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BY THE COMMITTEE CONSISTING OF

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Dedication

I dedicate this dissertation research to my dad, Issahaku Yamusah, who passed away on December 3rd, 2023.

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Abstract

The purpose of my dissertation is to improve understanding of historical, current, and future infill and sprawl expansion and their causes across primary and secondary cities. The West Africa urban system (WAUS) is a global hotspot of rapid urbanization and urban expansion. Although urbanization is associated with industrialization and economic growth, most African governments have limited resources, services, and infrastructure to manage the negative impacts (e.g., biodiversity, habitat, and cropland losses) associated with urban expansion, including sprawl that expands the urban footprint and infills within previous urban developments. Previous studies on urban expansion in West Africa have mostly focused on a few individual primary cities with over one million urban populations. The numerous secondary cities with less than one million urban population are also important components of the urban system, providing services, markets, and education centers for many rural residents in West Africa. Also, cities are increasingly interconnected, and changes and associated impacts extend beyond localized scales, requiring detailed understanding of urban expansion dynamics for the entire network of cities. This research achieved the purpose of the dissertation in three interconnected ways. First, I used satellite data to comprehensively analyze infill and sprawl expansion from 2001 - 2020 across 1603 cities in Ghana, Togo, Benin, and Nigeria. The findings from this research show that more than half (54%) of the expanded area occurred in smaller cities, and 73% was sprawl. Sprawl-to-infill ratios were higher in smaller cities than in larger cities, and the annual expansion rates of larger cities decreased over time while those in smaller cities were stable or increased. This research also found that proximity to larger cities increased smaller cities' expansion rates in Nigeria, but more remote cities had higher expansion rates in Ghana, Benin, and Togo. Second, I used a mixed-method approach to understand the causes of sprawl and infill expansion in primary and secondary cities, using Ghana as a case study. In primary cities, high cost of land and rent, travel costs, and fewer land allocation regimes were important considerations, whereas in secondary cities, lower land, rent, and travel costs and more diverse land allocation were important factors. These factors are more favorable in the periphery because land and rental costs are mostly cheaper, especially in secondary cities; this likely explains the higher sprawl-to-infill expansion. Interviews also suggest that new developments reflected the aims of the powerful urban stakeholders, including the chiefs and political elite. Third, this research used **FUT**ure **U**rban-**R**egional and **E**nvironment **S**imulation (FUTURES) to model future urban expansion across Ghana, Togo, Benin, and Nigeria from 2020 – 2050. This research finds that input variables varied across small, medium, and large cities. New developments were mostly influenced by proximity to previous developments, whereas elevation and hillshade were generally less important across cities. This research also finds high annual expansion rates of 3.8% to 14.3% across the study area, with most expansion occurring between 2030 – 2040. Overall, this dissertation research provides a detailed analysis of the historical, current, and future urban expansion of cities with varying population sizes in WAUS. It finds that smaller and more numerous cities contribute substantially to urban expansion and need to be incorporated into national and regional assessments of urban growth and its impacts.

Chapter 1: Introduction

1.1 Urbanization and urban expansion

Globally, the number of people living in urban centers compared with rural areas has continued to increase, with low-income countries increasing their urban populations 1.6 times faster than in high-income countries (United Nations, 2019). In Africa, it took only sixty years to grow from a 10% level of urbanization in 1950 to over 54% in 2020 (OECD & SWAC, 2020; Walther, 2021). In contrast, it took about a century in North America and three centuries in Europe to achieve similar increases (Curiel et al., 2017). In 2020, the annual increase in urban population was 0.4% in Europe, 1.2% in North America, and 3.5% in Africa (United Nations, 2019). The rapid urbanization rates in low-income countries, especially in Africa, are driven by natural population increase, rural-urban migration, and a complex web of political, cultural, and biophysical factors (Adhikari & de Beurs, 2017; Güneralp et al., 2017; Herrmann et al., 2020).

Urbanization in high-income and low-income countries is associated with increased industrialization, innovation, and economic growth. Ample research, however, has also found that urbanization causes several negative impacts on people, including heat waves and food insecurity. It also impacts the environment in many ways, including habitat fragmentation, biodiversity loss, and climate change challenges (Mahmoud et al., 2016; Schug et al., 2018; Stow et al., 2016). Most negative impacts are due to urban expansion, defined as the increase in impervious surfaces such as buildings, concrete, asphalt, glass, and paved roads. The expansion can occur as sprawl that expands the urban footprint and infills within open spaces in previously developed areas (Angel et al., 2021).

In Africa, the number and distribution of cities are skewed, with few primary cities and many smaller secondary cities. In 2000, there were 5058 cities, which increased to 7720 in 2015, with

7645 secondary cities and 75 primary cities (OECD & SWAC, 2020). These cities are generally increasing their populations and expanding their footprints. There has been a major emphasis of previous expansion studies and planning policies on the few primary cities in Africa (Adhikari & de Beurs, 2017; Bilintoh et al., 2023; Mensah et al., 2020; Stow et al., 2016; Tuffour-Mills et al., 2020). The many smaller cities are important economic growth poles that connect rural areas to megacities and provide rural residents with education, health, and market services (Marais & Cloete, 2017; Shores et al., 2019; Zimmer et al., 2020). The smaller cities also contribute substantially to regional and global environmental change, making them an important component of urbanization and urban expansion in Africa and worthy of study.

Although urbanization provides positive impacts, which we highlighted in the preceding paragraph, governments in Africa and most low-income countries have limited resources to manage unplanned urban expansion. Thus, the potential negative impacts of urban expansion on people and the environment are likely severe, especially in West Africa, one of the hotspots of rapid urbanization and urban expansion (Korah & Wimberly, 2024). Therefore, knowledge of the expansion dynamics of cities can support sustainable regional planning efforts in West Africa.

1.2 West Africa urban system

The West Africa Urban System (WAUS) comprises cities of various sizes and urban populations from Cabo Verde and Senegal in the west to Nigeria and Niger in the east. The WAUS had over 165 million urban residents and 47% urbanization level in 2020 (Walther, 2021). The urban centers grew rapidly from 152 in 1950 to 2296 in 2020 (OECD & SWAC, 2020). Urban expansion studies have focused on emerging megacities such as Lagos and Accra (Adhikari & de Beurs, 2017; Barnieh et al., 2020; Enoguanbhor et al., 2019; Mensah et al., 2020;

Stow et al., 2016; Tuffour-Mills et al., 2020). However, they have often overlooked the more than 2200 secondary cities with less than 1 million people, even though they currently contain 46% of the West African urban population, and this number is expected to grow above 50% by 2030 (Walther, 2021). These smaller cities also provide markets, education, and service centers for most rural residents (Marais & Cloete, 2017; Shores et al., 2019; Zimmer et al., 2020). Although some studies have analyzed urban changes in secondary cities, a comparative assessment of urban expansion across the entire network of cities is lacking (Chai & Seto, 2019). Therefore, there is a need for a comprehensive understanding of historical, current, and future urban expansion patterns and their causes across cities of varying population sizes in the WAUS. This information on the entire urban system's expansion dynamics can better support sustainable urban planning at the national and regional levels than studies focusing on individual cities.

1.3 Satellite data for urban expansion analysis

Satellite earth observations provide invaluable data to map the changes in urban land cover that result from urbanization (Barnieh et al., 2020; Chai & Seto, 2019). Satellite products such as the Global Human Settlement Layers (Pesaresi et al., 2015), Global Human Built-up And Settlement Extent (Wang et al., 2017), Global Man-Made Impervious Surface (Brown de Colstoun et al., 2017), Atlas of Urban Expansion (Angel, 2012), and the Global Impervious Area (Gong et al., 2020) have been developed to map urban land use land cover (LULC) change at a global scale. However, studies have found that these global urban land cover products underestimate urban extent and map urban land-use patterns inconsistently because the products are not optimized for West African landscape (Adhikari & de Beurs, 2016; Reba & Seto, 2020).

West Africa Atlas of Land Cover Change is the only regional land use and land cover change (LULC) product optimized for West Africa (Cotillon and Mathis, 2017). This urban LULC product has been used by studies in the region to monitor LULC transition and found that the built-area substantially increased from 493 000 km^2 in 1975 to more than 1 million km^2 in 2013 (Barnieh et al., 2020; Herrmann et al., 2020). This data is available at a 2 km resolution, which is too coarse to track the intricate urban expansion patterns, including infill and sprawl, especially in the many smaller cities in West Africa. In contrast, the Landsat archive provides a 30 m resolution data that allows consistent local, national, and regional level mapping. Multiple studies have used Landsat for urban planning applications and urban land cover assessment locally (Acheampong et al., 2018; Adhikari & de Beurs, 2017; Enoguanbhor et al., 2019). However, there is a lack of consistent regionally calibrated urban cover data at 30 m or higher spatial resolution to map annual urban expansion for West Africa, hindering comparisons of urban expansion across different-sized cities and countries in the region (Reba & Seto, 2020; Tulbure et al., 2022). Thus, regionally optimized urban cover data are better suited for analyzing urban expansion patterns in West Africa than globally calibrated data or localized data with inconsistent classification schemes.

1.4 Mixed-method analysis of urban expansion

Although satellite data is useful in identifying and quantifying urban expansion (infill and sprawl), it lacks information on individual-level behavior and how that influences sprawl and infill expansion across cities, necessitating integration with other data types. Several studies have complemented satellite data with field surveys, focus groups, and interviews to draw the sociocultural, economic, political, and institutional factors that cause urban expansion and its impacts at the neighborhood or individual city level (Abass et al., 2020; Anane, 2021; Anane & Cobbinah, 2022; Cobbinah et al., 2015). The survey and interview data moslty come from urban stakeholders, including planners, chiefs, urban residents, and landowners with relevant knowledge of urban expansion. Previous studies integrating satellite data with quantitative surveys and qualitative interviews, however, have focused on individual primary cities, limiting our understanding of the causes of urban expansion across multiple cities.

1.5 Urban expansion modeling

Satellite data and qualitative data are useful information in calibrating and parameterizing urban expansion models to better mimic future expansion. Most urban simulation models such as **FUT**ure **U**rban-**R**egional and **E**nvironment **S**imulation (Meentemeyer et al., 2013; FUTURES); **S**lope, **L**and use, **E**xclusion, **U**rban extent, **T**ransportation, and **H**ill shade (Clarke et al., 1997; SLEUTH), and future land use simulation (Liu et al., 2017; FLUS) require historical urban data from satellites to extrapolate expansion rates and patterns into the future. Qualitative data are usually time-consuming and costly to collect and analyze over large areas, and privacy issues and national sovereignty guidelines limit sharing across multiple groups and countries (Alexander et al., 2020; Carroll et al., 2021). Some models, such as InformalCity (Agyemang & Silva, 2019; TI-City) and ASSURE (Vermeiren et al., 2016), require qualitative information, such as locational decisions, sources of income, and religious affiliations to fit the models (An, 2012). Thus, satellite data and qualitative information are useful in calibrating and validating urban simulation models. These models can provide new insights into the patterns of future urban expansion, which can further support decision-making and planning across countries.

1.6 Purpose of dissertation and overview of chapters

The purpose of this dissertation is three-fold: 1) to quantify the historical expansion of cities from 2001 – 2020 using regional calibrated impervious data for West Africa; 2) to understand the causes of urban expansion in West Africa; and 3) to project the future urban expansion of cities from 2020 – 2050. There is no consistent regional urban impervious data that researchers, modelers, and interested stakeholders can use to conduct a comparative analysis of urban expansion across all cities and multiple countries. This research provides the first regional annual impervious cover dataset that captures all sizes of cities in the WAUS, and future studies can use the data processing methods to extend the data to other urbanization hotspots and project their changes. This research also provides the first comprehensive analysis of all cities' expansion in Ghana, Togo, Benin, and Nigeria, and the results can support national and regional planning efforts to maximize the positive impacts of urbanization and limit the negative impacts of sprawl expansion on livelihood sources and environmental change. Rather than focus on a few individual primary cities that mostly provide a localized understanding of urban expansion, this research emphasizes the need to study the entire urban system since cities are increasingly interconnected and the impacts of changes are much broader. Overall, the knowledge from this dissertation can support regional urban planning efforts and help countries assess their progress towards realizing the United Nations New Urban Agenda, African Urban Agenda 2063, and Sustainable Development Goals centered on cities.

Regional optimized impervious data with high enough spatial resolution (30 meters) can enable us to better understand how cities of varying population sizes contribute to urban expansion in the West African urban system (Chai & Seto, 2019; Tulbure et al., 2022; Xu et al., 2019). Most urban expansion studies have continued to focus on individual cities or a subset of cities, often due to the lack of regional impervious data and limitations of global urban cover products. However, cities are interconnected, and changes extend beyond individual boundaries. There are only a few primary cities, and many geographically dispersed secondary cities are likely located closer to sensitive ecosystems and prime agricultural lands. Understanding the expansion dynamics of the entire urban system is necessary to inform sustainable urban expansion policies in West Africa. Therefore, chapter two centers on using the Landsat archive to generate urban cover data to quantify and describe the amounts and rates of infill and sprawl expansion across cities of different sizes in Ghana, Togo, Benin, and Nigeria. It also analyzes how the location of smaller cities in the urban networks influences their expansion rates. This chapter has been published in *Sustainable Cities and Society*, and it is co-authored by Michael C. Wimberly.

Mixed-method research, including quantitative and qualitative data, can enable us to better understand the factors influencing sprawl and infill expansion in primary and secondary cities. In West Africa, urban expansion is caused by an interrelated set of natural urban evolution, land speculation, and blight factors (Cobbinah & Aboagye, 2017; Owusu, 2013). Most studies have posited that expansion is a natural process that infills and sprawls as the urban population grows (Abass et al., 2019; Owusu, 2013). In some cities, the flight from blighted, unattractive areas due to higher taxes, housing rents, crime rates, and crumbling infrastructure in inner cities has caused people to develop beyond existing urban boundaries preferentially (Cobbinah & Aboagye, 2017). Other studies found that weak land markets result in landowners holding onto lands in and around cities in expectations for land values to increase, meaning developers needing land to develop housing look beyond existing urban footprints (Afriyie et al., 2020; Kleemann et al., 2017; Kpienbaareh & Luginaah, 2020; Yiran et al., 2020). In Ghana, existing studies have described the specific factors that caused sprawl developments, including cost of land, speculative developments, land tenure arrangements, transport systems, and inefficient planning processes (Amponsah et al., 2022; Anane & Cobbinah, 2022; Ayambire et al., 2019; Cobbinah & Aboagye, 2017; Korah et al., 2017, 2019). These studies have consistently identified unregulated land markets and the failure of planning authorities to implement policies that strictly resist urban developments as the dominant causes of unregulated urban expansion in many individual cities. However, we know less about how these causes of sprawl and infill growth vary in secondary cities compared to primary cities in Ghana. Chapter three, therefore, focuses on the socio-cultural and economic factors causing sprawl and infill expansion in Ghana's rapidly expanding secondary and primary cities. This chapter is under revision in *Habitat International,* and it is co-authored by Laurel C. Smith and Michael C. Wimberly.

Urban expansion simulations are useful in understanding the future patterns of sprawl and infill (Dorning et al., 2015; Koch et al., 2018; Korah et al., 2024; Linard et al., 2013). Spatially explicit models of urban LULC change have been used to predict urban changes under alternative future scenarios, and the resulting projections enable hypotheses testing about urban growth dynamics to support land use planning (Brown et al., 2013). Although most of these modeling efforts, including cellular automata (CA), regressions, Markov Chain, and neural networks, have been applied in developed countries, there are also notable applications of urban LULC change modeling in individual cities in West Africa (Addae & Oppelt, 2019; Agyemang & Silva, 2019; Angel et al., 2021; Goncalves et al., 2019; Idowu et al., 2020; Linard et al., 2013; Okwuashi & Ndehedehe, 2021; Schug et al., 2018; Seto et al., 2012). The lack of consistent high-resolution data partly explains the focus of previous research on individual cities (Reba & Seto, 2020). However, future urban projections across the region's entire secondary and primary cities are lacking, limiting our understanding of where sprawl and infill growth will likely occur as West African countries urbanize (OECD & SWAC, 2020). To fill this knowledge gap, chapter four focuses on projecting the future expansion across cities in Ghana, Togo, Benin, and Nigeria. This chapter is in preparation for submission to *Landscape and Urban Planning*, and it is co-authored by Jennifer Koch and Michael C. Wimberly.

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Chapter 2: Smaller Cities Have Large Impacts on West Africa's Expanding Urban System

Keywords: Urban expansion, Secondary cities, Impervious surface, West Africa urban system

Abstract

Most African countries are rapidly urbanizing, and the associated expansion of developed areas impacts people and the environment. Urban expansion studies are often biased toward large cities with populations greater than 1 million, while small and medium cities with smaller populations are overlooked. These neglected cities contained a substantial 46% of the total urban population of West Africa in 2015, and are important markets and services hubs for most rural residents. We mapped and assessed the expansion of 1603 cities across Ghana, Togo, Benin, and Nigeria using impervious surface data generated from Landsat archives from 2001-2020. We classified pixels with >20% impervious as developed with 93% overall accuracy. Total developed areas increased 2.3-fold from 4001 km² in 2001 to 9402 km² in 2020. Of the expanded area, more than half (54%) occurred in small and medium cities, and 73% was sprawl. The mean annual expansion rate was 4.6%. Expansion rates and sprawl-to-infill ratios were higher in small and medium cities than in large cities, and the annual expansion rates of large cities decreased over time while those in small and medium cities were stable or increased. Proximity to large cities also increased smaller cities' expansion rates in Nigeria, but more remote cities had higher expansion rates in Ghana, Benin and Togo. Although much attention is focused on large megacities, these results show that smaller and more numerous cities contribute substantially to urban expansion and need to be incorporated into regional assessments of urban growth and its impacts.

