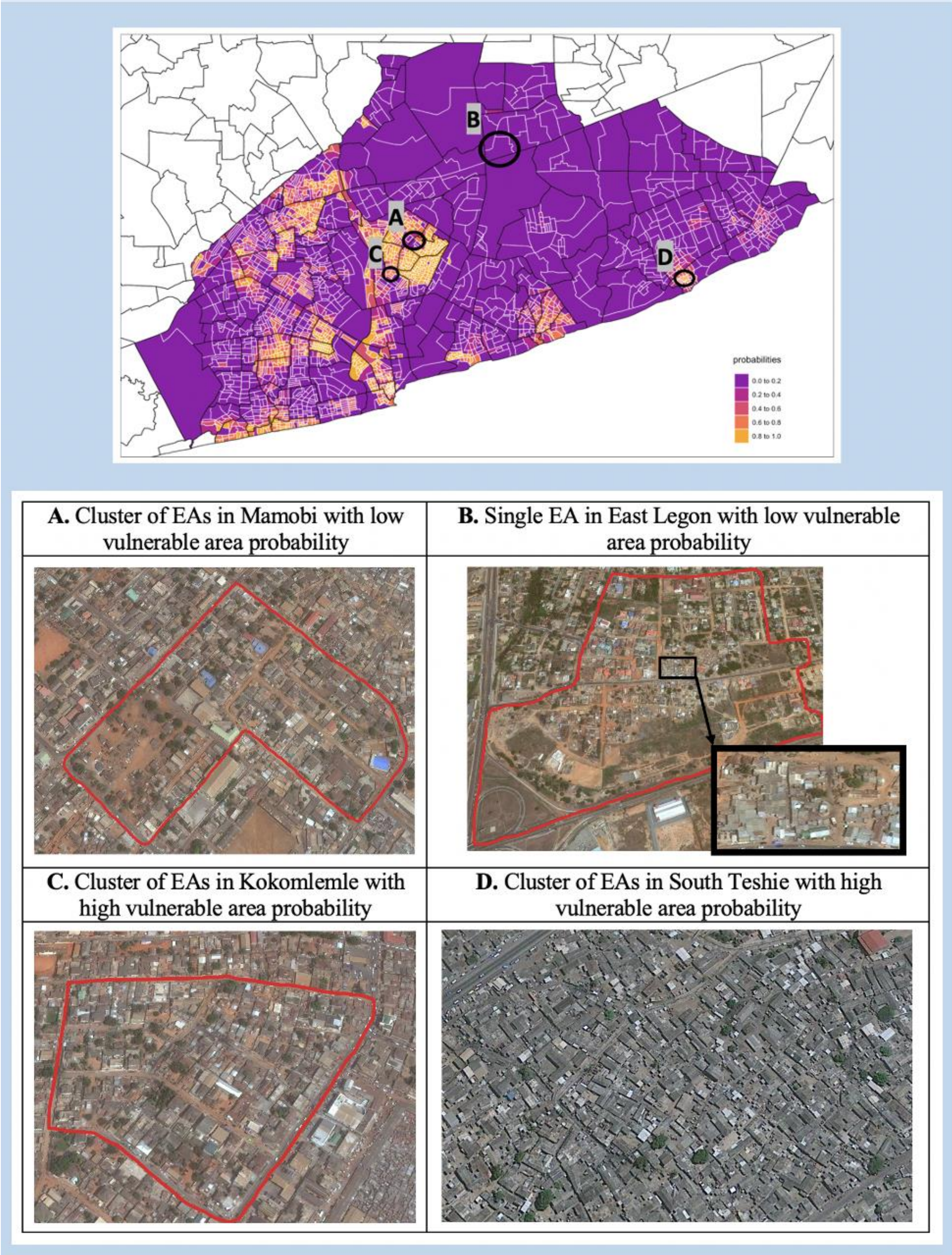


Figure 4: Prediction of vulnerable urban areas in the AMA. Examples A and B illustrate examples where EAs identified as slums by UN-Habitat were predicted as urban non-vulnerable in the regression model. Example C, in Kokomlemle, reflects a cluster of EAs having relatively high vulnerable urban area probability, however will not be classified dichotomously as a vulnerable urban area. Example D shows a cluster of EAs not identified as a slum by the UN-Habitat, which was identified as having a high vulnerable urban area

probability in the regression model. Maps Data: Google, ©2009-2021 CNES/ Astrium, Maxar Technologies

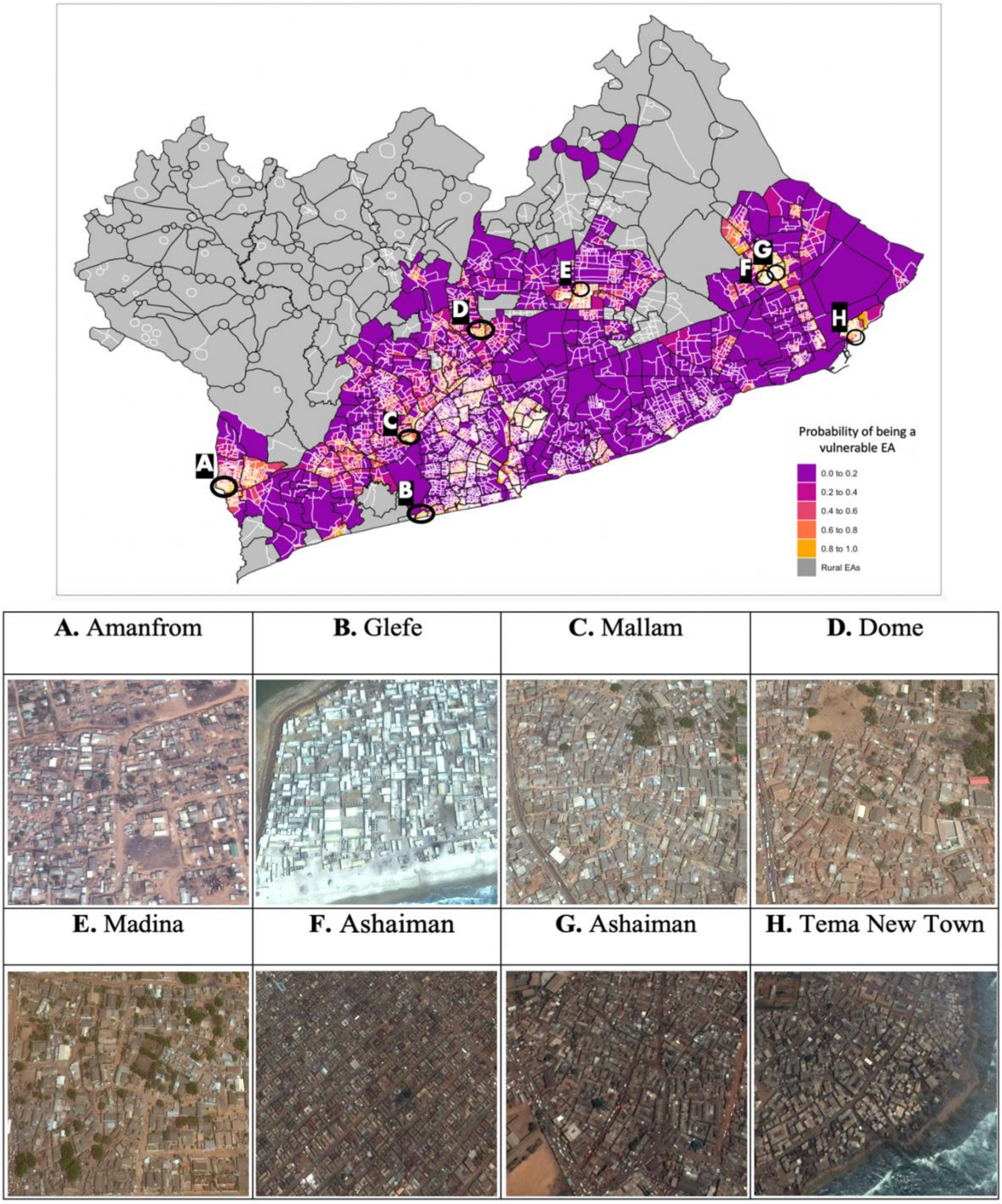


Figure 5: Prediction of vulnerable urban areas in the GAMA. Results of a Bayesian logistic regression model without random effects. Identified areas on the map are clusters of EAs with high probability of being a vulnerable urban area. The corresponding satellite images of these areas are located in the table. Rural EAs shown in grey. Maps Data: Google, ©2009-2021 CNES/ Astrium, Maxar Technologies