2.1 Introduction

Africa is one of the most rapidly urbanizing continents, taking only sixty years to grow from 10% of the population living in cities in 1950 to over 54% in 2020 (OECD et al., 2022; OECD/SWAC, 2020; Walther, 2021). In contrast, it took about a century in North America and three centuries in Europe to achieve similar population increases (Curiel et al., 2017). The rapid increases in urban population in West Africa are driven by natural population growth, rural-urban migration, and a complex web of political, economic, cultural, and environmental factors (Güneralp et al., 2017; Herrmann et al., 2020). Increasing urbanization is associated with urban expansion, defined here as increases in urban impervious surfaces such as concrete, asphalt, rooftops, paved roads, and parking lots (Bilintoh et al., 2023). Urban expansion may occur through infill, characterized by compact developments that contiguously increase existing developed areas, or sprawl, which has multiple definitions that incorporate inefficient use of land, low building densities, and dispersed physical expansion (Bhatta et al., 2010; Ewing, 2008; Frenkel & Ashkenazi, 2008; Galster et al., 2001; Hamidi & Ewing, 2014; Song & Knaap, 2004; Tsai, 2005). Urban expansion is a key component of global environmental change that threatens human health, biodiversity, food security, habitat conservation, and carbon sequestration (Güneralp et al., 2017; Seto et al., 2012). Governments in Africa have limited resources to manage sprawl and other negative effects of urban expansion; therefore, research is needed to understand the hotspots of rapid changes and help city, national, and regional authorities conduct planning and prioritize policy interventions.

2.1.1 Drivers of urban expansion in West Africa

The West Africa Urban System (WAUS), comprising 2296 interconnected cities, is one of the most rapidly urbanizing regions in the world with a 3.5% annual urban population increase in

2015 (OECD/SWAC, 2020). Here, we define an urban system as a set of cities with interlinkages where changes extend beyond individual boundaries (Bai et al., 2016; McPhearson et al., 2016). West Africa had a total urban population of 82 million across its 16 countries in 2000, and this increased to 200 million in 2020 (OECD/SWAC, 2020). Population increase in the region results in the reclassification of villages into urban centers, and the potential for better education, health, and employment in cities attracts migrants, mostly from rural areas (Amare et al., 2021; Carmody & Owusu, 2016; Herrmann et al., 2020). Additionally, globalization creates investment and employment opportunities but exacerbates inequalities because infrastructure and service provisions are mostly focused on a few urban centers (Korah et al., 2019; Yeboah et al., 2021). Thus, foreign policies, migration, and natural population increases are key drivers of the urbanization process in the region, resulting in the emergence of cities of different sizes. These processes increase demand for housing and drive the expansion of developed areas. However, analysis of urban expansion across different-sized cities for the entire regional urban system has been limited due to a lack of data and inconsistent definitions of cities across the region (Korah et al., 2024).

Although the primary cities, such as Lagos and Accra are important regional hubs, cities with populations below 1 million are often overlooked in research, planning, and policy interventions (Güneralp et al., 2020; Mahtta et al., 2022; Wolff et al. 2020). In 2015, cities below 1 million urban population contained over 60% of West Africa's urban population, serving as economic, health, and educational centers for many rural residents (Walther, 2021). Even more neglected are cities with populations below 50 thousand, which are often not included in national and international databases. Despite the limited attention, more than 65% of urban populations in West Africa live in cities below 1 million people (Curiel et al., 2017). Many of these smaller cities in the WAUS provide initial stops for rural migrants intending to settle in more nationally and globally integrated cities (OECD et al., 2022). Therefore, a comprehensive analysis of the expansion dynamics across cities can potentially assist planners, decision-makers, and environmental managers in implementing sustainable urban expansion policies.

This study focused on the West African countries of Benin, Ghana, Nigeria, and Togo, which together contain the majority of cities and urban population in the region and are characterized by similar challenges and drivers of urbanization as well as a wide range of city sizes. Common challenges across the four countries include unregulated land markets, tenure insecurity, segregated neighborhoods, housing and infrastructure deficits, and unguided expansion (Biney & Boakye, 2021; Cobbinah et al., 2020). Land markets are unregulated and generally influenced by the demand and needs of landowners (Akaateba et al., 2021; Cobbinah et al., 2020). Urban population increases overburden existing amenities and infrastructure, with significant housing deficits of 28 million units in Nigeria, 3.5 million in Benin, 1.8 million in Ghana, and 500 thousand in Togo (Bah et al., 2018; Ezennia, 2022; Olanrewaju et al., 2016). Also, real estate development has risen since the 2007/2008 financial crisis, and African cities such as Accra and Lagos are seen as frontiers for new development (Goodfellow, 2020; Watson, 2014). Land acquired through eminent domain has often been repurposed for high-end real estate development (Korah, 2020; Yeboah et al., 2021). Although governments aim to modernize urban landscapes, unregulated land markets and insecure tenure contribute to land dispossession, and emerging development mostly targets the middle- and high-income classes (Gillespie, 2016; Shin, 2016). Apart from real estate developments (largely for profit), individual developments are increasing, and many new developments are unregulated due to ineffective planning frameworks (Akeem et al., 2018; Kleemann, Inkoom, et al., 2017). These challenges will likely increase in the region as urban populations and the number of cities continue to grow; therefore, it is important to understand the patterns of expansion as a step towards realizing the UN Sustainable Development Goal 11, that seeks to achieve inclusive and resilient societies by 2030.

2.1.2 Geospatial analysis of urban network expansion

The growth of cities depends on their sizes as well as their spatial arrangement within the urban system (Curiel et al., 2017; Shores et al., 2019). Gibrat's law, which posits that growth rate is independent of size, has been used as a null model in previous urban expansion studies (Egidi et al., 2020; Ning et al., 2022; Zhao et al., 2015). Some studies found that cities with large populations had higher urban expansion rates due to their increased national, regional, and global interconnections (Glaeser & Shapiro, 2003; Xu et al., 2019). Other studies found that less populated cities expanded more rapidly (Güneralp et al., 2020; Zhao et al., 2015) or that there were no differences in expansion rates across different-sized cities (Kourtit & Nijkamp, 2013). Analyses of the relationships between city size and expansion rates are often based on population, although a few studies in China have used urban developed area as a measure of city size (Jia et al., 2020; Ning et al., 2022; Zhao et al., 2015), In addition to city size, the pattern of the urban network also affects urban expansion. Large cities with populations over 1 million are regional and global centers of investment with more health, educational, and economic opportunities than smaller cities. These attractors influence the expansion rates of primary cities and secondary cities located nearby (Curiel et al., 2017; Zimmer et al., 2020). Therefore, analyzing the effects of city size and characteristics of nearby cities on urban expansion is essential for understanding historical changes and projecting future urban expansion across national and regional urban systems. To date, no such comprehensive analysis of urban change exists in Africa.

Satellite-based urban land cover products such as the Global Human Settlement Layers (Pesaresi et al., 2015), Global Human Built-up and Settlement Extent (Wang et al., 2017), Global Man-Made Impervious Surface (Brown de Colstoun et al., 2017), and the Global Impervious Area (Gong et al., 2020) provide data on urban impervious surfaces. These data have been used to quantify urban land changes and analyze economic and ecological impacts. However, the existing data are globally calibrated and are not necessarily suitable for regional analysis since they overestimate or underestimate urban extent in some study areas due to different impervious morphologies across regions (Tulbure et al., 2022). Also, most global products only provide data for larger primary cities and do not include smaller secondary cities, especially in Africa. Novel sources of regionally optimized urban land cover data encompassing a wide range of city sizes are needed to support sustainable regional, national, and local urban planning and enable research on the impacts of urban expansion on people and the environment.

2.1.3 Study rationale and objectives

This study uses a comparative case study methodology that analyzes the expansion of different cities in the four West African countries. Several studies in China have used similar methods to describe and model the relationship between growth rates and city size (Jia et al., 2020; Ning et al., 2022; Zhao et al., 2015). However, most previous studies have only analyzed a subset of the largest cities, whereas our study analyzed an entire West African urban system encompassing all cities over a wide range of sizes. Our study also considers the spatial pattern of urban expansion at two levels: the arrangement of cities within the broader urban network and the relative amount of sprawl versus infill development within individual cities. In the context of this study, we defined sprawl from a structural perspective: sparse developments occurring at the periphery and detached from previously developed areas (Angel et al., 2021; Jia et al., 2022).

The main objective was to characterize the urban expansion dynamics of cities in Ghana, Togo, Benin, and Nigeria. We addressed three questions. 1) How do urban expansion rates vary among cities with different populations? 2) How do relative amounts of sprawl versus infill expansion vary among cities with different populations? and 3) How do the rates of urban expansion vary with city size and spatial arrangement within the urban system?

Because of the limitations of global urban datasets highlighted in the preceding paragraph, we use a Random Forest machine learning algorithm and LandTrendr time series algorithms to generate a regional impervious surface dataset from 2001-2020 using Landsat 7 and 8 data. These data enabled us to quantify the amount and rates of changes within city boundaries and model the associations of growth rates with city size and proximity as predictors. Thus, our research is the first to provide a comprehensive assessment of expansion dynamics of all the cities in West Africa. Given that cities are interconnected, changes in one or more cities may influence the expansion of other cities, and our research also explores these relationships.

2.2 Materials and Methods

This research involves multiple stages including urban change data generation, classification of urban change data, validation, classification of cities, summary of developed areas within Africapolis city boundaries, and modeling the relationship between expansion rate and predictors (developed area and gravity index). These processes are summarized in a flow chart (Figure 1).

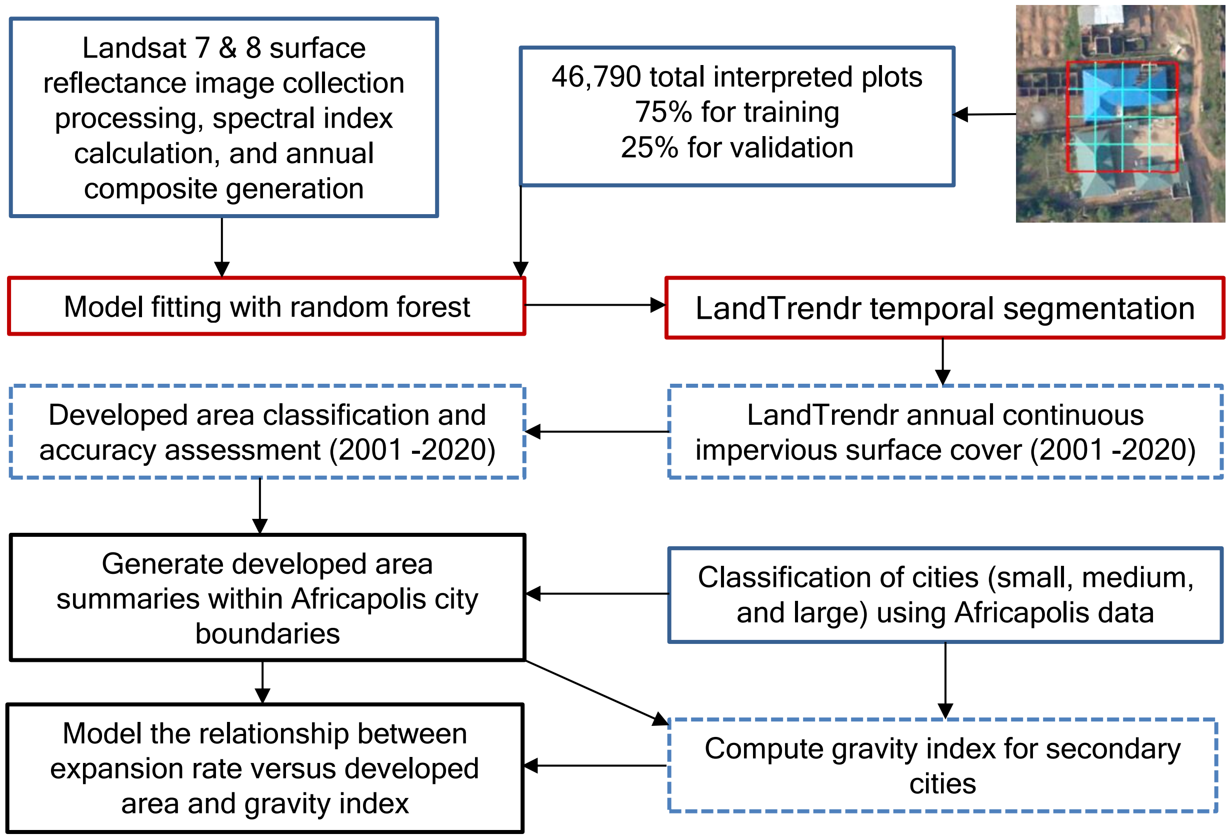

Figure 1: Flow chart showing the data processing and analysis methods used in this study. The blue boxes indicate raw data, the red boxes indicate algorithms used to process the data, the dashed blue boxes show processed data, and the black boxes show the data summary and analysis stages.

2.2.1 Study area

We focused on Ghana, Togo, Benin, and Nigeria, which cover approximately 1.3 million km^2 and contain 73% of the urban residents in West Africa. The number of urban centers also grew rapidly from 152 to 2296 between 1950 - 2020 (OECD/SWAC, 2020). The four countries also contain 70% (1603) of the 2296 cities in the region. For consistent analysis of cities' expansion, we used the Africapolis city boundaries, which are based on a continuous built-up area with less than 200 meters between individual buildings and at least 10,000 population (OECD/SWAC, 2020). To our knowledge, this is the only database that consistently identifies cities across Africa, allowing for comparative studies. Based on Africapolis population data of cities in 2015, we grouped the 1603 cities across the four countries into three types: small (population > 10,000 and <= 50,000), medium (population > 50,000 and =< 1,000,000), and large (population > 1,000,000). The small and medium types are the secondary cities with less than a million population, whereas the large type represents the primary cities with over a million people (Korah et al., 2023; Marais & Cloete, 2017). There were 1305 small cities (81%), 282 medium cities (18%), and 16 large cities (1%).

Large cities are more globally, regionally, and nationally connected than smaller cities, and they have been the primary focus of previous work on urban expansion. Most previous studies in Africa have used 1 million thresholds to delineate secondary cities (Korah et al., 2023; Marais & Cloete, 2017; Zimmer et al., 2020). We further classified secondary cities into two classes (small and medium) using a population threshold of 50 thousand because cities below this threshold are generally absent in international databases (Güneralp et al., 2020). Although small cities are typically more numerous than larger cities, they are usually not included in urban expansion studies (Güneralp et al., 2020). Medium cities are increasingly drawing research attention because of their dual roles, containing extra populations from large cities while redistributing goods and services to small cities and rural areas (Chai & Seto, 2019; Korah et al., 2017; Marais & Cloete, 2017). Within the study area, the small and medium cities are more geographically dispersed, and the large cities are clustered in the southern coastal areas (Figure 2).

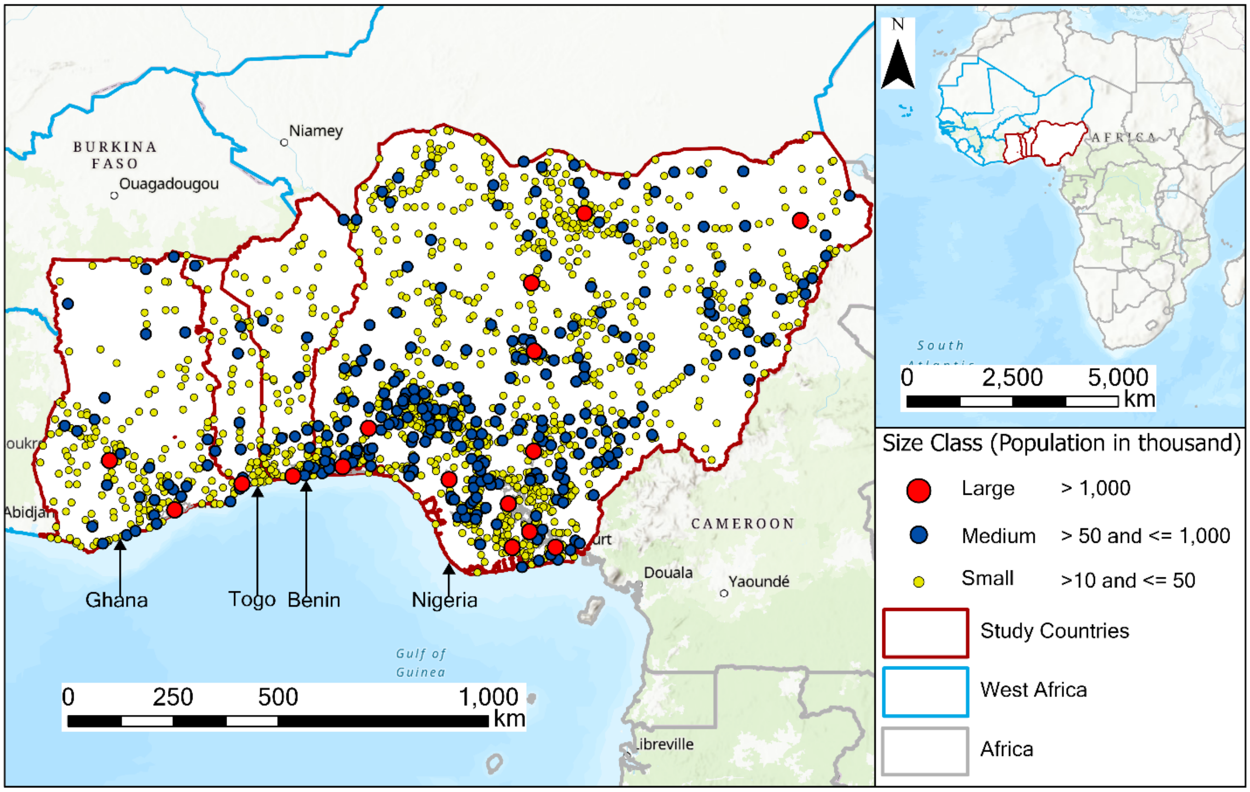

Figure 2: Distribution of 1603 cities in four West African countries and their populations in 2015. For the 1305 small cities (yellow), 984 are in Nigeria, 179 in Ghana, 97 in Benin, and 45 in Togo. For the 282 medium cities (blue), 235 are in Nigeria, 28 are in Ghana, 12 are in Benin, and 7 are in Togo. For the 16 large cities (red), 12 are in Nigeria, 2 are in Ghana, and 1 each are in Benin and Togo.

2.2.2 Urban cover change data

We generated annual spectral composites using all available Landsat 7 (Enhanced Thematic Mapper Plus) and Landsat 8 (Operational Land Imager) Level 2, Collection 2, Tier 1 Surface Reflectance products from 2001 – 2020. For each year, we masked clouds and cloud shadows from the annual collection of images using the C function of the mask algorithm (Foga et al., 2017, CFMASK). We computed 11 spectral indices, including normalized difference vegetation index (Tucker, 1979, NDVI), normalized burned ratio index (García & Caselles, 1991, NBRI), bare soil index (Rikimaru et al., 2002, BSI), normalized difference built-up index (Zha et al., 2003, NDBI), band ratio for built-up area index (Waqar et al., 2012, BRBA), built up area extraction index (Bouzekri et al., 2015, BAEI), urban index (Kawamura et al., 1997, UID), biophysical composition index (Deng & Wu, 2012, BCI), normalized built-up area index (Waqar et al., 2012, NBAI), combinational biophysical composition index (Zhang et al., 2018, CBCI), and visible red based built-up index (Estoque & Murayama, 2015, VRBI). These spectral indices distinguished urban impervious surfaces (buildings, roads, asphalt, and concrete areas) from other land cover types in the satellite images. We used a percentile reducer to generate annual composites of each spectral index.

We generated training and validation data using a stratified random sample of plots constrained within and outside Africapolis city boundaries. A 30m x 30m polygon with a 5 x 5 regular grid of points was created for each sample location, and each point represented 4% cover. We randomly selected equal numbers of locations inside and outside city boundaries, then manually estimated the percentage of the impervious cover for each location using very high-resolution (VHR) imagery from Google Earth Pro version 7.3. We obtained impervious cover estimates for all years with interpretable VHR data for each selected location. The total number of interpreted plots were 46410, with dates ranging from 2001 to 2020. Of the 46410 plots, 75% (34809 plots) was used to fit the model, and 25% (11599 plots) was used to evaluate the model performance.

Impervious surface maps were generated using methods from Wimberly et al. (2022). We combined Random Forest (RF) regression and the Landsat-Based Detection of Disturbance and Recovery (LandTrendr) temporal segmentation approach to predict impervious surface cover at a 30m resolution for the entire 1.3 million square kilometer area. RF employs a set of regression trees that recursively partition the data into branches based on a subset of explanatory variables. Using the 34809 randomly selected training plots, we fitted the RF regression model to estimate the annual percent impervious cover for each pixel in the Google Earth Engine (GEE) platform. Next, we applied LandTrendr to the annual RF predictions of impervious surfaces, resulting in breakpoints that distinguish consistent and sudden changes in the temporal trajectory. The LandTrendr segmentation method smooths noisy time series by fitting a linear model to each segment, with different line segments representing distinctive change trajectories (Kennedy et al., 2018). This method has proven effective at minimizing false signals of change by smoothing noisy data and filling data gaps that persistently hinder land use and land cover change analysis (Adhikari & de Beurs, 2017; Herrmann et al., 2020; Wimberly et al., 2022). Although LandTrendr is mostly used to monitor forest disturbance and recovery, it has also been used to detect urban changes (Mugiraneza et al., 2020).

We used the remaining 11599 plots of evaluation data to validate the processed LandTrendr impervious cover estimates using several accuracy metrics, including correlation, predicted-observed r^2, mean error, mean absolute error, and root mean squared error. Correlation measures the linear relationship between the observed and the predicted values. The predicted-observed r^2 shows how well a linear model can estimate observations from the predictions. Mean error measures the prediction bias. Root mean square and mean absolute errors quantify the difference between predicted and observed values.

We classified the processed LandTrendr continuous impervious cover into developed and undeveloped areas based on visual comparisons of different thresholds with very high-resolution imagery. Developed areas had pixel values greater than 20%, and undeveloped areas had pixel values less than or equal to 20%. We applied the rule that cells remained developed after conversion, even if the impervious surface dropped below 20% in subsequent years. This rule is a standard approach often used in urban expansion analysis due to the permanent nature of most impervious surfaces (Ding et al., 2022). We generated a confusion matrix for our binary classification and reported the overall accuracy, misclassification error, user's and producer's accuracy, and omission and commission errors.

2.2.3 Quantifying urban expansion

For each city, we computed the mean annual urban expansion rate (AER) from 2001-2020 using equation from (Ning et al., 2022; Zhao et al., 2015) as

$$AER = 100\% \times \left(\sqrt[n]{\frac{TDA_e}{TDA_s}} - 1 \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1).$$

TDA_s is the total developed area for the start year, TDA_e is the total developed area for the end year, and n is the time interval in years.

We summarized total developed areas and annual expansion rates in developed areas by city type and country. We also computed the standard deviation and skewness of the annual expansion rates to characterize their variability over time. We applied Mann-Kendall and Sen's slope trend analysis on the expansion rates to understand the change trajectories from 2001-2020.

Using the urban landscape analysis tool (ULAT), developed by the Center for Land Use and Education Research at the University of Connecticut, we characterized the spatial patterns of urban expansion. ULAT employs a set of iterative rules that identifies new developments and categorizes them into three expansion types: infill, extension, and leapfrog, based on their densities and proximity to previously developed areas. 1) Infill represents new developments within the initial developed open lands that increase the contiguity of developed areas; 2) Extension expands outwards and is located adjacent to previously developed areas; and 3) Leapfrog expansions are sparse developments detached from previously developed areas. Extension usually occurs at the periphery and most leapfrog development is isolated and dispersed, which are important structural characteristics of sprawl (Angel et al., 2021; Jia et al., 2022). Therefore, we combined the three ULAT categories into two classes: infill and sprawl (extension plus leapfrog) and summarized the results as the ratio of sprawl to infill to understand the expansion patterns in different countries and city types.

2.2.4 Modeling city size and average annual urban growth rates

We used univariate linear regression models to analyze the influence of initial developed area on expansion rate across all cities. We also used multivariate linear regression to analyze the combined effects of developed area and gravity index to large cities on expansion rates of the small and medium cities, as shown in equations (2) and (3). We measured the gravity index as the sum of areas weighted by squared inverse distances (Polyakov et al., 2008; Wanyama et al., 2023). We transformed AER and the predictors (developed area and gravity index) using a common logarithm to minimize outlier effect on the model.

Simple linear regression (SLR):

$$AER_i = b_0 + b_1 TDA_i + e_i \dots\dots\dots\dots\dots\dots (2)$$

Multiple linear regression (MLR):

$$AER_j = b_0 + b_1 TDA_j + a_2 GI_j + \ e_j \dots\dots\dots\dots\dots\dots (3)$$

In equations (2) and (3), the *AER* is the annual expansion rate, b_0 is the intercept for AER, b_1 and b_2 are the regression coefficients, TDA is the total developed area, GI_j is the gravity index, *e* is the error, *i* indexes all cities, and *j* indexes small and medium cities.

The gravity index was initially calculated on a per-pixel basis as

$$\mathrm{GI}_p = \sum_k \frac{TDA_k}{D_{kp}^2} \dots\dots\dots\dots\dots\dots\dots (4)$$

In equation (4), GI_p is the gravity index for pixel p in small and medium cities, TDA_k is the total developed area for large city k, and D_{kp} is the distance between city k and pixel p. The mean value of GI_p was then calculated within each small and medium city boundary to generate GI_j.

2.3 Results

2.3.1 Validation and classification accuracies

The continuous impervious cover estimates had 0.90 correlation, 0.81 predicted-observed r^2, -0.03 mean error, 5.7 mean absolute error, and 9.93 root mean squared error. Overall, 93% of the reference data were correctly classified (Table 1). The developed area user and producer accuracies were similar, and the corresponding commission and omission errors were approximately equal. Thus, the classification did not systematically overestimate or underestimate developed areas.

Table 1: Confusion matrix of undeveloped and developed areas classifications. The overall accuracy of the data is in bold, and the misclassified error is in bold italics.

		Observation			
	Class	Undeveloped	Developed	User	Commission
Prediction	Undeveloped	9157	425	0.9556	0.0444
	Developed	407	1610	0.7912	0.2088
	Producer	0.9574	0.7911	**0.9283**	
	Omission	0.0426	0.2089		***0.0717***

2.3.2 Quantities and rates of urban expansion

The total developed area increased 2.3 times from 4001 km² in 2001 to 9402 km² in 2020, with varying changes in different countries and city types (Figure 3 and S1). Across the study area, most of the urban expansion occurred in small and medium cities. The total area of urban expansion was 5401 km², with 2106 km² (39%) in medium and 775 km² (14%) in small cities compared to 2520 km² (47%) in large cities.

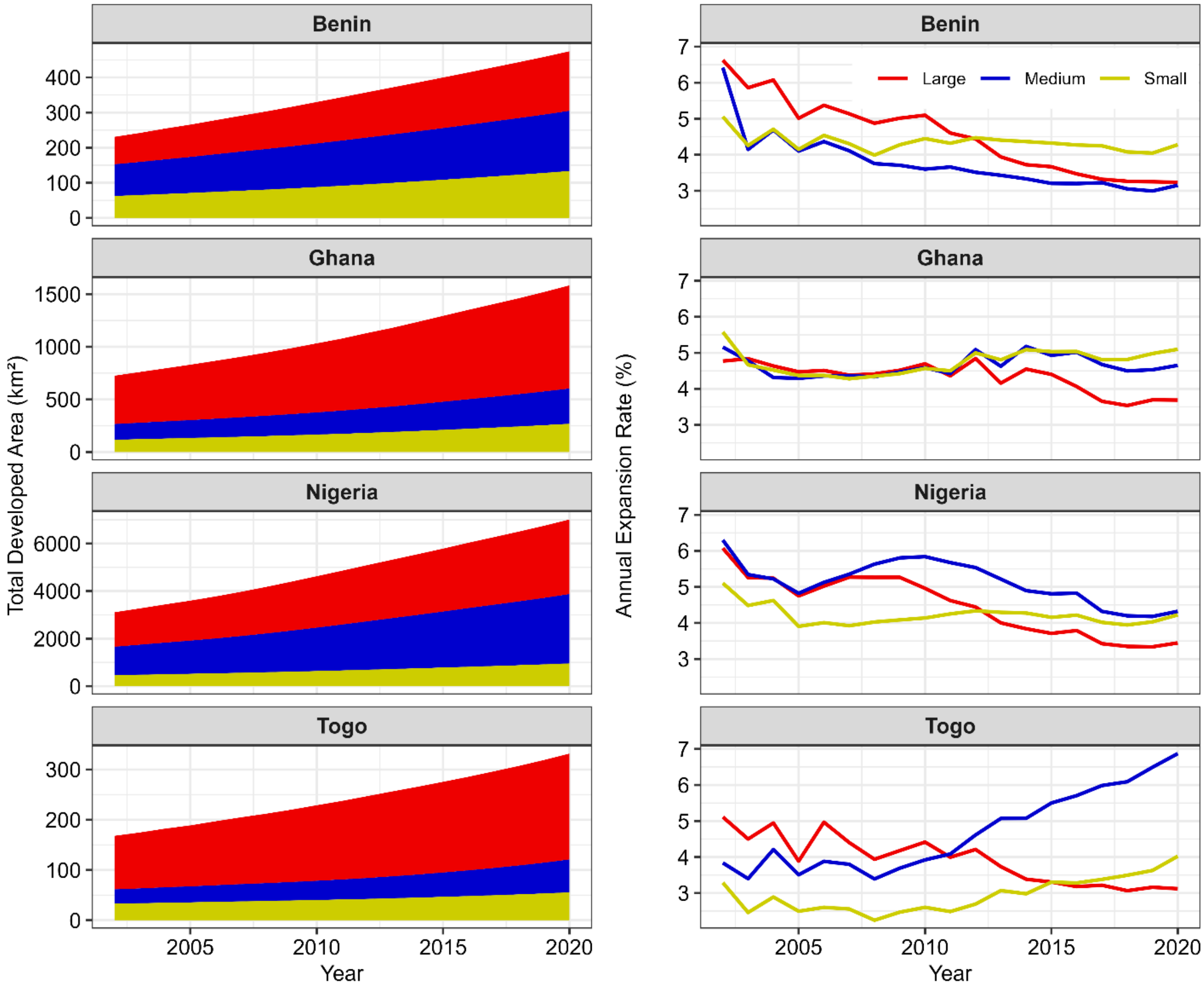

Figure 3: Developed areas and expansion rates for city types in each country. Large cities are in red, medium cities are in blue, and small cities are in yellow. The area graphs on the left represent the total developed area for each city type in each country, and the line graphs on the right are the corresponding annual expansion rates.

Across the study area, average annual expansion rates varied over 20 years, and rates were generally highest in medium cities in Nigeria and Togo, large cities in Benin, and small cities in Ghana (Table 2 and Figure 3). As a result, the overall percentage of total developed area in medium cities increased from 34.5% to 37.1%, while large cities decreased from 49.5% to 47.9% and small cities decreased from 16.0% to 15.1%. The mean expansion rates were highest in

Nigeria, followed by Ghana, Benin, and Togo (Table 2). In Nigeria and Togo, expansion rates were highest in medium cities. In Ghana, expansion rates were highest in small cities, and medium cities rates were higher than in large cities. Benin was the only country with the highest expansion rate in large cities. Across the countries, the AER year-to-year standard deviation ranged from 0.39 in Ghana to 1.09 in Togo. At the city level, the highest standard deviation was in large cities, except in Togo. The year-to-year skewness values were mostly positive, indicating asymmetric distributions where growth was relatively low in most years with higher rates occurring in a few years. The exceptions were in Nigeria, the skewness in medium and large cities was close to zero, and in Ghana the skewness in large cities was negative.

Table 2: Descriptive statistics of mean annual expansion rate from 2001 – 2020.

	2001		**2020**		**AER**			
City Type	**Developed (km²)**	**Percent**	**Developed (km²)**	**Percent**	**Mean (%)**	**Std. Dev**	**Skewness**	**N**
Benin	**217.52**	**100**	**474.33**	**100**	**4.19**	**0.83**	**0.60**	**110**
Small	59.60	27.40	133.69	28.18	4.34	0.24	1.17	97
Medium	84.77	38.97	171.19	36.09	3.77	0.80	1.87	12
Large	73.15	33.63	169.46	35.73	4.52	1.05	0.28	1
Ghana	**690.75**	**100**	**1583.14**	**100**	**4.46**	**0.39**	**-0.35**	**209**
Small	111.27	16.11	268.80	16.98	4.75	0.34	0.47	179
Medium	141.26	20.45	334.72	21.14	4.65	0.30	0.54	28
Large	438.22	63.44	979.61	61.88	4.32	0.41	-0.63	2
Nigeria	**2931.72**	**100**	**7012.58**	**100**	**4.70**	**0.72**	**0.29**	**1231**
Small	436.95	14.90	956.97	13.65	4.21	0.29	1.54	984
Medium	1127.76	38.47	2915.56	41.58	5.16	0.60	-0.03	235
Large	1367.01	46.63	3140.06	44.78	4.47	0.84	0.04	12
Togo	**160.75**	**100**	**331.77**	**100**	**3.89**	**1.07**	**0.84**	**53**
Small	32.01	19.91	55.55	16.75	2.94	0.49	0.47	45
Medium	27.40	17.05	65.40	19.71	4.68	1.12	0.49	7
Large	101.34	63.04	210.82	63.54	3.93	0.68	0.23	1

The distribution of expansion rates across city types changed over the study period (Figure 3). There were declining trends of expansion rates in large cities across all four countries (Table

S1). Medium cities' expansion rates declined in Benin and Nigeria and increased in Togo. Small cities expansion rates increased in Ghana and Togo. At the beginning of the study period, expansion rates in large cities were mostly equal to or higher than in small and medium cities (Figure 3 and S1). However, by the end of the study period, expansion rates in large cities were lower than rates in small and medium cities in each country.

The distribution of urban expansion hotspots was uneven across the four countries from 2001 – 2020 (Figure 4). In Ghana, there were high expansion rates throughout most of the country except the extreme northern and southern regions. In Togo and Benin, higher expansion rates were concentrated in the northern parts. In Nigeria, the most rapidly expanding cities were concentrated along the coastline. However, there were high expansion rates in some administrative units in central and northern parts of the country.