*5.4.6 Child mortality in rural and urban neighbourhoods with varying probabilities of vulnerability*

Using a strict probability cut-off for identifying neighbourhoods as vulnerable (i.e., at least 80% of EAs have a vulnerable urban area probability over 0.8), child mortality in vulnerable urban areas (8.8% probability of dying before the age of 5, sd =1.2%) was similar to non-vulnerable urban areas (9.0%, sd =1.5%) (**Figure A11**), and both had higher child mortality than rural neighbourhoods in the GAMA (6.9%, sd =1.6%). Our results were similar after applying a moderate cut-off if at least 50% of EAs had a vulnerable urban area probability above 0.80 (vulnerable: 8.9%, std deviation (sd) =1.7%; other urban: 9.0%, sd =1.4%) (**Figure 6**), and lenient cut-off if at least 50% of EAs had a vulnerable urban area probability above 0.50 (vulnerable: 9.1%, sd=1.5%; other urban: 8.9%, sd=1.4%).

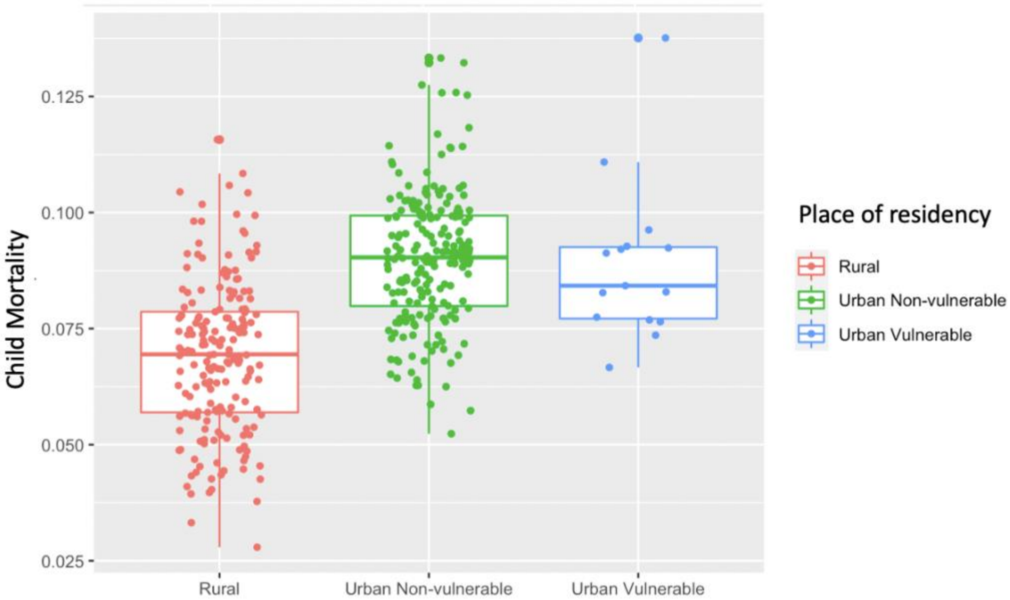


Figure 6: Neighbourhood child mortality estimates for rural, urban vulnerable, and urban non-vulnerable places of residency. Boxplots show the distribution of child mortality based on place of residency, with each point representing one neighbourhood.

## 5.5 Discussion

We found that approximately one in five EAs, accounting for an estimated 22% of Greater Accra's population, had a high probability (>80%) of being a vulnerable urban area. There were vulnerable urban EAs dispersed across the entire GAMA that were heterogenous in their size, location and types of vulnerability (e.g., lower elevated vulnerable EAs along rivers and coasts), though common features across vulnerable urban areas in Accra included a higher population density, lower elevation, lower vegetation abundance, lower percentage of households having piped indoor drinking water, and higher percentage of households using public toilets as a sanitation facility. Despite these differences, we did not observe a difference in child mortality between vulnerable urban areas and other urban areas in the GAMA. To the best of our knowledge, this study is the first to predict vulnerable urban areas across all of the GAMA, and provided the first vulnerable urban area identification model to assess the association between housing, density, and environmental characteristics with vulnerable urban area classification. As it was evident that density, environmental and housing characteristics had varying importance in predicting vulnerable urban areas, this indicates that the additive slum index score, a method commonly used to identify slum households and communities in LMICs, makes an erroneous assumption that each of the UN-Habitat's five housing criteria contributes equally to vulnerability. Prior to this report, one paper using a machine-learning random forest technique evaluating which housing and environmental variables may be more important for predicting slums in Accra; however, no quantifiable weights or statistical significance were reported (32). We identified and located urban areas in the GAMA that could benefit from policies or interventions to improve living and environmental conditions. Our methods can inform future studies aiming to assess changes in the GAMA over time, or identify vulnerable urban areas in other LMIC cities.

In the regression models, population density was strongly associated with vulnerable urban area classification, and we observed many clusters of high population density within vulnerable urban areas in the GAMA. These findings align with previous research in Accra which found that accounting for population density in slum identification models generally improved prediction (25,32). Living in densely-populated and overcrowded areas may put populations at an increased risk of communicable diseases (203), and can create difficulties in accessing health care if there are not sufficient health workers serving a high population area, as shown in cities in India, Iran, and Kenya (204–208).

Lower elevations also increased the odds of an EA being classified as vulnerable, which supports past literature in Accra (32,209–211). Many low-income areas in the GAMA, like Sodom and Gomorrah, are located in low elevation areas along to the Odaw River that are susceptible to flooding (94,212). Previous studies in Accra found that populations living in lower elevated areas were at increased risk of diarrhoeal diseases and other communicable diseases such as malaria and cholera due to frequent flooding, contaminated food sources following flooding, and standing water bodies (105,106).

Our results associating lower vegetation abundance with higher odds of an EA being a vulnerable urban area supports previous slum identification studies in Accra (25,213), and a number of studies conducted in other global cities in India and Rwanda (107,108). Vulnerable urban areas were characterized as having densely-packed housing due to rapid population growth, and therefore have fewer parks and green spaces (92,211-213) . Generally, living in areas with greater NDVI and green space has been associated with perceived health benefits and better mental health (109).