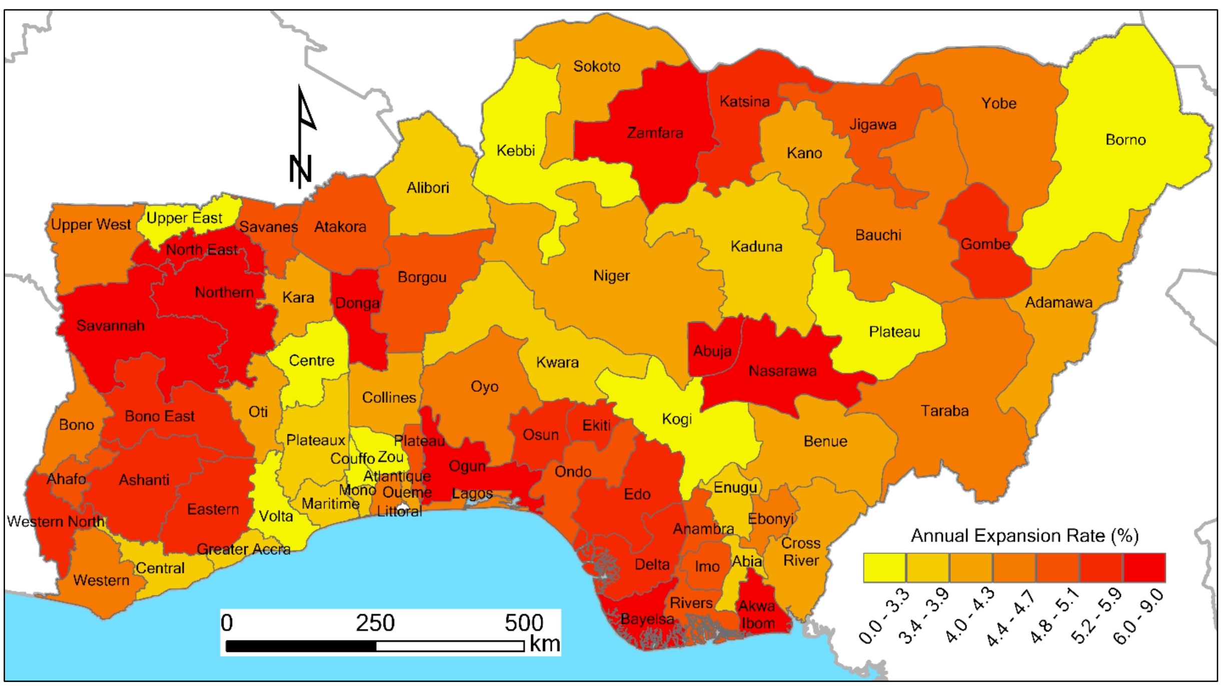

Figure 4: Annual urban expansion rates from 2001 – 2020 across administrative unit level-2 boundaries.

2.3.3 Patterns of sprawl and infill expansion

Across the study area, 73% of the total expanded area occurred as sprawl. Of the total sprawl area, 57% occurred in small and medium cities. Sprawl expansion was generally higher than infill in all countries and city types over the 20-year time span (Figure 6). Except in Togo, where medium cities sprawled the fastest until 2010, sprawl expansion has consistently occurred faster in small compared with medium and large cities. There were statistically significant increases in sprawl-to-infill ratio slope values over time except for large and medium cities in Nigeria and large cities in Togo (Table S2). The increases in sprawl-to-infill ratios were higher in smaller cities than in larger cities (Figure 6).

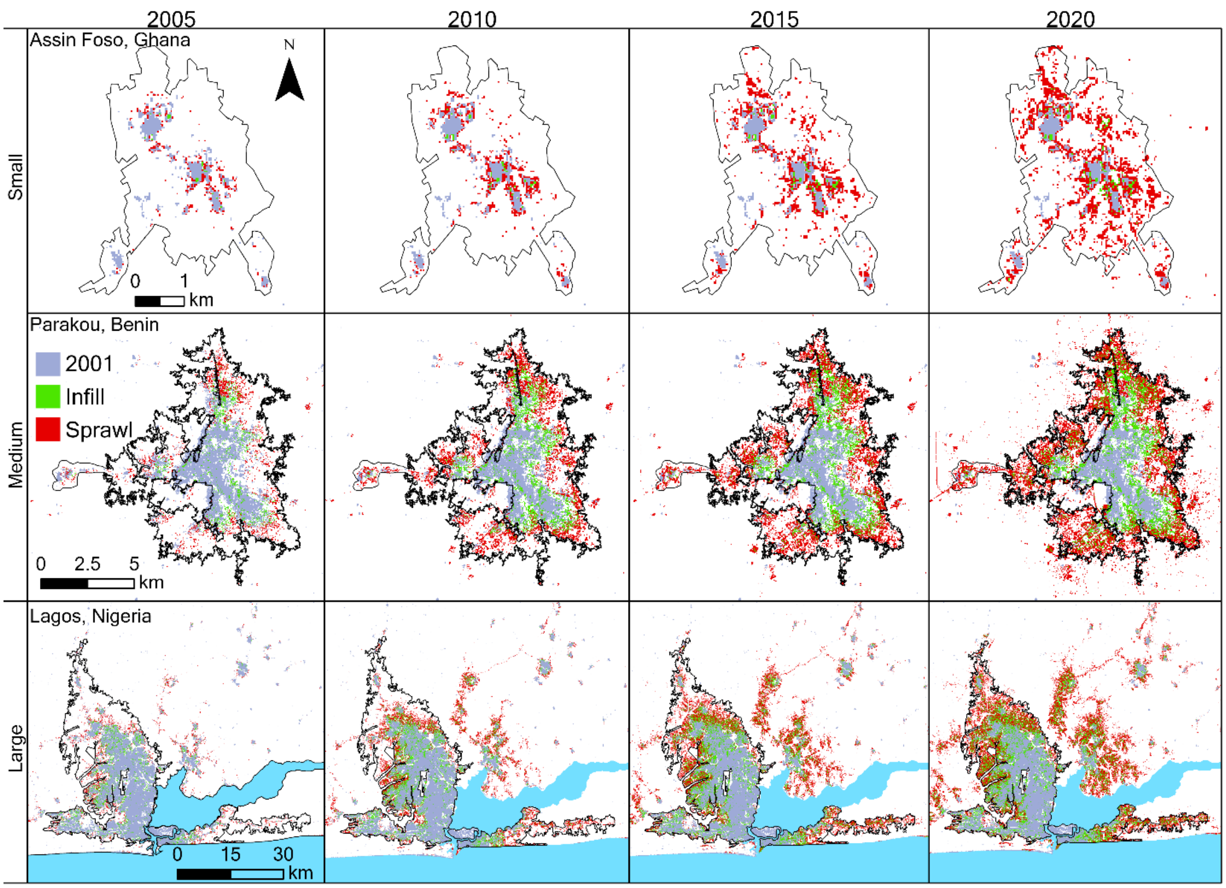

Figure 5: Sprawl and infill patterns of small, medium, and large cities.

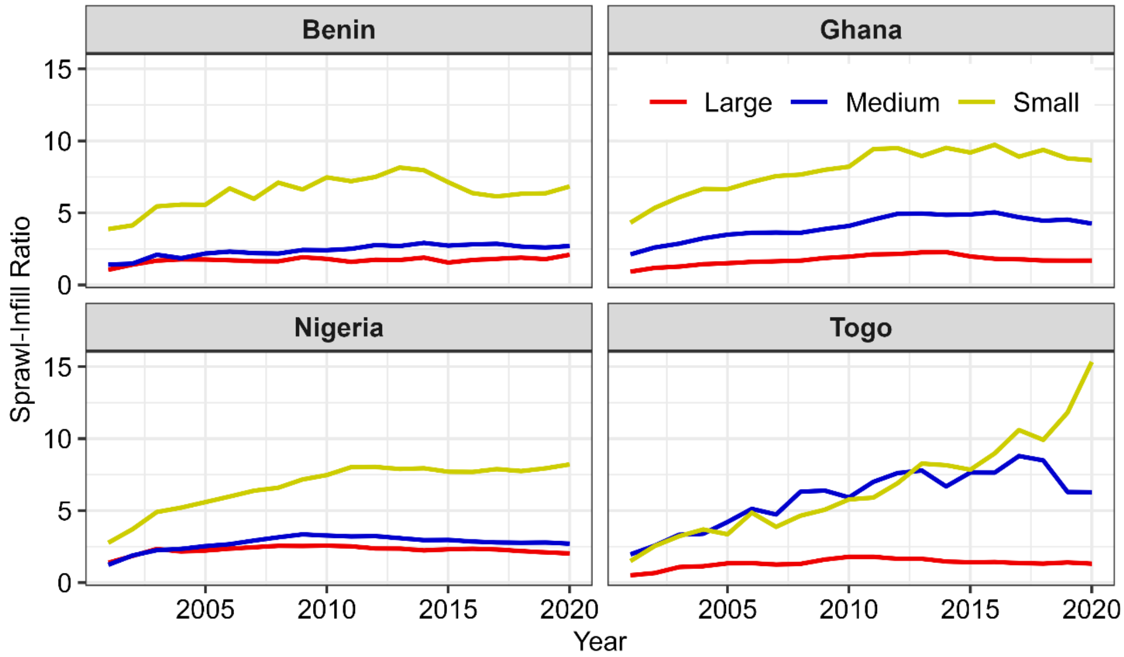

Figure 6: Sprawl-infill ratio for large, medium, and small city types in each country.

2.3.4 Expansion rate in relation to developed area

Using a univariate regression model, we modeled relationships between annual expansion rates from 2001-2020 and developed area in 2001. The model shows that expansion rates were inversely related to initial developed areas (Figure 7 and Figure S3). This relationship was significant at an alpha-level of 0.05, except in Togo. As developed area increased, the mean expansion rate decreased, with the fastest decline in Ghana (Table 3). Thus, we generally found cities that started with smaller developed areas grew faster than cities with larger developed areas.

Table 3: Summary of relations between expansion rate and initial developed area.

Study Area	Slope	Standard Error	P-Value	Confidence Interval (95%)	Multiple R-squared
Benin	-0.1288	0.0256	0.0000	[-0.1796, -0.0780]	0.1894
Ghana	-0.2600	0.0628	0.0001	[-0.3838, -0.1362]	0.0765
Nigeria	-0.0930	0.0139	0.0000	[-0.1202, -0.0658]	0.0354
Togo	-0.1021	0.0756	0.1830	[-0.2539, 0.0496]	0.0346

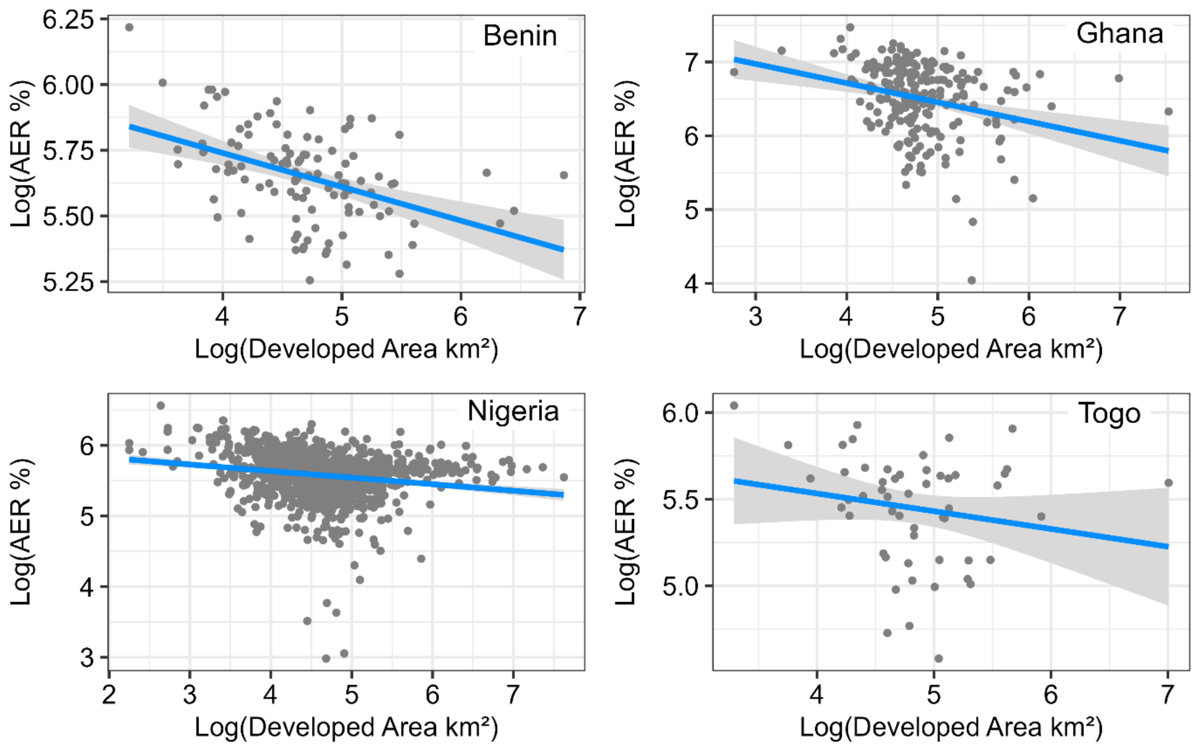

Figure 7: Relationship between annual expansion rate (2001-2020) and initial developed area (2001) for each country. The blue and gray portions are the linear regression lines and 95% confidence bounds.

2.3.5 Expansion rate in relation to developed area and gravity index

We used multivariate linear regression to model the relationships between annual expansion rate from 2001-2020, developed area in 2001, and gravity index (a measure of primary cities' influence on expansion in secondary cities) in 2001. The highest values of the gravity index occurred in small and medium cities near large cities (Figure S2). There were statistically significant negative associations between expansion rate and developed area in Benin, Ghana, and Nigeria (Table 4 and Figure 8). There were also statistically significant negative associations with gravity index in Benin and Togo and a positive association in Nigeria. The partial R^2 values indicated that urban expansion rates had stronger associations with developed area than with the gravity index except in Togo, where the relationship with the gravity index was stronger (Table 4).

Table 4: Summary of relations between expansion rates and predictors. The alpha-level of significant predictors was set at 0.05.

Study Area	Predictor	Slope	Standard Error	P-Value	Confidence Interval (95%)	Partial R-Squared
Benin	Developed Area	-0.1538	0.0262	0.0000	[-0.2057, -0.1019]	0.2455
	Gravity Index	-0.0439	0.0150	0.0035	[-0.0730, -0.0147]	0.0775
Ghana	Developed Area	-0.1481	0.0319	0.0000	[-0.2110, -0.0851]	0.0957
	Gravity Index	-0.0225	0.0250	0.3690	[-0.0718, 0.0268]	0.0040
Nigeria	Developed Area	-0.1320	0.0143	0.0000	[-0.1601, -0.1040]	0.0628
	Gravity Index	0.0939	0.1564	0.0000	[0.0632, 0.1245]	0.0275
Togo	Developed Area	-0.1082	0.0760	0.1610	[-0.2609, 0.0446]	0.0397
	Gravity Index	-0.1968	0.0444	0.0001	[-0.2860, -0.1076]	0.2864

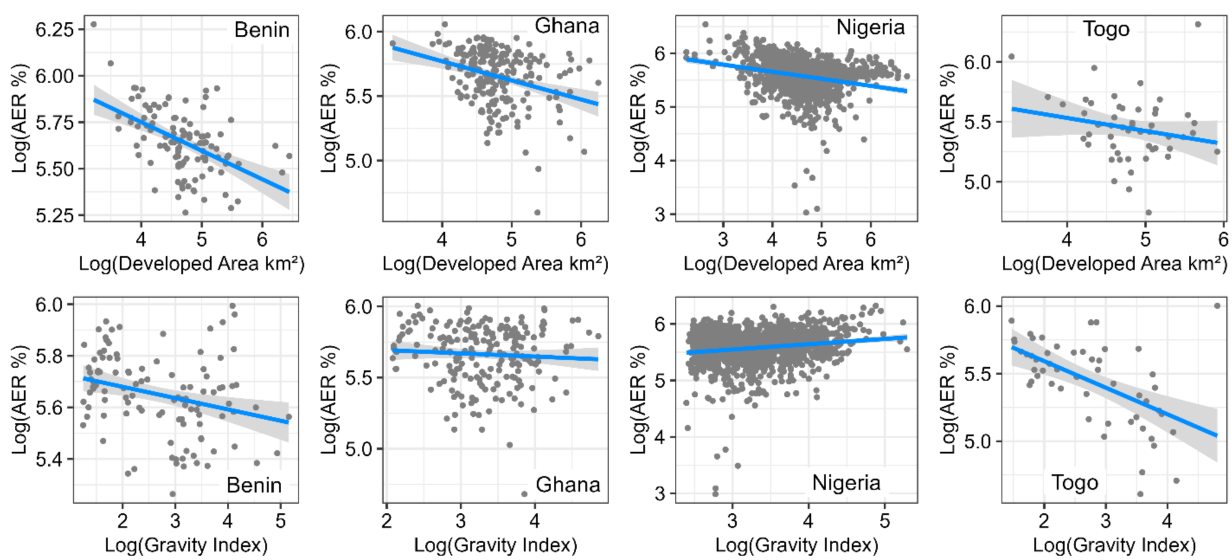

Figure 8: Relationships between mean annual expansion rate (2001-2020), initial developed area (2001) and gravity index (2001) for each country. The initial developed area is in the top row, and the gravity index is in the bottom row.

2.4 Discussion

2.4.1 Patterns of urban expansion rates

We quantified the expansion of 1603 cities in four urbanizing West African countries, including 16 large, 282 medium, and 1305 small cities from 2001-2020 and found high rates of urban expansion across all countries and city sizes. Over the entire study area, the total developed area more than doubled (2.3 times) over the 20-year period and there was a 4.6% mean annual increase in developed area. At a country level, the highest urban expansion rates were in Nigeria, followed by Ghana, Benin, and Togo. The mean annual expansion rates across administrative boundaries generally ranged from 3.9 % to 9.0% (Figure 4). These high rates are similar to results reported from urban expansion studies in China and India (Ning et al., 2022; Seto et al., 2011; Zhao et al., 2015). In more developed regions of the world like Europe, North America, and Oceania, the annual increase in developed areas is generally lower than 3.9% (Seto et al., 2011). The higher expansion rates in West Africa are likely compounding inefficient planning efforts in the region, especially in cities lacking basic services and planning institutions.

Our results showed that smaller cities were generally expanding faster than larger cities, and this result was consistent when comparing city types based on population and when analyzing individual cities based on their developed area. These results are in agreement with a study of 130 cities in China and a global synthesis of urban expansion, which found that cities with populations below 1 million have faster growth rates than more populous cities (Güneralp et al., 2020; Schneider & Mertes, 2014). In contrast, a study of 200 global cities, including 25 African cities, found larger cities grew faster between 1990 and 2014 than smaller cities (Xu et al., 2019). Our research was distinctive from these previous studies in that it focused on a specific region of West Africa with a high density of cities and included all cities down to a minimum population size of 10,000. This type of detailed regional assessment is needed to capture these smaller but more numerous cities that account for a substantial percentage of the developed area in West Africa and contribute substantially to the regional trends of urban expansion.

Diffusion-coalescence theory recognizes the differential patterns of new developments based on whether cities are in an early or late phase of urbanization (Dietzel et al., 2005). Some studies have found that regardless of the stage of urbanization, urban expansion occurs more rapidly than urban population growth, resulting in more sprawl through time (Angel et al., 2021; Seto et al., 2011). We found that most increases in new developed areas were sprawl at the periphery of previous developments, with significantly higher rates of sprawl in small than medium and large cities. This result suggests that cities with relatively lower populations are in the diffusion stage of expansion with more areas to expand outward, whereas larger cities tend to be in the coalescence stage with more compact expansion (Jia et al., 2020, 2022; Li et al., 2022; Lösch, 1940). Thus, the ratio of sprawl to infill expansion in West Africa corroborate urban expansion studies in Asia and Africa that found expansive growth into the periphery and more rural lands, however, with insignificant ratio of sprawl to infill in large and medium cities in Nigeria, and large cities in Togo (Cobbinah & Aboagye, 2017; Gao et al., 2016; Jia et al., 2020; Schneider & Mertes, 2014; Xu et al., 2019; Zhao et al., 2015).

2.4.2 Urban networks effects on expansion rates of cities

Previous studies often found spatial disparities with city size, with more economic, health, and educational opportunities in large cities than in smaller cities due to their national, regional, and global interactions (Glaeser & Shapiro, 2003; Seto et al., 2011). These opportunities have historically attracted more people to large cities, increasing demand for existing infrastructures and new developments and influencing the growth of nearby cities (Curiel et al., 2017). In West

Africa, we found that urban expansion rates increased as developed area size decreased in all countries except Togo. Results indicate that expansion rates decreased with gravity index in Benin and Togo but increased in Nigeria. The results from Nigeria corroborate some previous studies that found increased expansion rates in secondary cities through time due to influence from large cities (Curiel et al., 2017; Zimmer et al., 2020). Also, analysis of how a city's location influences expansion rates is often lacking in previous studies. Our findings show that smaller cities' expansion rates vary depending on their location within the urban system, although this relationship was insignificant in Ghana. These variations in expansion rates and gravity index relations across countries highlight the diverse urban expansion patterns in West Africa, and diverse factors and policies may influence expansion rates.

Urban expansion dynamics are complex, and knowledge about their causes is critical for effective resource allocation and planning (Wu, 2014). Across the four countries, cost of living, urban population growth, and land tenure systems all influence the demand for and access to lands for new developments within and across cities (Cobbinah & Aboagye, 2017; Yiran et al., 2020). At a national level, differences in government policies may explain the different effects of city size and proximity to large cities on urban expansion. In Ghana, small cities expanded more rapidly than large cities, but the expansion rate was not sensitive to gravity index of large cities. The National Urban Policy and the National Spatial Planning Frameworks aim to redistribute urban populations, plan and manage expansion effectively, improve spatial interconnections among different hierarchy of cities, and improve quality of life (GUTT, 2019). These plans have likely influenced historical patterns of urban expansion by encouraging more new developments in smaller cities regardless of their location within the urban system.

In Nigeria, urban expansion rates were highest in small cities that were close to one or more large cities. The 2006 Urban Development Policy, the National Urban Development Policy, and many other ambitious Strategic Regional Development Plans aim at reducing regional disparities through redistribution of investment projects to ensure balanced growth; however, they focus on the largest cities and emerging new major economic centers (Akeem et al., 2018). The resulting expansion in large cities likely has spillover effects that influence nearby secondary cities' higher expansion rates. Terrorist activities in some parts of Nigeria also potentially caused out-migration of people from insecure locations to more connected and safer areas in and around large cities.

Through the Decentralized City Management Project in Benin and National Housing Strategy in Togo, infrastructural development and services are upgraded for low-income neighborhoods across cities in both countries (UN-HABITAT, 2017). Also, the high expansion rates in northern part of Togo is potentially due to diversity of agricultural opportunities that results in development of market towns and encourage trade (OECD/SWAC, 2020). Thus, the availability of opportunities and infrastructural and service improvement across cities are likely reasons for the negative relationships between proximity to larger cities and expansion rates in smaller cities in Benin and Togo.

2.4.3 Implications of results

Across the study area, the increase in urban expansion potentially has economic, social, and environmental implications. Due to land insecurity in most African countries, rapid urban expansion in smaller cities may encroach on prime agricultural lands and potentially dispossess vulnerable groups from their lands and livelihood sources (Boone et al., 2014). Dispossessing of lands for urban expansion may further deepen poverty as most vulnerable groups lack the skills and training to transition easily into other employment activities in African cities (Boone et al., 2014). Also, urban expansion may create unequal access to housing due to the recent emergence of real estate developers that target the rising middle- and high-income earners (Korah et al., 2019; Yeboah et al., 2021). New developments may deplete urban vegetation, potentially increasing urban heat islands and energy costs (Marcotullio et al., 2022; Song et al., 2020). Additionally, most urban expansion in African cities is unguided with ineffective planning frameworks, and most expansion occurs before the provision of services and infrastructure, meaning negative effects of urban expansion may increase, calling for policymakers and city authorities to prioritize limited resources in managing growth in areas that may pose more threat to people and the environment.

Previous studies worldwide have found that urban expansion threatens food security, biodiversity, habitat conservation, and carbon sequestration (Liu et al., 2019; Tu et al., 2021). Although some studies found increased risk of floods and heat stress with infill expansion, most impacts of urban expansion are associated with dispersed and fragmented sprawl development (Amponsah et al., 2022; Marcotullio et al., 2022; Yiran et al., 2020). Also, sprawl makes it costly for city authorities to extend water, sewage, and power lines (Cobbinah & Aboagye, 2017; Kleemann, Inkoom, et al., 2017). However, sprawl expansion dominated in each country, increasing faster in the numerous but relatively smaller cities (Figure 5 and Figure 6). Sprawl in the more numerous and geographically dispersed small cities is likely more challenging to manage and regulate than in the fewer large cities and has a much broader geographic footprint that can affect a diversity of sensitive ecosystems and croplands.

The higher sprawl than infill expansion patterns suggest that planners, policymakers, and city government regulations must recognize the expansion patterns of cities and appropriately plan for expansion. In most fast-growing smaller cities, city authorities can take appropriate actions to better plan for increasing populations through vertical developments that efficiently use land and develop infrastructure and services in anticipation of peripheral expansion (Chen, 2022; Shin, 2016). Also, the secondary cities are in the early stage of expansion, with mostly sprawl expansion; therefore, proactive initiatives that strictly preserve prime lands, encourage mixed land uses, and enforce planning regulations in fast-expanding cities, together with a well-functioning land market and tenure security can minimize the likely negatives of urban expansion, especially among vulnerable populations (Amponsah et al., 2022; Boone et al., 2014; Woo & Guldmann, 2011).

Also, our findings imply that urban expansion in large cities may spill over to neighboring smaller cities, especially in Nigeria, where the gravity index had a statistically significant positive association with growth rates in secondary cities (Table 4). Urban expansion impacts may extend beyond city boundaries, and although national and regional planning frameworks exist, planning efforts are mostly implemented and enforced at the city level (Chen & Liu, 2023; Zhou et al., 2022). Thus, comprehensive multi-city planning and monitoring efforts can potentially help city authorities take common actions to address the negative externalities while optimizing the positive externalities. This can help city governments in the region create more resilient, environmentally conscious, and livable societies.

2.4.4 Study limitations and prospects for future research

Specific limitations of our study include data gaps resulting from Landsat 7 scan line errors, clouds, and cloud shadows. However, we ensured that our land cover mapping was consistent over time by applying temporal segmentation with the LandTrendr. Also, it is possible that allowing only positive changes in our classification omitted areas of declining development, especially in submerging coastal cities and cities affected by terrorism, especially in the Northern part of Nigeria. Given that our study captured only horizontal expansion, it may not accurately capture urban expansion in large and medium cities where vertical expansion occurs. Also, cities are dynamic and continuously expanding. Additionally, our study focused on two variables, including developed area and gravity index, to understand their relationships with expansion rate. However, urban expansion is more complex in the region, and the low multiple and partial R-squared values emphasize that many additional city-level factors also contribute to urban expansion rates in the region.

In future research, extending these data to capture additional areas and to include vertical infill expansion can improve urban expansion monitoring more broadly across Africa. Further research is also needed to analyze the factors that drive city-level variation in urban expansion, but this work will require developing additional regionally consistent datasets on relevant social and environmental drivers. More comparative research on the impacts of expansion, including health, economic, climate change, and environmental resources for urban systems in Africa, is also needed. Additionally, planners and policymakers need to give particular attention to the expansion of smaller secondary cities and develop urban containment policies that fit the diverse expansion patterns in the region. For example, European countries have used greenbelts and urban growth boundaries to contain expansion (Pourtaherian & Jaeger, 2022). In North America, taxes, subsidies, and strict planning and zoning regulations have been successful in controlling expansion (Woo & Guldmann, 2011). In Africa, most studies recommend compact expansion with high-density mixed land uses that reduce the urban footprint (Amponsah et al., 2022). However, more studies are needed to evaluate the effectiveness of urban expansion containment policies for African cities with varying sizes. These efforts can better support city, national, and

United Nations-Habitat urban initiatives, including the Sustainable Development Goals 2030, New Urban Agenda 2030, and African Urban Agenda 2063 planning efforts in Africa.

2.5 Conclusion

In this study, we used a novel impervious cover dataset to map and quantify the expansion dynamics of 1603 cities across Ghana, Togo, Benin, and Nigeria in West Africa. We found very high annual urban expansion rates (4.6%) across the region, including 4.2% in Benin, 4.5% in Ghana, 4.7% in Nigeria, and 3.9% in Togo, consistent with rates in Asian countries. These expansion rates are concerning due to inefficient planning interventions and limited resources to manage expansion in the four countries. Most expansion was sprawl, which occurred faster in small than medium and large cities in all countries and showed an increasing trend of sprawl except for large and medium cities in Nigeria and large cities in Togo. The smaller cities are more numerous and geographically dispersed, and their expansion is likely to have greater impacts than the fewer large cities where expansion rates have declined over the past two decades. The positive relationship between the proximity to large cities and urban expansion rates in Nigeria agrees with previous studies, but was in contrast with negative relationships in Togo and Benin, likely reflecting different urban development plans, historical planning structures, and national security threats. There is a need to rethink research, planning, and policy interventions directed toward large cities since more expansion is occurring in medium and small cities. These smaller cities are more vulnerable to the negative impacts of expansion due to limited infrastructure and other basic services. Also, more than two-thirds of future urban populations are projected to live in cities below 1 million in the next 25 years. Our study provides new insights about hotspots of expansion that can inform sustainable planning efforts in the region. We suggest that broader and consistent regional urban cover data for the continent can help practitioners and modelers evaluate the current and future impacts of different-sized cities' expansion on populations and the environment across multiple countries and subregions. Future studies need to further explore how local drivers, including multi-city planning and development policies, influence the expansion patterns and assess the impacts of the changing West Africa urban system.

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Chapter 3: Understanding Urban Expansion Across Primary and Secondary Cities in Ghana

Keywords: Urban expansion, Sprawl, Infill, Secondary cities

Abstract

Understanding urban expansion patterns (infill and sprawl) offers localized information that can assist city authorities in taking action toward realizing inclusive and resilient cities. Yet, previous studies mostly focused on individual primary cities and overlooked the secondary cities. Using urban impervious cover data derived from satellite imagery, we compared the rates and patterns of expansion for two primary cities with four secondary cities in Ghana. The developed area more than doubled in both city types; however, mean annual expansion rates between 2001 and 2020 in secondary cities (5.28%) were higher than in primary cities (4.32%). We also conducted 63 semi-structured interviews with urban stakeholders to understand these expansion patterns. Interviewees generally prefer locations with favorable housing options, including lower land and rent costs, lower litigations, proximity to infrastructure, service, and potential profit of real estate. Their observations indicate that cheaper housing costs and different allocation regimes in the periphery have caused the higher sprawl-to-infill ratio, especially in secondary cities. Interviews also suggest expansion aims vary among stakeholders, and new developments reflect the aims of the powerful. These complex interactions of factors and conflicting rationalities mean that sustainable urban expansion policies need to recognize specific city- and individual-level conditions.

3.1 Introduction

In an increasingly urbanized world, sustainable and inclusive planning and development strategies require understanding the causes of urban expansion across multiple cities. Urban expansion entails compact infill developments within open land in cities and sprawl developments that leapfrog and extend outwards from previously developed areas (Angel et al., 2021). With annual expansion rates higher than 4.0%, urban expansion in Asia and Africa significantly exceeds the rates in other world regions such as Europe and North America (Seto et al., 2011). Urban expansion is associated with improved infrastructure, centers of innovation and economic growth (Mahtta et al., 2022). However, ample research also documents the negative social, health, economic, and climate change impacts of urban expansion (Bren d'Amour et al., 2017; He et al., 2016; Liu et al., 2019). These challenges tend to result from sprawl expansion, although studies have also detected increased heat stresses, floods, and urban fires related to infill expansion (Møller-Jensen et al., 2023; Zhao, 2011). These challenges often reinforce existing disparities, especially in cities and individuals with limited resources to cope and adapt. Thus, comprehensive understanding of enabling factors can help decision-makers implement sustainable expansion policies.

Globally, urban expansion continues to increase with natural urban population growth, migration, and rural transformation, resulting in the reclassification of rural areas into urban. Most studies exploring the spatial patterns of expansion have found that individual preferences, crime rates, and land accessibility generally influence locations of new developments (Cobbinah & Aboagye, 2017). Rising income levels and global real estate investment further increase new development in cities (Korah et al., 2019; Yeboah et al., 2020). Preference for greenery, serene neighborhoods, and profit motivation through land and property speculation mostly influence sprawl (Tagnan et al., 2022; Yang et al., 2021). Likewise, individual decisions – such as proximity to basic service centers, work, and markets – mostly result in infill expansion (Bibri et al., 2020). Research documenting the diverse factors enabling urban expansion is useful for decision-making and planning. City authorities can identify the diverse factors in particular areas and take actions to limit expansion types that are more costly to manage while encouraging new developments in places that are less costly to people and the environment.

In West Africa, most knowledge about enabling factors of urban expansion comes from individual case studies of primary cities with over 1 million residents. The secondary cities with populations of less than 1 million are also expanding rapidly and currently contain over 60% of the total population in the region (Marais & Cloete, 2017). More numerous and geographically dispersed, secondary cities embody intermediate centers between primary cities and rural areas, offering access points to better education, health, markets, information, and job opportunities for rural-to-urban migrants (Shores et al., 2019). They too potentially contribute to land dispossession of vulnerable populations and cause planning challenges for city authorities. Achieving sustainable and inclusive expansion requires understanding their diverse profiles. Secondary cities are important components of urban systems; it is vital, therefore, to center them in urban expansion research, planning, and policy interventions. A comparative understanding of expansion dynamics in primary and secondary cities can better inform sustainable planning and decision-making across cities currently expanding under similar conditions.

Since 2000, most cities in Ghana expanded their footprints by 5.0% annually (Agyemang et al., 2019; Korah & Wimberly, 2024c). Urban expansion infills open lands in cities and sprawls at the peripheries, yet comparative studies on rates and patterns of expansion are often lacking. Also, the number of urban centers in the country has grown, with few primary and numerous secondary cities. Urban population growth, increasingly numerous secondary cities, and their expansion largely have negative impacts, especially on vulnerable populations (Cobbinah et al., 2020). Urban expansion encroaches on agricultural lands, dispossessing vulnerable people of their livelihood sources. Land prices are held secret among landowners, with each landowner deciding the pricing of their lands with no regulations. Unregulated land markets create unequal access to urban land. Additionally, real estate investment has increased in Ghanaian cities, providing multiple housing options; however, new developments may cause unintended disenfranchisement. Understanding how these dynamics vary in secondary compared with primary cities can fortify the efforts of planners and policymakers to design and implement sustainable urban expansion policies.

Our main objective is to understand the factors influencing urban expansion in primary and secondary cities. We specifically asked three questions: How do secondary cities' expansion rates and patterns vary compared with primary cities? How have socio-cultural and economic factors influenced the spatial pattern of urban expansion in secondary compared to primary cities? How have different actors engaged and shaped urban expansion across secondary compared with primary cities? We used the West Africa Dataset of Impervious Surface Cover (WADISC) data to quantify urban expansion rates, which we complemented with semi-structured interviews with knowledge-rich urban stakeholders. This mixed method enabled us to understand the difference in patterns of urban expansion and how multiple factors and actors influence urban expansion across primary and secondary cities.