The housing characteristics associated with vulnerable urban area classification included the use of public toilets, having piped indoor water as a drinking water source, and having cement or concrete walls. Shared public toilets are common in many low-income communities in Ghana, including South Teshie and Nima where public toilets are also often distantly located, unhygienic, and lack privacy (216,217). There are concerns about the use of shared toilets within low-income communities, as poor sanitation has been associated with diseases such as diarrheal illnesses and gastroenteritis (216,218,219). As indoor piped water is the most improved source of drinking water as defined by the World Health Organization (WHO) but also requires substantial infrastructure investment and maintenance (220), it is not surprising that this decreased the odds of being considered a vulnerable urban area in our study. Having durable housing materials such as cement or concrete walls can protect a dwelling from environmental conditions, and recently has also been shown to have protective effects from insect-borne diseases such as malaria when compared to unimproved wall materials (221–223). In one study conducted in Zambia, cement or concrete walls significantly reduced the risk of malaria when compared to grass walls (OR=0.22, 95% CI 0.09-0.52) (182).

Although the associations with vulnerable urban area classification were not statistically significant, features including household crowding (i.e., people-to-bedroom ratio), percentage of dwellings as rooms within a compound, and percentage of households with cement floors were clustered in many vulnerable urban areas in our study. Coastal vulnerable urban areas had clustering of slate/asbestos roofing whereas inland vulnerable urban areas such as Nima and Sodom and Gomorrah did not. This is likely due to several inland vulnerable urban areas using a different roofing material homogenously across the neighbourhood, such as the use of corrugated iron roofing in Nima (58). Buildings in vulnerable urban areas are often constructed with materials that are readily available in the surrounding area, as many families do not have the financial security to purchase more improved and resistant building materials. A lack of statistical significance in associations between variables such as home ownership or cement walls with vulnerability may due to overlap in these variables relative to vulnerability across Accra (25). For example, high housing prices and interest rates contributed to nearly half of GAMA residents living in dwellings that were rented (82). It is likely that the housing characteristics in Accra's vulnerable urban areas differ drastically to the very high-income gated communities in Accra, however when comparing vulnerable versus other urban EAs in the AMAUH slum map, including middle-income EAs, considerable overlap in housing characteristics was observed.

Our predictive model identified 42 EAs in AMA as vulnerable (i.e., >80% probability of being vulnerable) that were not identified as slums by AMAUH (196). For example, several EAs in South Teshie had a high vulnerable urban area probability (>80%) in our model. Teshie is mixed-income neighbourhood where poor populations tend to be localized on the coast (217). South Teshie has a large portion of citizens employed in the fishing industry, and low fish prices contribute to sustained poverty (224). Previous field studies show that a high proportion of households in South Teshie lack access to private sanitation and instead rely on public facilities with issues of cleanliness and accessibility (217,224). Discrepancies, such as the vulnerable EAs in South Teshie, could be due to administrative decisions, the subjective nature of interviewing AMA residents, or on the reliance on housing characteristics encompassing UN-Habitat's definition of a slum without consideration of environmental quality or population density.

Although most of Nima, Mamobi and New Town neighbourhoods were identified as slums by the AMAUH map, our model identified pockets within these neighbourhoods with low vulnerable urban area probabilities (< 20%). Satellite imagery showed that a cluster of three EAs with low vulnerable urban area probabilities in Mamobi had individual housing units surrounded by green space along with a police station, churches, and retail shops. This was likely a non-vulnerable urban area within a large vulnerable urban area as predicted by the model. Similarly, a single EA in East Legon whose centroid fell within a slum pocket in the AMAUH map had a very low probability of being a vulnerable urban area. East Legon is a generally high-income residential area of Accra (58). Satellite imagery indicated a formal structure in this EA, many stretches of green space, and large residence buildings including several luxury apartments. However, in small pockets within East Legon there are emerging areas of vulnerability, as was the case in this EA. As the majority of the area was generally high-income, this EA overall was identified as having a low probability of being a vulnerable EA. This illustrated that the model may be unable to detect temporary and/or small vulnerable urban areas, although the majority of this EA did appear high-income.

Our predictive model identified several EA clusters with high probabilities of being vulnerable urban areas in GAMA where previous slum identification had not been conducted. Satellite images of these areas showed densely packed houses connected mainly by footpaths and limited access to roads. The neighbourhood of Madina had a high vulnerable urban area probability in our model, and is a low-income community that emerged from a forced resettlement program of Nima/Mamobi residents to make room for a highway project in the 1970s (225). This suggests that displaced residents from forced vulnerable urban area evictions in Accra are not always placed in neighbourhoods with improved living conditions. Also identified as vulnerable in our model is Glefe, a densely populated neighbourhood situated between a lagoon and the ocean that is very susceptible to flooding and erosion (209–211,226). This low-income neighbourhood is segregated from the AMA by Lake Bebu and lacks urban planning, roads, access to water and sanitation, and proper drainage (209). Finally, Tema New Town, an area identified as a vulnerable cluster in our model, is a coastal neighbourhood that was developed without compliance to formal planning regulations and lacks proper drainage systems so is vulnerable to flooding (227). Although several neighbourhoods identified as vulnerable in our model appeared to be vulnerable based on satellite imagery, one potential exception was in the neighbourhood Ashaiman. This neighbourhood was identified as vulnerable in our model, however several of its EAs had structured blocks of housing developed in rows with road access. This area likely was identified as vulnerable by our model because housing was still dense and there was limited green space. A high proportion of housing structures were compounds (~81% of households), where many households live together in adjacent single rooms. Ashaiman was a target area for slum upgrading programs conducted by the Tema Ashaiman Municipal Slum Upgrading Facility (TAMSUF) in 2009 (20), so it is possible that some of these EAs were undergoing development during the Ghana Census in 2010.

In light of the many studies associating poverty and low socioeconomic status with higher child mortality (146,153,163,155–162), an unexpected result from our study was the similarity in child mortality between vulnerable and non-vulnerable urban areas in the GAMA. It is possible that mother and child health initiatives in Accra have resulted in more equitable child mortality outcomes between areas of varying socioeconomic status. For example, a country-wide National Health Insurance with free delivery services and treatment of children under 3 months old was established in 2008.

The logistic regression model, which combines both survey and remote sensing data that are publicly available, overcomes the shortcomings of strictly census-based methods that do not consider population density or environmental characteristics, and satellite-imagery methods that do not account for household characteristics. The 2010 Ghana Census is the most recently available Ghanaian Census, and using census data allowed us to present the spatial distribution of vulnerability across the GAMA, which more current surveys like Ghana's DHSs would not be able to do. The use of the census data also allowed us to map vulnerability in GAMA at a fine-spatial level, the EA-level, while a number of previous vulnerable urban area identification studies were not spatially-resolved (26,27,33). Our regression models created dummy independent variables based on the most commonly observed household characteristics in Accra, and avoided subjectively dichotomizing unimproved versus improved housing characteristics which could result in erroneous decisions of what constitutes an improved housing characteristic. For example, indoor piped drinking water is considered more improved by the WHO than all other drinking water sources that would be categorized as improved using a dichotomous definition, including collected rain water, outdoor pipes, tube wells, or public taps (220).

By predicting the probability of EAs being classified as vulnerable urban areas, this continuous measure provides information on relative inequalities in vulnerability between neighbourhoods not observed using a dichotomous vulnerability classification. For example, some of the most vulnerable urban areas, such as Sodom and Gomorrah, had vulnerable urban area probabilities between 80-100%, while some areas not as vulnerable but still low-income, such as Kokomlemle, had vulnerable urban area probabilities between 60-80%. Both Kokomlemle and Sodom and Gomorrah are likely more vulnerable than high-income residential urban areas such as the Airport Residential area, where all EAs have a vulnerable urban area probability score below 20%. This continuous classification method can be used to prioritize where policies and interventions should be targeted to improve housing and environmental conditions.