3.2 Materials and Methods

3.2.1 Study Area

In Ghana, the percentage of total population living in cities grew from 38.4% in 2000 to 50.4% in 2020, and the number of cities increased from 138 to 225 (OECD/SWAC, 2020). Of the 17 million urban residents in 2021, 53% live in secondary cities with populations between 10,000 and 1 million people and 47% in primary cities with over 1 million urban residents. We focused on the two primary (Accra and Kumasi) cities and four rapidly growing secondary cities: Takoradi, Tamale, Techiman, and Wa (Figure 9). Each city has a different share of Ghana's urban population, with 30.8% in Accra, 16% in Kumasi, 3.4% in Takoradi, 3.0% in Tamale, 1.4% in Techiman, and 0.9% in Wa (OECD/SWAC, 2020).

Historical development plans and global integration since structural adjustment programs have fostered disparities in urban population growth and development. While in the past, most infrastructure, service provision, and foreign direct investments have targeted Accra and Kumasi, current urban development plans seek to decentralize and redistribute populations to multiple economic growth poles (Agyemang et al., 2019). These aims have potentially increased governmental infrastructure and service provision in smaller cities, increasing their developed area through time. However, most urban expansion studies largely focus on individual primary cities. Therefore, analysis of the urban patterns and factors influencing expansion across multiple secondary and primary cities offer lessons for decision-making, planning, and future research.

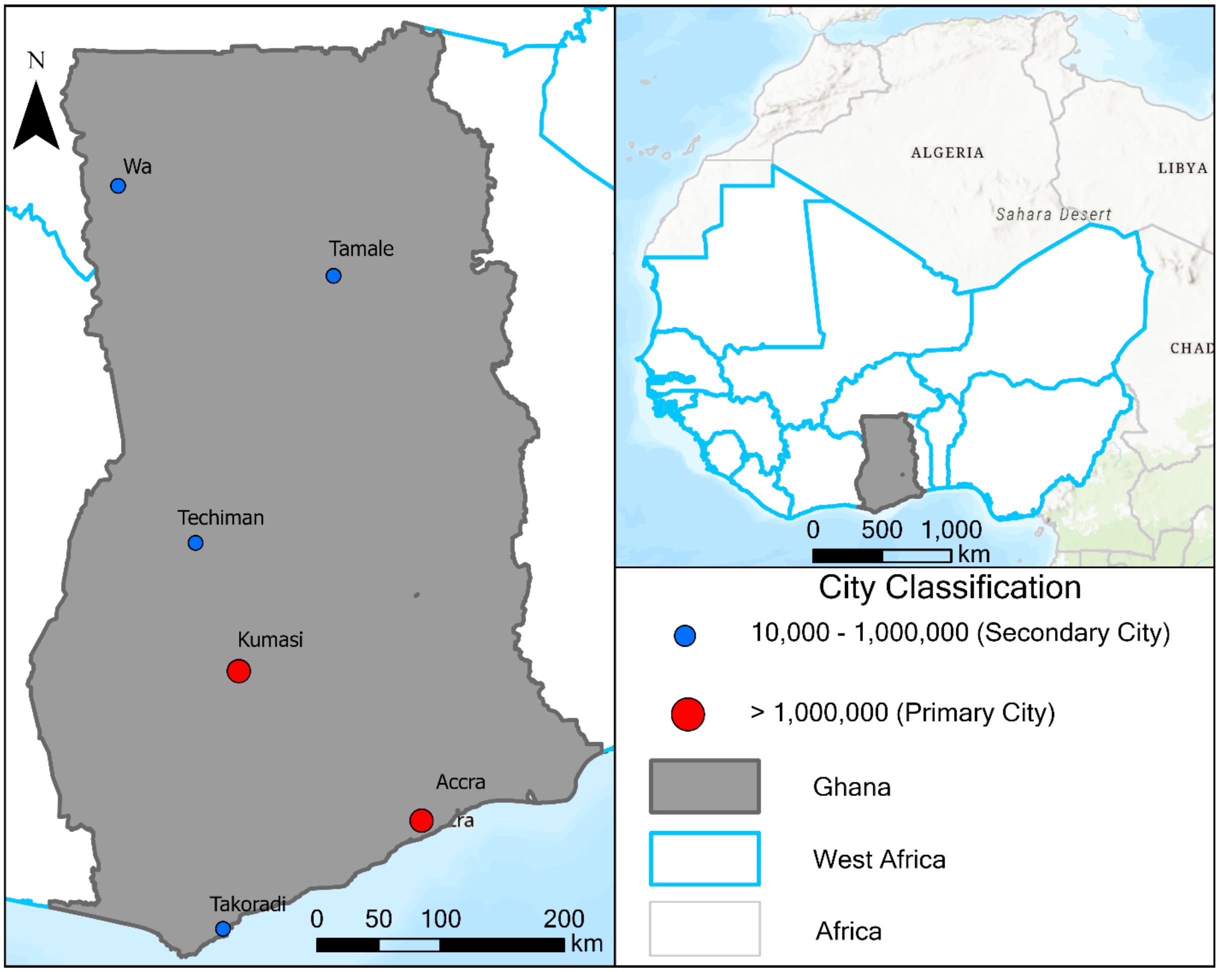

Figure 9: Locations of study cities in Ghana. The secondary cities are in blue dots, and primary cities are in red dots.

3.2.2 Methods

Our comparative case study method afforded in-depth understanding of general and context-specific analyses among cases with a similar topic (Goodrick, 2014). We purposively selected four secondary and two primary cities for our comparative analysis. Using a mixed-method research approach, we employed urban expansion data and semi-structured open-ended interviews with knowledge-rich urban stakeholders, including urban residents, developers, planners, and landowners (Table 5).

We used the WADISC dataset, specifically developed for city- to regional-scale analysis of urban expansion across four countries in West Africa (Korah & Wimberly, 2024a, 2024b). This dataset classified developed lands as 30 m grid cells with > 20% impervious cover with 93% overall accuracy (Korah & Wimberly, 2024b). We extracted the developed areas for the study areas using Africapolis city boundaries (OECD/SWAC, 2020). We then computed the total developed area, expansion patterns, and annual expansion rates from 2001-2020. We summarize the total developed area for each city and primary and secondary cities. We employed the urban landscape analysis tool (ULAT) to generate cities' infill and sprawl patterns. We generated the annual expansion rate as

$$AER = 100\% \times \left(\sqrt[n]{\frac{TDA_e}{TDA_s}} - 1\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1).$$

TDA_s is the total developed area for the start year, TDA_e is the total developed area for the end year, and n is the time interval in years (Ning et al., 2022).

For semi-structured interviews, we randomly and purposively identified most of our participants, but also identified others based on referrals. Planners and real estate developers have public visibility on the websites of their institutions or associations; this makes it less challenging to identify and recruit them. Customary landowners, including chiefs, priests, and family heads, lack such public visibility, so identifying and recruiting them was far more difficult. Fortunately, identified participants recommended other potential participants. When possible, we recruited and consented research participants in person and via phone calls. Attentive to cultural differences, socio-economic positionalities, and uneven power relations, we also tailored our approach to identify and recruit participants through email and WhatsApp texts. Interviews with participants mostly focused on locational determinants for new developments, planning and zoning challenges, and managing urban expansion (Table 5). During in-person interviews with participants, we took handwritten notes and, when possible, audio-recorded the conversation. Participants could see and immediately adjust their responses for interviews conducted through email and WhatsApp texts. Likewise, we sent transcripts of recorded audio to participants so they could confirm their consent and clarify or correct as needed. Verification with participants helped ensure the reliability of our interview responses.

We employed inductive coding to organize interview transcripts using NVivo. We input audio recordings and transcripts based on city type to identify key factors influencing expansion. After identifying the main factors, we sifted systematically through our field notes to ensure consistency with summarized factors. The rich qualitative data we collected through interviews and analyzed by inductive coding provides detailed descriptions and narratives on diverse factors and stakeholders influencing urban expansion in secondary compared with primary cities.

Table 5: Summary of research participants across cities in Ghana.

Participants	Interview Topics	Primary	Secondary
Planners	Planning and zoning challenges, implications, and managing urban expansion.	3	5
Landowners	Land costs in different locations and purpose of leasing lands.	3	7
Developers	Land access, the purpose of acquiring lands, building projects, and cost and benefit of locational choice for projects.	2	7
Urban residents	Access to land, services, cost of living, and locational choice within the city.	12	24

3.3 Results and Discussion

3.3.1 Urban expansion rates and patterns in cities

The total developed area across the six cities increased from 482 km² in 2001 to 1096 km² in 2020, representing 614 km² in urban expansion. Most of the expansion occurred in primary cities; secondary cities only contained 12% of the expanded area. However, the average expansion rate was highest in secondary cities, which slightly increased the proportion of total developed area from 9% to 11%, while the primary cities decreased from 91% to 89%. Although the primary cities contain a larger proportion of the total developed area, the secondary cities are increasing their footprint faster (Table 6). Additionally, the ratio of sprawl to infill was consistently higher in the secondary than primary cities (Figure 10 - 11). Before 2005, the ratio of sprawl to infill in the most sprawling primary city (Kumasi) was generally equal to or lower than in the secondary cities. After 2005, the ratio was substantially higher in the secondary cities than either Kumasi or Accra.

Table 6: Developed area and mean annual expansion rates of cities from 2001-2020.

Cities	2001 Developed (km^2)	2001 Percent	2020 Developed (km^2)	2020 Percent	Annual Expansion Rate (%)
Primary Cities	**438.22**	**100**	**979.61**	**100**	**4.32**
Accra	341.34	77.89	690.35	70.47	3.78
Kumasi	96.88	22.11	289.26	29.53	5.93
Secondary Cities	**43.95**	**100**	**116.79**	**100**	**5.28**
Takoradi	17.70	40.27	37.66	32.24	4.05
Techiman	13.21	30.06	41.89	35.87	6.26
Tamale	7.19	16.36	22.35	19.14	6.15
Wa	5.85	13.31	14.89	12.75	5.04

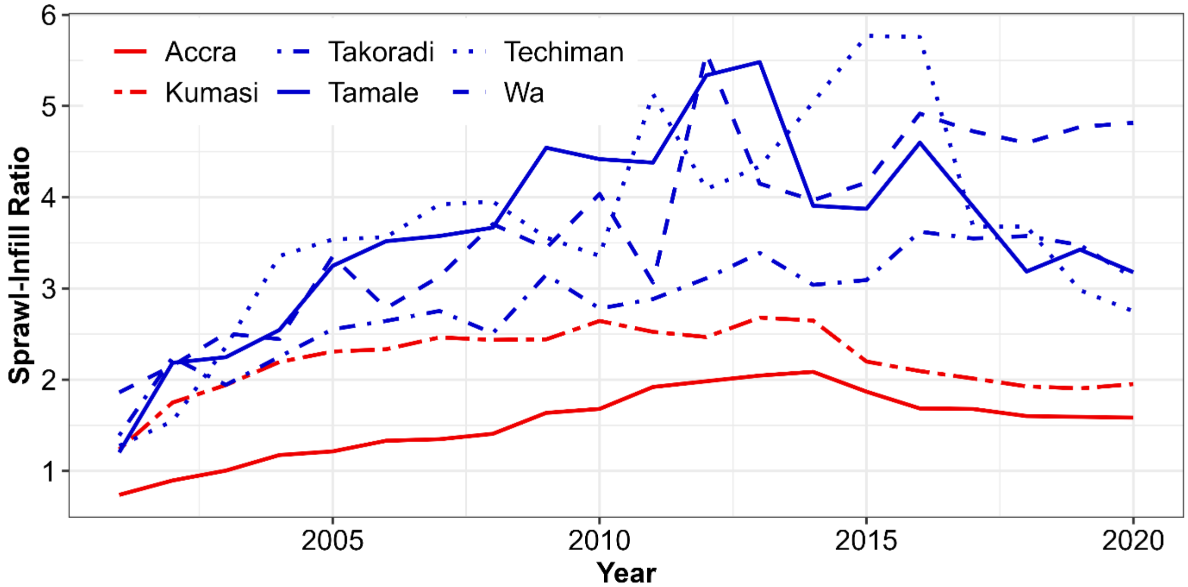

Figure 10: Primary and secondary cities annual sprawl-infill ratios from 2001 – 2020. Primary cities are in red, and secondary cities are in blue.

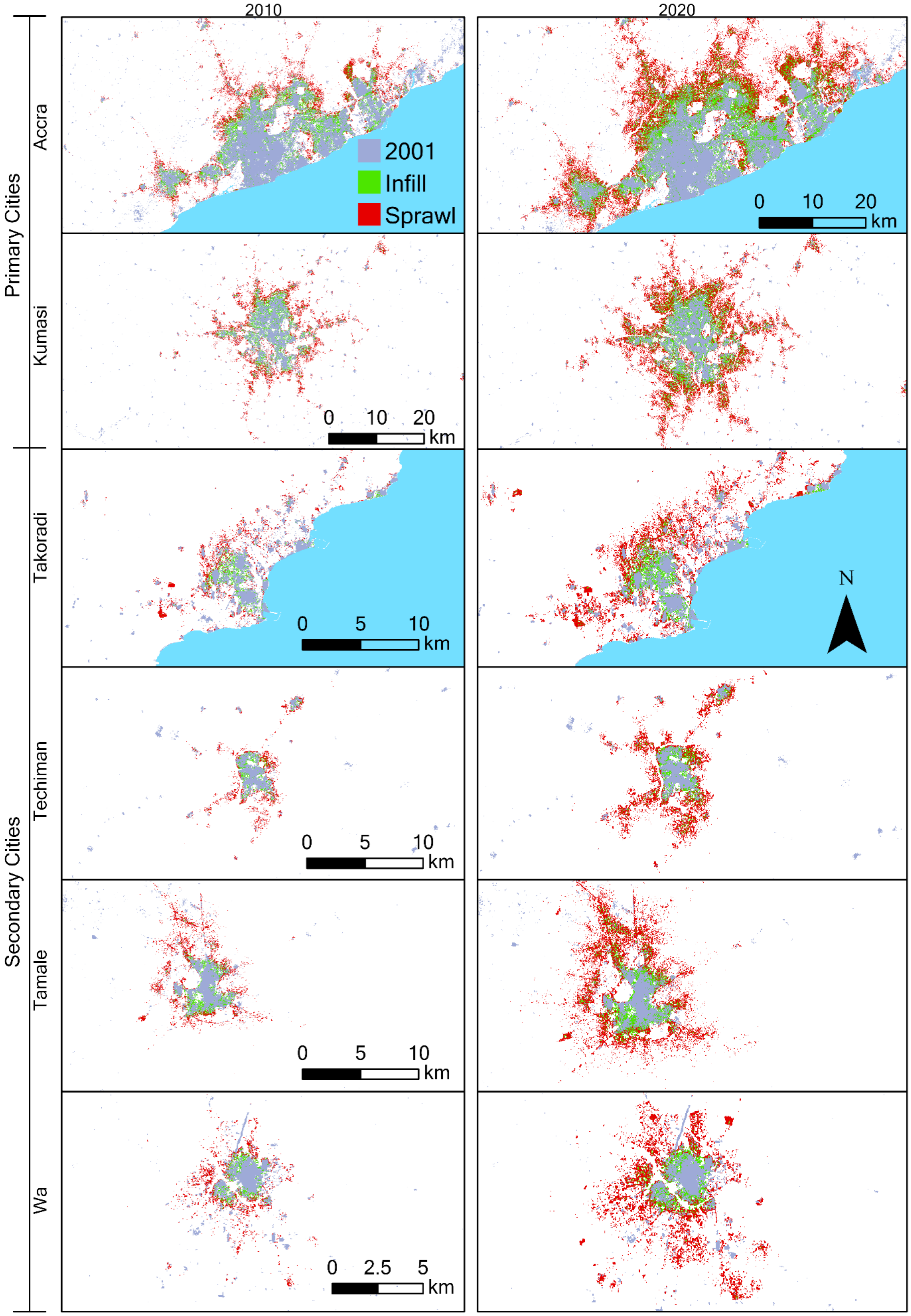

Figure 11: Primary and secondary cities expansion patterns in 2010 and 2020.

3.3.2 Sprawl and infill patterns: lessons learned from qualitative interviews

Interviews with planners, urban residents, landowners, and real estate developers indicate that several interconnected factors have influenced city expansion rates and patterns (Table 6 - 8) and (Figure 10 - 12). These include land and rent costs, proximity to infrastructures and services, land tenure arrangements, nature of neighborhoods, and speculative developments, all of which influence demand for housing in specific locations. These dynamics vary across primary and secondary cities (Table 7). In some cases, uneven power relations among urban stakeholders also (re)enforce inequalities and (re)shape the housing ambitions and aspirations of vulnerable populations across cities.

Figure 12: Development patterns observed in Ghana. The images on the left show sprawl, and the right show infill expansion. The top row images are from very high-resolution images in Google Earth Pro, and the bottom row images are from field observations in 2023.

Table 7: Summary of participants' preferences for infill or sprawl in primary compared to secondary cities.