Our study is not without limitations. When comparing model fit between the regression models, the regression model with independent neighbourhood random effects had the lowest WAIC score and was selected to assess the association between the independent variables and vulnerable urban area classification. Thus, some degree of residual spatial confounding between the neighbourhood-level random effects and fixed effects is possible. Spatial confounding may occur in linear mixed models with spatial random effects, and can impact the bias and precision of results (228). As the coefficients were similar in models with and without independent effects, we assumed that the degree of spatial confounding is not biasing the results. The data used for this analysis is mostly from 2010, the year of the most recent census, and may not be reflective of urban development in Accra in the present day. We were also unable to track temporal changes in vulnerable urban area development over time since a census has not be conducted since. It would be beneficial to incorporate data from the upcoming 2021 Ghanaian Census to evaluate how vulnerable urban areas may have emerged or disappeared over the past decade, as well as assess if there have been any changes in important health outcomes such as child mortality. We also assumed that NDVI was similar between the years 2010, when census and slum map data were available, and 2015, when satellite imagery were available. A study of NDVI in Accra between 2002 and 2010, using purchased Quickbird satellite imagery, noted that although vegetation cover in Accra did decrease in these eight years, in a regression analysis there was not a significant change in vegetation abundance between 2002 and 2010 related to 2002 neighbourhood-level housing quality indices ($R^2$=0.089, p=0.015) (213). This illustrated that NDVI did not change significantly depending on housing quality, and areas of varying socioeconomic status experienced similar declines in NDVI. Finally, our assessment of child mortality was conducted at the neighbourhood-level rather than the EA-level, the unit of analysis for our regression models, which could mask differences in child mortality due to vulnerability across a neighbourhood. Future studies could explore health inequalities at finer spatial scales than we were able to conduct for this study. For example, in East Legon where there are vulnerable urban areas built in close proximity to high-income housing, it should be investigated whether these vulnerable pockets have lower child mortality due to improved resources in the surrounding area or if there exist significant inequities within this small geographic area.

Ongoing research should also transition away from the use of the term “slum” and the stigmatization it brings (59–61,229), towards terminology such as “vulnerable urban areas” which emphasizes physical location and environment over populations and communities. Additionally, as household and density characteristics derived from census data as well as environmental quality characteristics derived from remote sensing data were associated with vulnerable urban area classification, mixed data sources should be used to identify vulnerable urban areas when governmental classifications do not exist, and field-based mapping is infeasible.

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# Chapter 6. Discussion and Conclusions

## 6.1 Discussion

We used a Bayesian logistic regression approach to identify vulnerable urban areas in Accra, and explored potential inequalities in child mortality outcomes between rural, vulnerable urban, and non-vulnerable urban areas. To the best of our knowledge, this was the first study to predict vulnerable urban areas across the entirety of the GAMA, and the first study to quantify the associations between housing, density, and environmental characteristics with vulnerable urban area classification. By using both census and remote sensing data, this classification method was among the few techniques to use a diverse set of data sources to classify vulnerable urban areas. The resulting EA-level probability of being vulnerable provides a measure of vulnerability at a fine spatial scale, and identifies clusters where future interventions are warranted to improve housing and environmental conditions.

The results of this research are synchronous with the ongoing progress of upgrading vulnerable urban areas globally as a major goal of the SDG-11 to improve living conditions in vulnerable urban areas (122). Vulnerable urban identification is the first step in determining areas where increased resources and development is needed most. In addition, SDG-3 aims to reduce global child mortality to 25 deaths per 1,000 live births by 2030 (45). It is therefore crucial to investigate the distribution of child mortality in LMICs to inform localized policy and interventions, and assess whether there are significant inequalities between areas of varying vulnerability. Inequalities exist in Accra's well-documented vulnerable urban areas encompassing: environmental hazards such as flooding which may destroy food supplies and propagate communicable diseases (94,105,106,212); inadequate sanitation facilities with unhygienic conditions and increased risk of gastroenteric disease transmission (216,218,219); and unemployment with lack of financial opportunities (82,224,230). Identifying vulnerable urban areas in the context of Accra specifically is therefore essential as several other undocumented vulnerable urban areas exist which may experience similar inequalities.

Chapter 2 discussed my decision to use the term “vulnerable urban area” rather than the term “slum” in describing urban areas characterized by a range of features including poverty, high population density, poor infrastructure, and lack of greenspace. This terminology transitions away from a pejorative term which has been known to stigmatize communities and justify large-scale forced evictions (18–20). We chose the term “vulnerable urban area” since this term emphasizes the role that physical place and environment has on social, economic, and environmental equity.

My literature review in Chapter 4 described the limitations of existing slum identification research using survey data, including: weighting the predictor variables equally; relying on dichotomous definitions of vulnerable urban areas which could result in misclassification; lacking assessment on how the predictor variables are associated with vulnerable urban area classification; and focusing solely on household characteristics without the consideration of neighbourhood or the surrounding environment. Bearing in mind that the vulnerable urban area population in SSA is expected to rise from 294 million in 2010 to 621 million in 2030 (3–5), it is crucial to be able to identify vulnerable urban areas and assess their inequalities in order to inform local policy to improve housing and environmental conditions in such areas.

Using two logistic regression models introduced in Chapter 5, we determined that approximately one in five EAs in the GAMA had a vulnerable urban area probability above 0.80, which represents over 750,000 Ghanaian citizens. Several variables were associated with vulnerable urban area classification including the use of public toilet facilities, elevation, population density, use of improved wall materials, and vegetation abundance. The mean child mortality in vulnerable urban areas was similar to non-vulnerable urban areas.

A combination of survey and remote sensing data can be used to identify vulnerable urban areas when governmental classification does not exist, and field-based mapping is infeasible. Vulnerable urban area probabilities within the GAMA should be updated with data from the upcoming 2021 Ghanaian Census to assess if vulnerable urban areas have emerged or been improved over the past decade. The distribution of vulnerable urban area probabilities in Accra may be used to justify localized interventions and policies to improve housing and environmental conditions such as improving sanitation facilities and ensuring equitable drinking water access. This model can also be applied in other urban city settings where at least a small portion of the city has prior information on where vulnerable urban areas are located, to assess if similar associations exist between housing, density, and environmental characteristics with vulnerable urban area classification, and to apply the model to predict other vulnerable urban areas where prior identification has not occurred.

Although there were no significant differences in child mortality between vulnerable and non-vulnerable urban neighbourhoods, future research should continue to investigate inequalities between vulnerable and non-vulnerable urban neighbourhoods, including studying child mortality variability within neighbourhoods at finer spatial scales. Other social, environmental, and economic inequalities may also be investigated between vulnerable and non-vulnerable urban areas, both in Accra as well as other LMIC urban settings.

## 6.2 Conclusions

An estimated one billion people worldwide live in vulnerable urban areas in cities, further perpetuating cycles of poverty, environmental pollution, inadequate housing and services, and social inequalities. My thesis aimed to develop a model which could predict the probability of an area being vulnerable, quantify the relationship between housing, density, and environmental predictor variables with vulnerable urban area classification, and explore potential inequalities in child mortality between vulnerable and non-vulnerable urban areas. I showed that population density, type of sanitation facilities, elevation, vegetation abundance, and wall materials were associated with vulnerable urban area classification in Accra. I also mapped the probability of EAs being vulnerable across the entirety of GAMA, and illustrated that there were several EAs with high probabilities, including areas which were previously identified as non-vulnerable by the AMAUH, as well as areas without prior classification at all. Through descriptive statistics I found no significant differences in child mortality between vulnerable and non-vulnerable urban areas as an application of the vulnerable urban area prediction model. Further research is warranted to predict vulnerable urban areas using both census and remote sensing data in other SSA countries, and to use these reported probabilities to address social, environmental and economic inequalities, including inequitable health outcomes. A goal of multiple governmental and global agencies, including the UN, is to reduce the prevalence of vulnerable urban areas. It is therefore imperative to identify these areas in order to assess progress in improving living conditions in these areas, and ensure economic, social, and environmental equity across entire cities.

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# Appendix: Supplementary Information

In the following appendix, further information, figures and tables will be reported to elaborate on the discussion and results of the thesis paper.

**Supplementary Figures:**

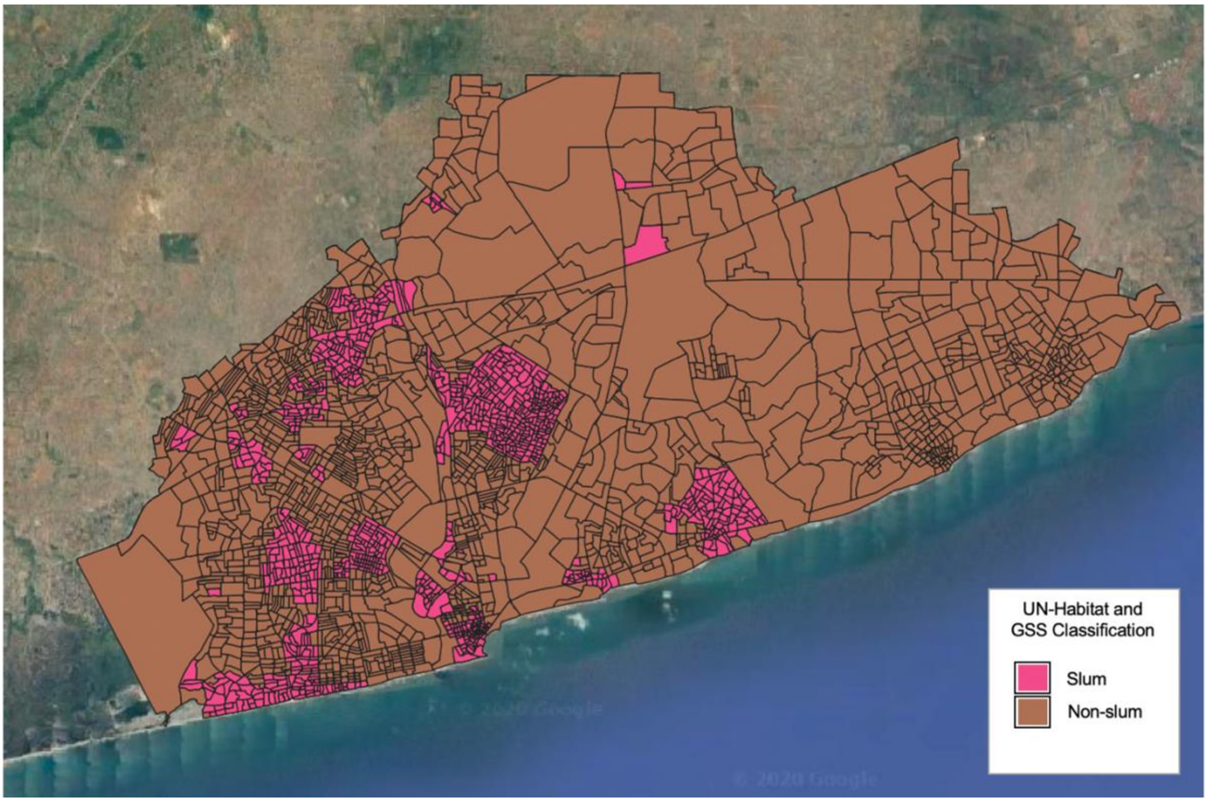


Figure A1: Classification of EAs as slum or non-slum based on whether EA centroids fell within slum settlement and pockets outlined by the AMAUH slum map (94).

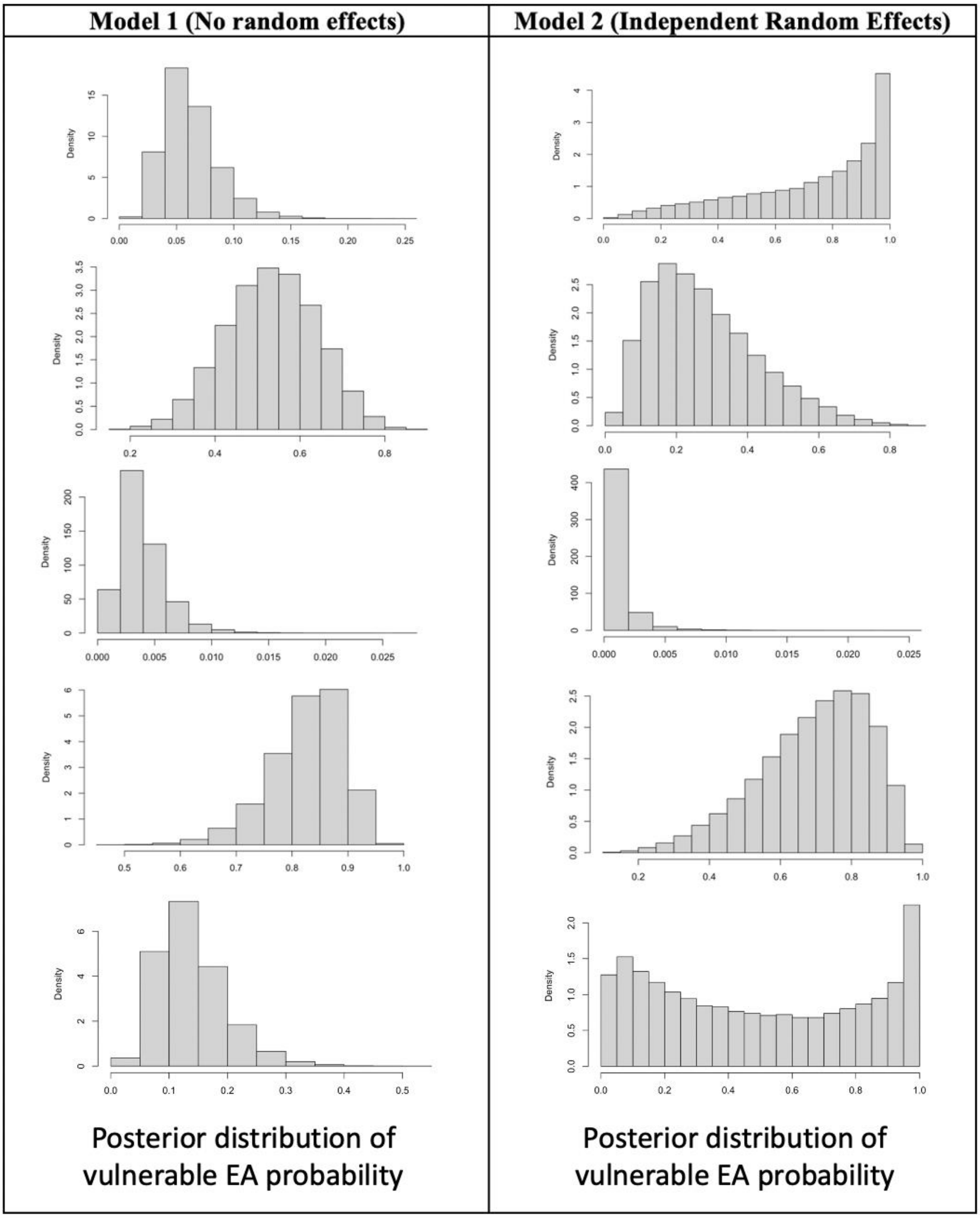


Figure A2: The posterior distribution of vulnerable EA probability predictions in the AMA. The five histograms show comparisons of five EAs (same between Model 1 and Model 2) that were removed at random from the fitted model and subsequently predicted.