City	Primary		Secondary	
Enabling factors in cities	**Infill**	**Sprawl**	**Infill**	**Sprawl**
Land/rent cost	Higher cost	High cost	Low cost	Lower cost
Proximity to services	Less concern	More travel time and cost	Less concern	Less travel time and cost
Land tenure security and allocation regimes	Frequent land litigations and less diverse allocation regimes	Fewer land allocation regimes	Infrequent land litigations and more diverse allocation regimes	More diverse land allocation regimes
Nature of neighborhoods	More noise and frequent crimes, less green spaces	Less noise, crimes, and more green spaces	Less noise and crime, more green spaces	Less noise, crimes, more green spaces
Speculative development	Lower speculation	More speculation, motivated by long-run profitability	Lower speculation	More speculation, motivated by short-run profitability

3.3.3 Land and rent cost

Observations from most participants indicate that cost of land and rent varies across cities, with significantly higher costs in primary than secondary cities. Also, within cities, land costs are relatively cheaper at the outskirts than open lands in city centers (Table 8). In primary cities, the average cost of a single plot of land was GHS 450,000 in the city center and GHS 250,000 in the periphery. Also, the average cost of monthly rent was GHS 500 in the city centers and GHS 300 in the periphery. In the secondary cities, costs were relatively lower, averaging GHS 200,000 in the city centers and GHS 15,000 in the periphery. Likewise, the average rental cost for a single room was GHS 250 a month in the center and GHS 150 in the periphery. These differences in cost influence housing and land demand within and across cities, with most residents preferring cheaper locations. Our interview findings are consistent with other studies that found less expensive housing options attract urban residents, increasing housing demand in the peripheries, especially in secondary cities. Additionally, our study shows that housing and land cost varies among each set of primary and secondary cities, and across all six cities, costs tend to increase with city size.

Table 8: Land and rent costs across cities. These lease estimates from participants are for single plot of land and single room self-contained.

City	Cost of Land (GHS)		Rent (GHS)	
	Center	Periphery	Center	Periphery
Accra	400,000 - 500,000	150,000 - 300,000	700 -1000	250 - 400
Kumasi	350,000 – 450,000	150,000 – 200,000	500 - 850	200 - 350
Takoradi	60,000 – 250,000	12,000 – 100,000	375 - 750	200 - 350
Techiman	50,000 – 200,000	15,000 – 70,000	200 - 500	100 - 300
Tamale	60,000 – 100,000	10,000 – 30,000	250 - 400	100 - 300
Wa	40,000 – 100,000	10,000 – 20,000	250 - 350	80 - 250

*The United States Dollar (US$) to Ghana Cedis (GHS) average exchange rate during the interview period (June/ July 2023) was 1.0 US$ to 11.20 GHS.

3.3.4 Proximity to infrastructure and service and economic centers

Proximity to roads, work, schools, markets, and health centers are important locational determinants within cities (Kleemann et al., 2017; Salem et al., 2019). Most participants prefer to live in locations within walkable distance from services and critical infrastructure. Across cities, urban residents consistently mention that the time and cost involved in accessing services and movement to the workplace influence their locational decisions. In primary cities, interviewed residents in sprawling parts of the city spend more than double the time and cost to access the market, education, and health centers than in secondary cities. Thus, distance to services was a less important consideration before developments in secondary cities, probably due to the smaller area size, resulting in residents spending less time and cost accessing services in the city center (Table 7). Two participants emphasize these differences.

> I chose Osu because I wanted to stay close to the Ministries where I work. Also, going to other places, such as the shopping and entertainment centers, is closer than the outskirts of Accra. I mean, I can easily walk to work without spending on transportation (Urban resident in Osu, Accra, June 3, 2023).

> I previously resided in the outskirts of Kumasi, where I had to spend more than double the time and money on transportation. Although I live on the outskirts of Tamale, the distance to the market and my job is not far. For me, access to water and electricity were major considerations (Urban Resident, Tamale, June 16, 2023).

These participants' observations corroborate previous studies that found individual preferences for locational choices vary (Tagnan et al., 2022; Yiran et al., 2020). However, we found that residents in infill locations in primary cities prefer proximity to work, whereas residents in secondary cities are more concerned about access to services rather than distance from economic centers. This is because sprawl locations, especially in smaller secondary cities, generally lack services, and the few resources are generally focused on infill locations in primary cities.

3.3.5 Land tenure arrangements and allocation regimes

More than 80% of lands in Ghana are owned and managed by customary landowners, including chiefs, priests, and heads of several landowning families (Anane & Cobbinah, 2022; Cobbinah et al., 2020). In the absence of land litigations, open lands within city centers were more secure because they were closer to people, and landowners were unable to lease lands to multiple clients. Due to less frequent monitoring of peripheral lands, participants quickly develop to prevent multiple land sales and litigations with landowners; this explains the higher sprawl-to-infill ratio, especially in secondary cities. Additionally, interviewed planning officials indicate that different land allocation regimes among customary landowners mostly influence sprawl developments because multiple families decide when to allocate their lands, resulting in dispersed developments (Table 7) and (Figure 12).

> Land has been bequeathed to present generation by ancestors and for that matter, it is a family property which is only managed by whoever becomes the head of family. But there is also intra-fighting among members of the same family over ancestral land. As a result of land Commission's failure to share completed documents with landlords and greed among some family members, land is sold to multiple clients which creates embarrassment and may end up in the court (Landowner in Wa, June 9, 2023).

This landowner's observations regarding land tenure arrangement challenges are consistent across cities and most previous studies on urban development (Agyemang et al., 2019; Akaateba et al., 2021). Despite contestations among and within landowners, customary landowners largely influence sprawl due to disorderly allocation, especially when managed by family heads. In contrast, statutory ownership, which includes lands owned and managed by the state, mostly encourages infill developments because of orderly land allocation and strict leasing agreements (Korah et al., 2019).

3.3.6 Nature of neighborhoods

Most urban residents highlight the need for serene, secure, and spacious neighborhoods. Consistent with previous studies, congestion and frequent crimes characterize city centers (Yiran et al., 2020), and these issues are more evident in primary than secondary cities. Also, some residents decide to live in certain neighborhoods regardless of noise and crime rates due to cultural reasons, with some preferring to stay close to their families and unwilling to leave their ancestral homes (Razzu, 2005). Most residents prefer to relocate to serene and peri-urban areas for privacy purposes when their economic circumstances improve. However, migrants are more likely to rent or develop in the peripheral neighborhoods due to weaker social bonds than indigenous residents. Also, noise and crime rates are important considerations before renting and developing, with most participants emphasizing their preference for sprawl locations where crime rates are generally lower (Table 7). Relocating to the periphery occurs more often in secondary cities, mostly because housing costs are low, residents spend less time and cost to access services, and as a consequence there is more development in the periphery of secondary cities than in primary cities. This probably explains why secondary cities have a higher sprawl-to-infill ratio than primary cities (Figure 10).

3.3.7 Speculation and expectations

Globally, real estate has been the safest investment since the 2007/2008 financial crisis (Goodfellow, 2017; Yeboah et al., 2020). The real estate sector has continued to boom, especially in low-income countries, with African cities considered the new frontier of global real estate investment, where both local individuals and foreign developers converge to develop urban landscapes in ways mirroring property development in high-income countries. Due to the potential for profit, speculative developments emerging in anticipation of profit or extension of electricity, water and roads are more likely located in the periphery than in the city center in primary and secondary cities. The availability of land influences speculative developments, with some landowners holding on to lands in anticipation of land value increases; this means developers tend to look beyond such lands, potentially resulting in sprawl (Figure 12). Since land for real estate developments is already scarce in primary cities, the speculative developments influencing sprawl expansion appear to happen faster in secondary cities.

The profitability of multi-purpose or single-use developments varies in the short- and long-run, potentially influencing sprawl and infill patterns (Interview, Official of Ghana Real Estate Developers Association, June 3, 2023). Currently, developers find single-use housing more profitable in the short-run than multi-purpose housing; however, they expect this to change in the long run due to population increase and rising income levels (Table 7). The generally lower rates of infill and sprawl expansions in primary cities are likely due to developers expecting future increase in demand for multi-purpose housing, which takes more time and costs more to build. In contrast, single-use housing costs less to construct, with immediate returns from rent, especially in secondary cities (Interview, Developer, Tamale, June 16, 2023).

3.3.8 Actors involved in urban development

A complex set of relations and uneven power dynamics among and within diverse actors contribute to the nature of urban expansion in cities. Stakeholders aim to develop land in particular ways in cities, resulting in conflicting rationalities and uneven urban landscapes (Fält, 2016; Korah et al., 2019). Urban population growth naturally increases demand for housing, and most residents aim for more affordable housing options that are secure in terms of crime and tenure, with access to basic services and infrastructure. The preferences of residents with the economic power and resources to navigate the everyday challenges in African cities drive housing demand in locations that suit them. Most urban residents are more vulnerable with far limited choices; instead of following preference, they locate in certain neighborhood based on their cultural ties, entrenched poverty and unequal access to land.

Most customary landowners mentioned economic hardships and support for their children's education as potential motivation for leasing lands. In particular, family heads prefer to lease lands to elite and individuals with capital to develop immediately after lease. In addition, unregulated land markets result in many vulnerable residents being deprived of land access because they are often outcompeted by political elite, diasporans and multinational corporations (Boone et al., 2014). Additionally, statutory land ownership can deprive the vulnerable of land access in city centers of primary cities because the state mostly partners with private real estate developers to repurpose eminent domain lands. As one landowner observes:

> In the city center, land demand is very high because one can engage in several business opportunities, and the politicians have the money to purchase such lands at any price. So, if the client can afford it, we proceed with the lease (Landowner, Techiman, June 21, 2023).

Thus, land allocation to populations with economic power to acquire and develop housing most likely increases urban expansion across cities. However, preferential allocation of lands to clients was lower in the periphery, probably due to less competition.

Real estate developments have continued to increase with globalization and neoliberal activities (Goodfellow, 2017; Watson, 2014). Optimism about Africa's urban future and its potential for capital accumulation has inspired state authorities to partner with high-end real estate developers to manage, plan, and invest in housing in ways that convey Africa is modernizing (Watson, 2014). Interviews with real estate developers show that developments, especially in primary cities, consisted of mostly high-end hotels in city centers and residential hostels at the periphery. Although real estate activities potentially increase expansion in cities, most of the housing is largely for profit, targeting the rich and rising middle-income class (Goodfellow, 2017). Also, private-public partnerships in real estate development play a considerable role in housing and tenure rights deprivation, especially in primary cities, where eminent domain lands are often repurposed for profit (Korah, 2020). Real estate developers dictate the type of development to invest in, given current land conversion cost and expectations of profitability. Major real estate development activities were focused on primary cities mostly due to the higher potential for long-run investment returns from rent compared to secondary cities, where short-run benefits of developments are high.

> For us [real estate developers], the aim is to ensure that all Ghanaians have access to housing of their choice and the opportunity to realize the dream of home ownership. We believe that

> every family, no matter how poor, has the right to a basic structure that can protect them from the elements. So, we often operate as entrepreneurs in an open and competitive environment (Ghana Real Estate Developers Association, Accra, July 03, 2023).

Although this observation aligns with what urban participants said about their desire to own a home, the activities of most real estate developers likely create unequal access to housing since they operate in a competitive market, largely motivated by profit (Goodfellow, 2017; Korah, 2020).

Planners are largely responsible for controlling and managing the physical expansion of cities. Yet building without permits is a norm in Ghana, resulting in haphazard developments (Korah et al., 2019). In addition, land litigation among and within statutory and customary landowners is common, making it difficult for planners to enforce planning and zoning schemes in contested lands (Akaateba et al., 2021). This is mostly influenced by chiefs (powerful landowners) and the political elite, who are very influential in decision-making and resource allocation (Anane & Cobbinah, 2022). Also, overnight developments by some low-income residents compound planning challenges because planners have limited resources and logistics to control unplanned expansion. In Ghanaian cities, such expansion sometimes encroaches on lands earmarked for public parks, flood-prone zones, and forest reserves; however, the planning institutions are unable to acquire and preserve such lands. Chiefs influence planning in infill and sprawl areas in primary and secondary cities. Yet, political influence and overnight development are mostly found in the centers of primary cities.

> In Accra, planners face many challenges, including land ligations that may threaten officers' lives [while they are] intending to collect data and plan. Also, the high cost of base maps from the Lands Commission and Survey departments makes accessing detailed information about an area difficult. There is a lack of political will from the district assemblies to commit financial resources because they want to see a return on their investment. Unfortunately, physical planning is not a priority. Planning involves teamwork, but most districts lack competent planning officials (Planner, LUSPA, Accra, June 4, 2023).

This planner's observation corroborates previous studies on the challenges of spatial planning in Ghana (Akaateba et al., 2021; Cobbinah et al., 2020). Managing and controlling expansion requires collaborative effort; however, most planning institutions receive limited support from district assemblies, making it difficult to hire planners and purchase logistics needed to enforce planning regulations. Interviewed planners reveal that most planning institutions have one physical planner instead of a minimum of four, especially in secondary cities.

3.4 Policy Implication and Recommendation

Our study demonstrates that most urban expansion was sprawl, meaning new developments could rapidly deplete cropland lands and sensitive ecological zones, especially in secondary cities. Also, infill expansions tend to encroach on public spaces and flood-prone areas where land cost is generally cheaper, likely increasing flood risk among vulnerable populations. City governments can help planning departments acquire and preserve protected areas and lands prone to flooding. City authorities can also implement localized proactive policies, including high land and property taxes that can potentially reduce unplanned developments. Increases in infill and sprawl expansion likely reflect improved infrastructure and economic growth in cities (Mahtta et al., 2022). Therefore, decision-makers need to leverage the opportunities associated with expansion while minimizing the social and environmental impacts. Also, factors influencing urban expansion vary within and across primary and secondary cities. Such context-specific understanding of urban expansion means regulatory policies need to consider the unique dynamics of cities because taxes, subsidies, and penalties to control expansion may work differently across cities.

Due to limited resources, ineffective planning frameworks, and interference from chiefs and political elites, most developments occur without building permits, confounded by overnight developments. There is a need for more collaboration between planners, residents, and customary landowners, especially Chiefs, in spatial development planning and zoning, with strict guidelines for monitoring and enforcing development control. In short, spatial development plans need to account for the multiple rationalities among stakeholders.

3.5 Conclusion

Annual urban expansion rates were generally higher in secondary than primary cities. However, the rate in Kumasi was higher than in two secondary cities, including Takoradi (4.05%) and Wa (5.04%). The sprawl-to-infill ratio has been consistently higher in secondary cities since 2005, likely impacting ecosystems, croplands, carbon sequestration, and biodiversity more than in primary cities. In primary cities, the high cost of land and rent, travel costs, and fewer land allocation regimes were important considerations, whereas interviewees in secondary cities indicate lower cost and more diverse land allocation as important concerns. These considerations are more favorable in the periphery because land and rental costs are mostly cheaper, especially in secondary cities, this likely explains the higher sprawl to infill expansion. Although urban residents prefer cheaper housing options, real estate developers shape accessibility to housing, especially in city centers of primary cities, where potential for profit is mostly high. The conflicting rationalities underscore the nature of expansion, with political elites, chiefs, and indigenous residents mostly flouting planning and zoning schemes. Future studies need to investigate how legal regulatory tools can better control urban expansion across cities. Due to diverse expansion patterns, myriad influencing factors, and conflicting rationalities, more collaborative efforts and strict localized planning and zoning schemes can potentially regulate inefficient urban land expansion. Future studies need to investigate how different legal regulation tools can better control urban expansion across cities.

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Chapter 4: Projecting Urban Expansion Across the West Africa's Urban System

Keywords: FUTURES, West Africa urban system, urban expansion, cities, input variables

Abstract

Most previous spatiotemporal urban simulation studies in West Africa mostly focused on individual cities with an urban population of over a million. However, cities of varying population sizes in the region are increasingly interconnected, and urbanization extends beyond individual city boundaries. To further explore potential future development patterns and for consideration of their implications for urban planning and environmental protection, we used the **FUT**ure **U**rban **RE**gional and **S**imulation (FUTURES) model. First, we calibrated and validated FUTURES for the study area, and then we projected urban expansion in West Africa until 2050 with a one-year time step and a spatial resolution of 30 meters. The results indicate that the lack of consistent, high-resolution spatial data for the input variables limited FUTURES' ability to represent urban expansion differences for cities of different sizes (small, medium, and large cities). New developments were mostly influenced by proximity to previous developments and elevation and hillshade were generally less important factors across cities. Simulation of potential future developed areas indicated an increase in the simulated developed area increased of 8.7 times between 2020 and 2050, with most of the expansion occurring between 2030 – 2040 and generally high annual expansion rates of 3.8% to 14.3% across the study area. Also, the simulation results show dispersed urban expansion, which is often costly to people and the environment. Overall, the availability of consistent finer-scale input data would tremendously increase the quality of projections. Urban expansion modelers can also run multiple future simulations of urban expansion across the study area and incorporate policy-relevant scenarios to better support decision-making in West Africa.

4.1 Introduction

In 2022, 57% of the global population resided in urban centers, and projections are that 90% of future urbanization will occur in low-income countries compared to 10% in high-income countries (OECD et al., 2022). Most low-income countries in Africa display an increase in their urban populations annually by 3.5%, whereas in high-income countries in Europe and North America, the annual growth rate is 0.6%. Diverse factors influence urban population growth, including technological innovations, economic growth, natural population increase, migration, and rural transformation (Gollin et al., 2016; Henderson et al., 2017). These factors manifest in the landscape through increased demand for new developments, resulting in urban expansion. However, the emergence of developed areas in the landscape depends on several conditions, including proximity to existing cities and other biophysical, institutional, and infrastructural characteristics. These conditions can be represented through spatial variables and incorporated into spatiotemporal simulation models to project future urban growth, defined here as increases in urban populations and developed areas (Berberoğlu et al., 2016; Chaudhuri & Clarke, 2019). In Africa, more and better information about potential future urban growth trajectories is needed to evaluate the potential social and environmental impacts and inform urban policies and planning strategies.