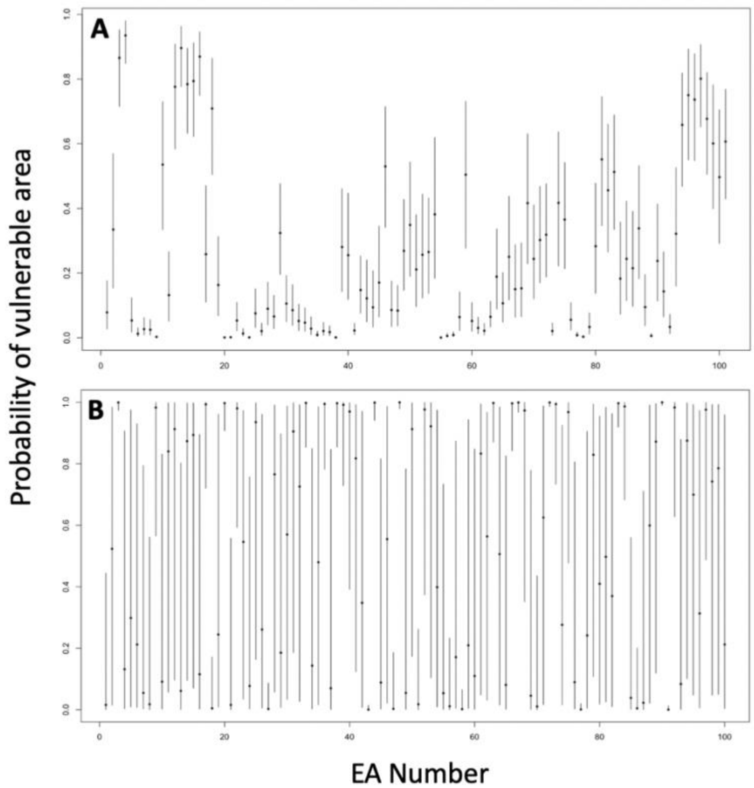


Figure A3: Segment plots of the posterior distribution of vulnerable EA probability predictions in the AMA. The top segment plot (A) is showing the vulnerable area probability distributions from Model 1 with no independent random effects, whereas the bottom segment plot (B) is the vulnerable area probability distributions from Model 2 with independent neighbourhood random effects. Each segment plot is showing the point estimates and 95% posterior credible intervals of the vulnerable urban area probabilities for a sample of the same 100 EAs.

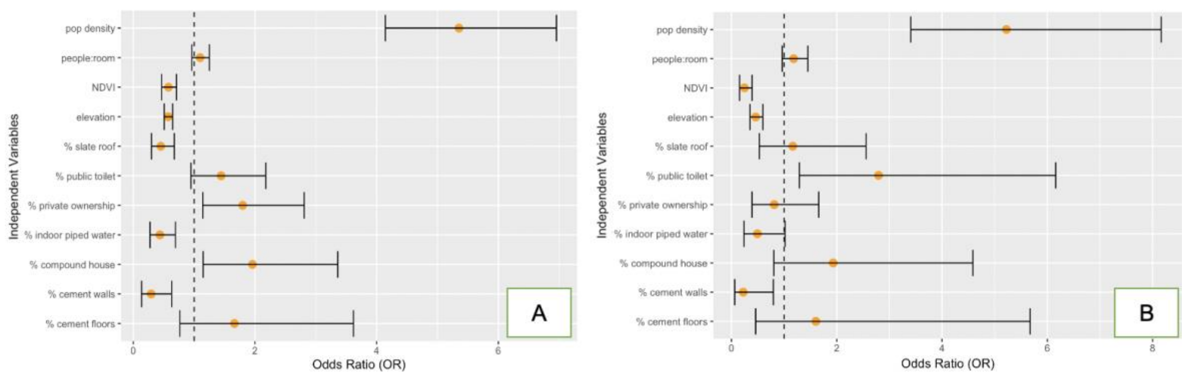


Figure A4: The odds ratio (OR) and 95% credible intervals illustrating the association of vulnerable urban area classification with various housing, density, and environmental characteristics, using a Bayesian logistic regression model with no neighbourhood-level random effects (a), and a Bayesian logistic regression model with spatially-structured random effects (b).

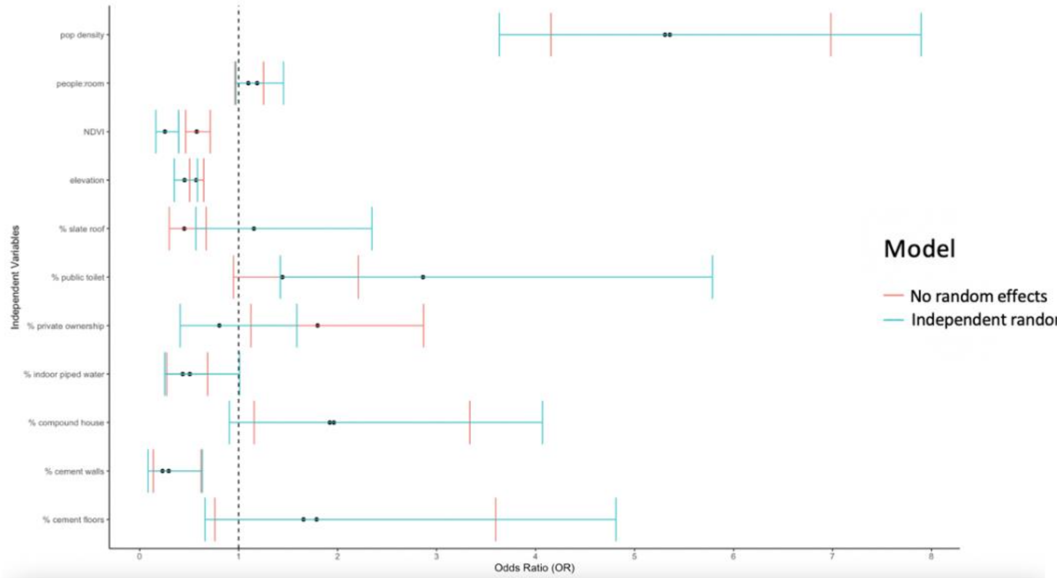


Figure A5: The odds ratio (OR) and 95% credible intervals illustrating the association of vulnerable urban area classification with various housing, density, and environmental characteristics, using a Bayesian logistic regression model with no neighbourhood-level random effects (red), and a regression model with independent random effects (blue).

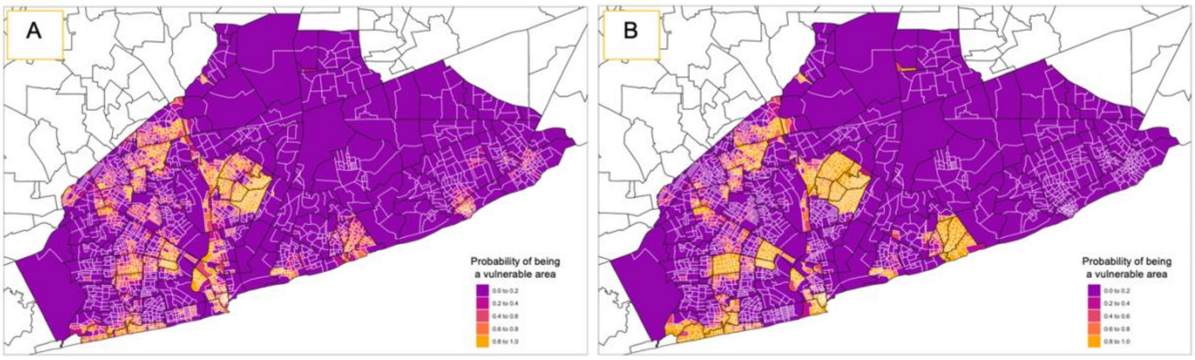


Figure A6: The fitted probabilities of EAs being vulnerable urban areas within the AMA, with black boundaries illustrating neighbourhoods and white boundaries illustrating EAs. The vulnerable urban area probabilities are derived from a Bayesian logistic regression model with no neighbourhood-level random effects (a), and a Bayesian logistic regression model with spatially-structured random effects (b).

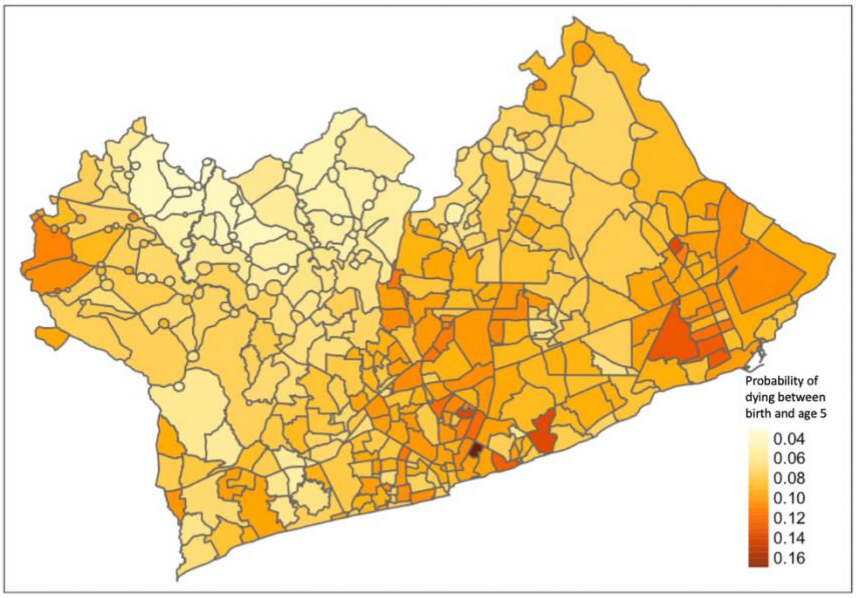


Figure A7: Mapping of child mortality estimates across the GAMA, using the indirect maternal age cohort method.

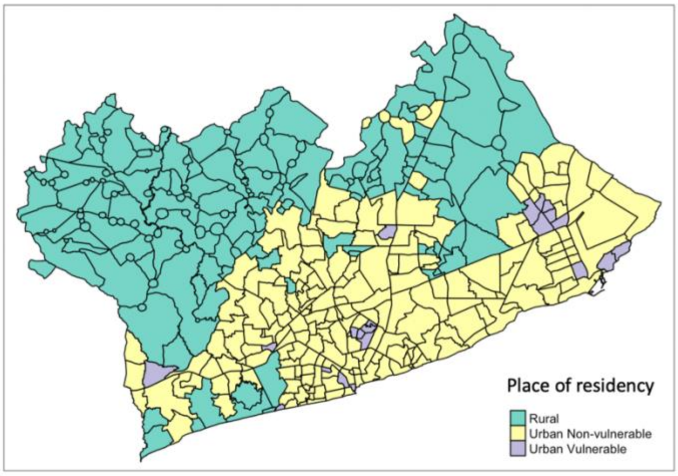


Figure A8: Place of residency in the GAMA using the standard vulnerable urban area classification, where an urban neighbourhood is classified as vulnerable if at least 50% of its EAs have a vulnerable urban area probability of 80% or more.

Figure A9: The Odaw River in Accra. On the bottom right map, the river is drawn in blue.

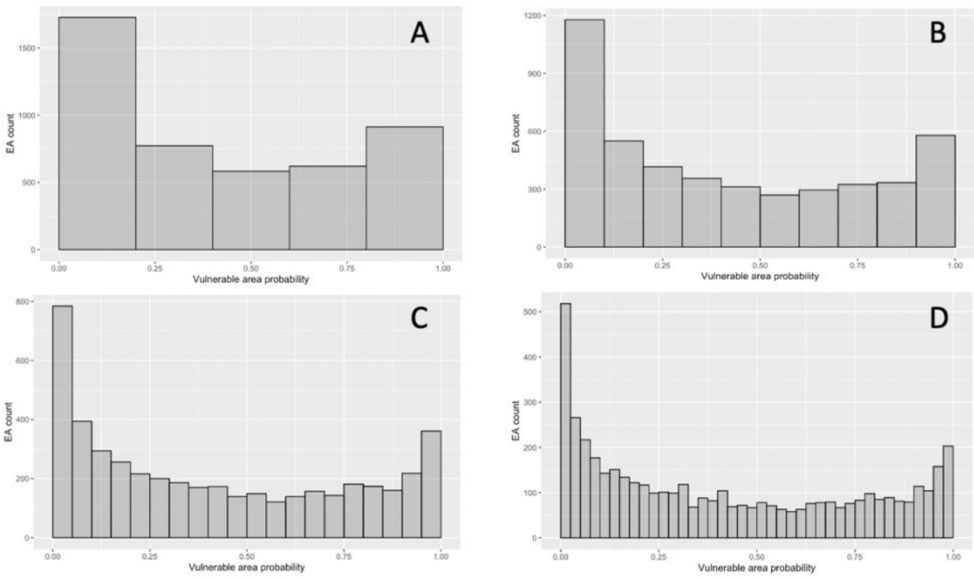


Figure A10: Histograms showing the distribution of vulnerable urban area probabilities in urban EAs within the GAMA, using A) 5 bins, B) 10 bins, C) 20 bins, and D) 40 bins.

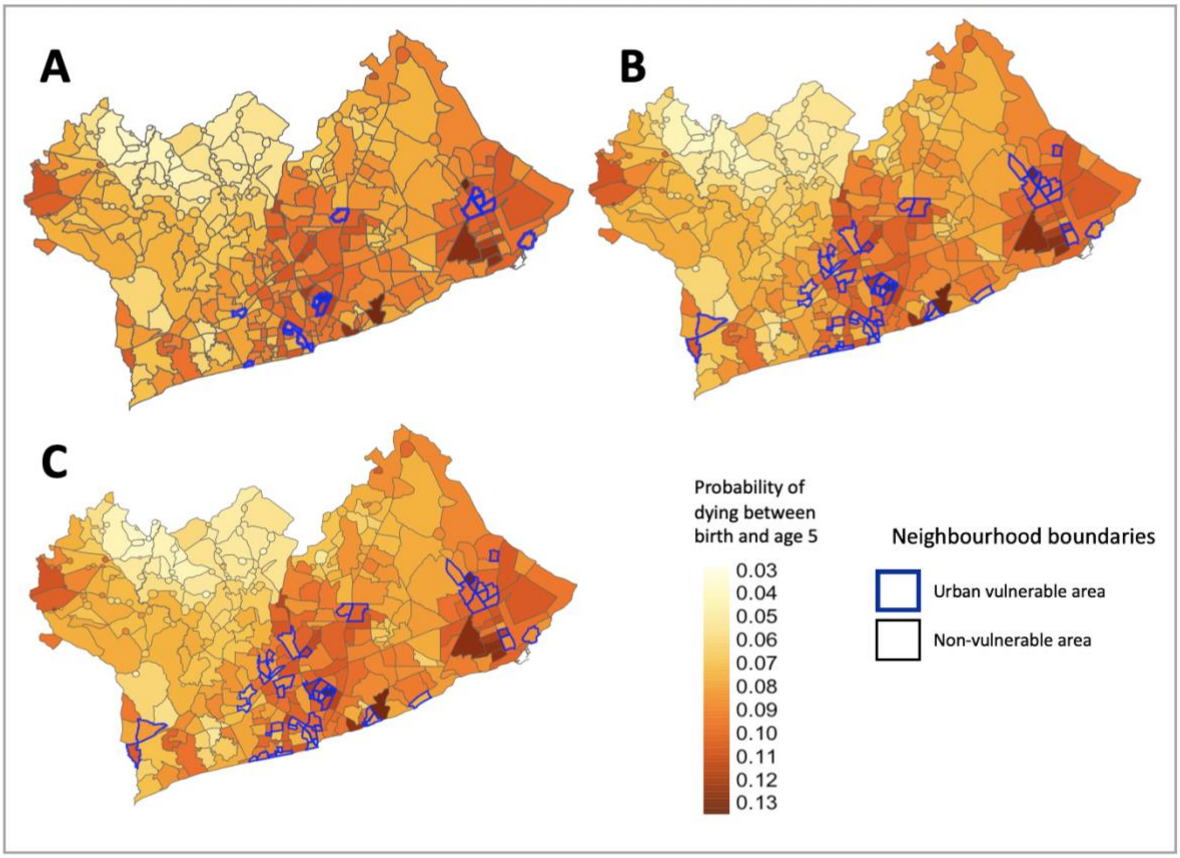


Figure A11: Comparing the distribution of child mortality estimates across GAMA between rural, urban vulnerable and urban non-vulnerable neighbourhoods. Map A is highlighting vulnerable neighbourhoods in blue (vulnerable if >50% of EAs have a vulnerable area probability >0.80). Map B is highlighting vulnerable urban areas using a stricter cut-off point (vulnerable if >80% of EAs have a vulnerable area probability >0.80), while map C is highlighting vulnerable urban areas using a more lenient vulnerable urban area cut-off (vulnerable if >50% of EAs have a vulnerable area probability >0.50).

**Supplementary Tables:**

**Table A1. Census questions relevant to UN-Habitat's five criteria of slum households. Response options in bold represent the most commonly observed categories for each census question and were used as predictor variables in the logistic regression model.**

| 2010 Ghana Census Question (Question asked in Census and Question Code) | Response Options |
|---|---|
| How many of the rooms are used for sleeping? (BEDROOMS) | Number from 1-24 |
| Number of people per household (A20TOTAL) | Number from 1-48 |
| Who owns the dwelling? (OWNERSHIP) | -Being purchased (i.e. mortgage)<br>-Owned by household member<br>-Relative, not a household member<br>-Other private agency |

| | |
|---|---|
| | **-Other private individual**<br>-Private employer<br>-Public/Government ownership<br>-Other |
| What is the main source of drinking water for the household (WATER_DRINKING) | -Rain water<br>-Borehole/Pump/Tube well<br>**-Pipe-borne inside dwelling**<br>-Pipe-borne outside dwelling<br>-Protected spring<br>-Protected well<br>-Public tap/ Standpipe<br>-Bottled water<br>-Sachet water<br>-Tanker supply/ Vendor provided<br>-Unprotected well<br>-Unprotected spring<br>-River/Stream<br>-Dugout/Pond/Lake/Dam/Canal<br>-Other |
| What type of toilet facility is usually used by this household? (TOILET) | -KVIP<br>-Pit latrine<br>**-W.C.**<br>-Bucket/Pan<br>-No facility (e.g., bush/beach/field)<br>-Other<br>-Public toilet (e.g., WC, KVIP, Pit, Pan) |
| What is the main material used for the roof? (ROOF) | -Cement/Concrete<br>-Roofing tiles<br>-Metal Sheet<br>**-Slate/Asbestos**<br>-Bamboo<br>-Mud/Mud bricks/Earth<br>-Other<br>-Thatch/Palm leaves or Raffia<br>-Wood |
| What is the main material of the floor of this dwelling? (FLOOR) | -Burnt bricks<br>**-Cement/Concrete**<br>-Ceramic/ Porcelain/ Granite / Marble tiles<br>-Stone<br>-Terrazzo/ Terrazzo tiles<br>-Vinyl tiles<br>-Earth/Mud<br>-Other<br>-Wood |
| What is the main material of the outer walls of this dwelling? (WALLS) | -Burnt bricks<br>**-Cement blocks/ Concrete**<br>-Landcrete<br>-Metal sheet/Slate/Asbestos<br>-Stone<br>-Bamboo |

| | |
|---|---|
| | -Mud bricks/ Earth<br>-Other<br>-Palm leaves/ Thatch (grass)/ Raffia<br>-Wood |
| In what type of dwelling does the household live? (DWELLING) | **-Compound house (rooms)**<br>-Flat/Apartment<br>-Semi-detached house<br>-Separate house<br>-Huts/Buildings (same compound)<br>- Huts/Buildings (different compound)<br>-Improvised home (kiosk, container)<br>-Living quarters attached to office/shop<br>-Other<br>-Tent<br>-Uncompleted building |

**Table A2. Predictor Variables of the Bayesian logistic regression models.**

| Variable | Calculation | Data source |
|---|---|---|
| Living in compound house dwelling | Percent of households within an EA | Ghana 2010 Census |
| Home owned by private individual not in family | Percent of households within an EA | Ghana 2010 Census |
| Main drinking water source is piped water inside home | Percent of households within an EA | Ghana 2010 Census |
| Walls are made of cement/concrete | Percent of households within an EA | Ghana 2010 Census |
| Toilet facility used is a public toilet | Percent of households within an EA | Ghana 2010 Census |
| Flooring is cement/concrete | Percent of households within an EA | Ghana 2010 Census |
| Roofing is made of slate/asbestos | Percent of households within an EA | Ghana 2010 Census |
| Overcrowding in home | Standardized average household person to bedroom ratio (household size/# of bedrooms) in each EA | Ghana 2010 Census |
| Population density | Number of individuals for each EA divided by area of that EA (in $km^2$) (standardized) | Shapefile provided by the GSS |
| Elevation | Mean elevation above sea level in each EA divided by the mean elevation of a 5km buffer around each EA (standardized) | DEM raster data provided by NASA |

| | | |
|---|---|---|
| NDVI (vegetation abundance) | Average NDVI score in each EA (standardized) | Landsat-8 raster data from USGS EarthExplorer |

**Table A3. Cross validation for model selection. Reported MSE of predicted values against fitted values for vulnerable urban area probability, with various samples removed for prediction.**

| Number of EAs removed for prediction (% of overall sample) | Model 1 (no random effects) MSE | Model 2 (independent random effects) MSE |
|---|---|---|
| 60 (2.5%) | 0.012 | 0.189 |
| 90 (3.7%) | 0.013 | 0.142 |
| 120 (5.0%) | 0.013 | 0.165 |
| 150 (6.2%) | 0.008 | 0.167 |
| 180 (7.4%) | 0.021 | 0.150 |
| 210 (8.7%) | 0.020 | 0.171 |
| 240 (9.9%) | 0.024 | 0.184 |