Spatially explicit models of urban growth have been used to simulate urban changes under multiple scenarios, and the resulting projections can support researchers in quantifying the expansion types, implementing land use planning, and assessing urban expansion and its impacts (Chaudhuri & Clarke, 2014; Koch et al., 2018; Shoemaker et al., 2019). Thus, urban growth models are useful planning and decision-making support tools. They are also a great way to visualize the outcomes of planning policies, helping to avoid unintended consequences for people and the environment. Most modeling efforts, including cellular automata (CA), statistical regressions, Markov Chains, and neural networks, have been developed and applied in North America, Europe, and Asia (Clarke, 2018; Liu et al., 2017; Meentemeyer et al., 2013; Van Berkel et al., 2019). However, there have also been notable applications of urban growth modeling in Africa (Addae & Oppelt, 2019; Agyemang & Silva, 2019; Goncalves et al., 2019; Idowu et al., 2020; Linard et al., 2013; Okwuashi & Ndehedehe, 2021; Seto et al., 2012). Unlike in other world regions with regional-level urban change simulations, most future change projections for Africa are localized, focusing on individual cities. There is a need for larger-scale urban change projections in Africa to provide comprehensive and consistent estimates of future urban dynamics (Güneralp et al., 2020).

Urban landscapes are heterogeneous and are often classified using qualitative definitions with different classification schemes (Korah et al., 2024). As a result, studies in Africa have found that the lack of consistent urban cover data across countries and cities limited the ability to conduct large-scale regional urban simulations (Güneralp et al., 2020; Reba & Seto, 2020). Most of the previous urban simulations in the region used urban land cover data for three-time steps with nine-year temporal intervals, making it difficult for models to account for subtle changes (Aguejdad, 2021; Chaudhuri & Clarke, 2014). The West Africa Dataset of Impervious Surface Change (WADISC) was regionally calibrated with consistent annual classification of developed areas across Ghana, Togo, Benin, and Nigeria and addresses these limitations (Korah & Wimberly, 2024a, 2024b). Additionally, national road network data are generally inconsistent across countries and biased toward the largest cities. However, the global road inventory project has provided high-quality data across regions, countries, and cities (Meijer et al., 2018). These newer datasets can support consistent, large-scale urban growth simulations across multiple study areas in West Africa, where cities are growing rapidly.

In West Africa, previous urban growth simulation studies mainly focused on primary cities with greater than a million urban residents. While these primary cities have been the focus of future projections, secondary cities with populations of less than or equal to a million are expanding rapidly and contributing more and more to West Africa's urban footprint. Between 2001 and 2020, primary cities in the region expanded by 4.1% annually, whereas the secondary cities' expansion rate was 4.5% (Korah & Wimberly, 2024c). Also, secondary cities' share of the total urban population was 60% in 2020, and projections are that this percentage will increase to 66% by 2050. Projections of how current population growth rates and United Nations population projections translate into urban expansion patterns in the landscape across countries and cities in West Africa are lacking. To fully capture the impacts of urbanization across the region, these projections must encompass all cities (and types) within the regional urban network instead of just the largest cities.

Our main objective was to simulate the future urban expansion across Ghana, Togo, Benin, and Nigeria. We specifically asked three research questions: 1) How have different variables influenced urban expansion in cities of varying population sizes? 2) How do model patterns and quantity accuracy vary in cities of varying sizes? 3) How do the amounts and rates of expansion vary across different time intervals from 2020 to 2050? We calibrated the FUTURES model to simulate developed land change from 2016 to 2050 using the WADISC dataset and several input variables. These enable us to understand the best predictors and assess model accuracy.

4.2 Materials and Methods

The research involves several processes involving input data preparation, fitting with different sub-models, generation of variable importance, 20 simulation runs for each country, classification of average probabilities of future development, quantifying with landscape quantity and pattern to assess the simulation accuracy, and summary of expansion rates. We summarized these processes in a flow chart (Figure 13).

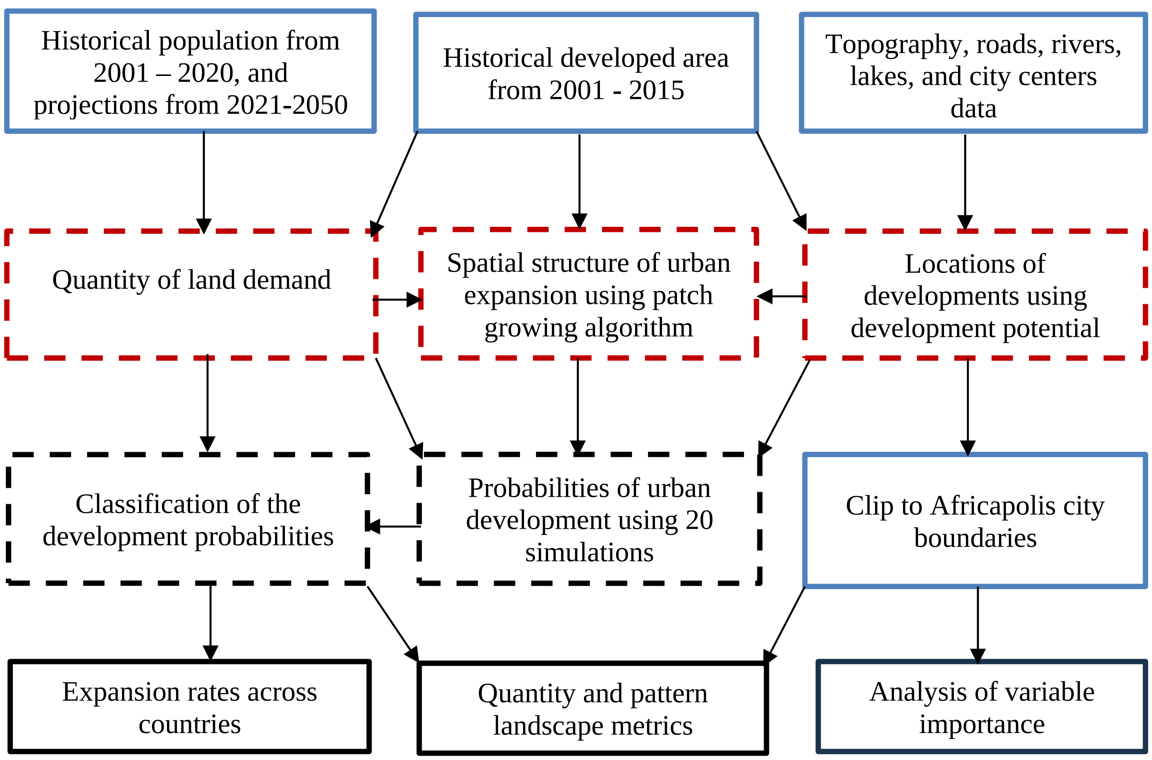

Figure 13: Flow chart showing the urban simulation process with FUTURES and analysis stages. The blue boxes show the input data, the dashed red boxes indicate the FUTURES sub-models used to fit the input data, the dashed black boxes show simulated outcomes, and the black boxes show the summary and analysis stages.

4.2.1 Study Area

This study focuses on Ghana, Togo, Benin, and Nigeria, covering an area of 1.3 million km²

(Figure 14). These countries contain 73% of the urban population and 70% of the cities in West Africa in 2020. Between 2000 and 2020, the four countries rapidly increased their urban population, with an annual growth rate of 4.5% in Togo, 4.1% in Benin, 2.8% in Nigeria, and 2.6% in Ghana (OECD/SWAC, 2020). We used the city class classification scheme from previous studies in the region (Korah et al., 2024; Korah & Wimberly, 2024c). Across the study area, 81% of the cities are small (population > 10,000 and <= 50,000), 18% medium (population > 50,000 and =< 1,000,000), and 1% large (population > 1,000,000). These cities are generally concentrated in the coastal part of the countries, with very sparse distribution northwards (Figure 14).

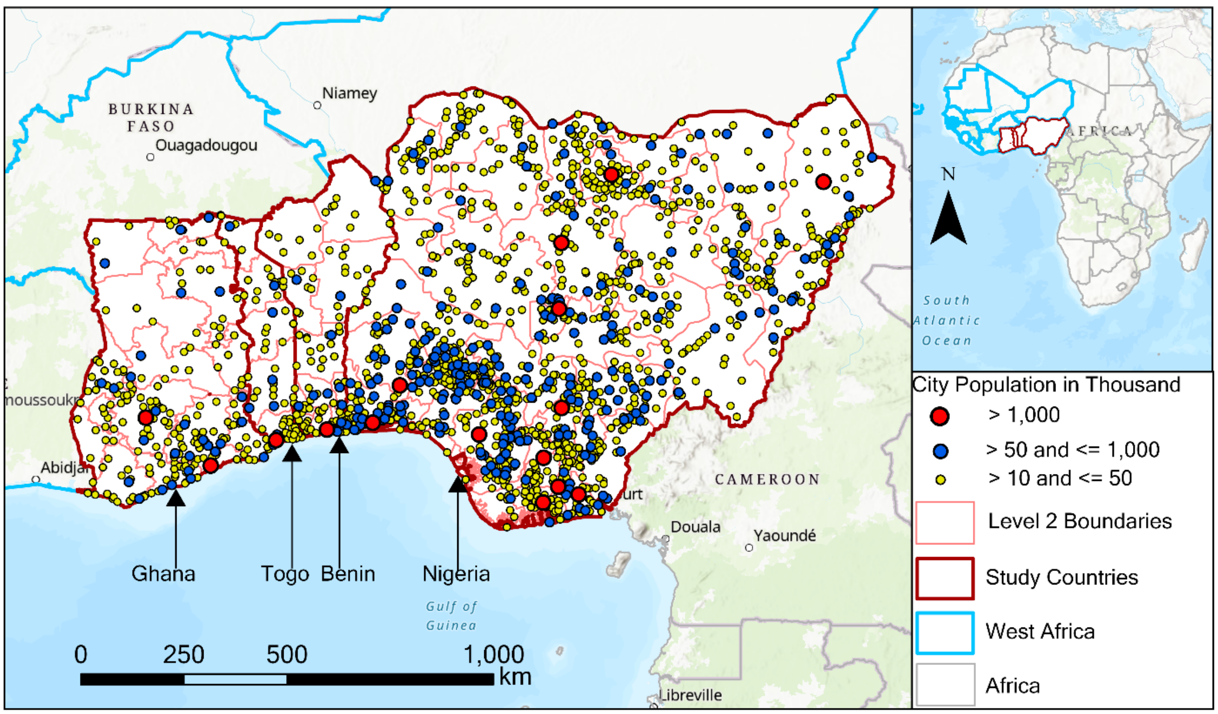

Figure 14: Distribution of small, medium, and large cities across administrative unit level 2 boundaries (FAO UN, 2014), in the study area. The level 2 boundaries represent the 16 regions in Ghana, 5 régions in Togo, 12 départments in Benin, and 37 states in Nigeria. The large cities are in red, the medium in blue, and the small cities in yellow.

4.2.2 FUTURES model

FUTURES is developed for regional scale simulations, and it couples three submodels, including POTENTIAL, DEMAND, and the Patch-Growing Algorithm (PGA), to simulate the location and extent of change (Dorning et al., 2015; Meentemeyer et al., 2013). The

POTENTIAL submodel identifies suitable locations for potential future developments based on multilevel logistic regression that establishes relationships between spatial predictors and urban land change. The DEMAND submodel associates population numbers and historical developed area maps to quantify the expected rate of developed land conversion at the national level. The per-capita land demand relationship can follow one of several trends: (1) linear; (2) logarithmic, where the land demand curve is concave, initially increasing faster but slowing in later years; or (3) exponential, with initially slow land demand and faster in future years. The PGA applies a stochastic approach that iteratively selects suitable locations, combining cells and patches to better mimic the size and shape of developments in space and over time (Meentemeyer et al., 2013). Previous applications of FUTURES found the model to produce informative results for urban planning and ecological assessment across the United States under different expansion and environmental management scenarios (Dorning et al., 2015; Pickard et al., 2017; Sanchez et al., 2020; Shoemaker et al., 2019; Van Berkel et al., 2019). Moreover, FUTURES was among the first urban simulation models to simulate the leapfrogging process (Meentemeyer et al., 2013), an especially important development pattern for West Africa, given the importance of secondary cities (Marais & Cloete, 2017). Thus, FUTURES is one of the few urban simulation models designed for regional-level mapping that captures the spatial structure of urban population growth and accounts for policy effects on developments across different levels.

4.2.3 Model input variables

FUTURES requires historical urban land cover data and several input variables to extrapolate expansion rates and patterns into the future. Across the world, most previous urban simulation studies use maps with long (5-10 years) temporal intervals, and only few used annual maps to compute potential demand, making it difficult to address subtle annual changes (and their feedback effects on the following time steps) in calibration. We used annual binary maps (developed or undeveloped) from WADISC, a regionally optimized dataset developed to detect urban expansion across multiple countries in West Africa (Korah & Wimberly, 2024a). Other variables used to generate suitability maps for future urban change projections included topography, distance to roads, city centers, and primary cities, rivers, and lakes, which attract new developments; protected areas; which restrict developments; and historical population trends and estimates over the study area (Table 9). Most of these suitability variables are stable over time; however, population changes rapidly through time, and using annual population data can enable FUTURES better mimic land demand at individual or multiple levels.

Table 9: Input variables used to project future urban change.

Input	Variable Description	Spatial Resolution	Temporal resolution	Source
Developed Area	Developed and undeveloped class	30m	Annual: 2001-2020	(Korah & Wimberly, 2024a, 2024b)
Social	Historical population Population projections	NA	Annual: 2001-2015 Annual: 2016-2050	(Bondarenko et al., 2020) (United Nations et al., 2022)
Topography	Elevation Slope Hillshade	30m	One year: 2000	(Farr et al., 2007)
Water Resources	Distance to lakes Distance to rivers	NA	One year: 2019	(Yan et al., 2019)
Policy	Protected areas Administrative boundaries	NA	One year: 2020 One year: 2014	(UNEP-WCMC & IUCN, 2017) (FAO UN, 2014)
Infrastructure	Distance to roads Distance to city centers Distance to primary cities	NA	One year: 2018 One year: 2015	(Meijer et al., 2018); (OECD/SWAC, 2020)

Note: We used 14 input variables consisting of slope, hillshade, elevation, distance from tertiary roads (DTRoads), distance from secondary roads (DSRoads), distance from rivers (Drivers), distance from primary roads (DPRoads), distance from primary cities center (DPCities), distance from local roads (DLRoads). Distance from lakes (DLakes), development pressure (DevPressure), distance to all roads (DARoads), and distance from all cities center (DACities).

4.2.4 Model parameterization and calibration

We calibrated the POTENTIAL submodel for projecting urbanization using a multilevel regression approach, which relates suitability variables and observed developed area change between 2001 and 2015 to estimate the probability of a cell changing to developed. To address spatiotemporal heterogeneity in the large study area, we calibrated the POTENTIAL submodel separately for each country. Additionally, we included a dynamic developed pressure variable. This variable assumes that proximity to existing developed cells increases the probability of new developments. As new developed areas are assigned, the proximity variable is recomputed at each time step as the weighted distance from neighboring cells, where smaller gamma (controls the search distance) values increase the influence of developed cells with distance (Meentemeyer et al., 2008, 2013). We randomly sampled 7000 points in undeveloped and 6000 in developed cells each in Benin and Togo; in Ghana, we sampled 8000 in undeveloped and 6000 in developed, whereas, in Nigeria, we sampled 9000 in undeveloped and 8000 in developed areas in both the Northern and Southern models. We selected these different points based on the size of each country. At each point, we extracted values for the variables, which we used in the generalized linear model to select the best predictors for generating the suitability surface for each country.

Additionally, we randomly selected an equal number of points in both developed and undeveloped areas across large, medium, and small cities. Across city types in Togo, we selected 1000 points each in developed and undeveloped; in Benin, we selected 1500 points; in Ghana, we selected 2500; and in Nigeria, we selected 5000 points. We used these randomly selected point to generate the importance of variables. This importance is measured as the change in residual sums of squares as each predictor is included in the model (Xie & Luo, 2022). The importance is scaled between 0 and 1, with the least influential variable having a value of 0 and the most influential variable having a value of 1.

For parameterizing the DEMAND submodel for the Status Quo scenario, we assume that historical population growth and urban change trends in each country will continue into 2050. Therefore, we used the no-change estimates from UN population projections and computed the future total population for each country from 2016 - 2050. These estimates were combined with annual urban maps from 2001 – 2015 to compute different demand files using linear, logarithmic, and exponential approaches, and the pattern with the lowest root mean squared error (RMSE) was selected for each country (Figure S4).

We calibrated PGA submodel to generate the patch size for each country and coefficients to fit future simulations. At the cell level, the PGA allocates random seeds across the POTENTIAL suitability surfaces for each country. Seeds that survive the Monte Carlo iterative process (with developmental potential higher than random) grow into patches of development. This allocation of seeds for development continues until the estimated per capita land demand for each country is met. Thus, the patch sizes reflect the historical spatial structure of developments from 2001 – 2015, which is assumed to be stationary over the simulation period.

4.2.5 Model simulation and validation

We generated 20 simulation runs across the study extent from 2016-2050 and computed the mean probability. Pixels with greater than 20% probability of being selected for development were classified as developed, and those with less than or equal to 20% were classified as undeveloped. Thus, to generate the accuracy metrics for our simulations, we compared the 2020 observed map with the simulated map for 2020. We generated a figure of merit by overlying three maps: the initial reference map for 2015, reference map for 2020, and simulated map for 2020 (Ke et al., 2015; Pickard et al., 2017; Pontius et al., 2008; van Vliet et al., 2016). The figure of merit (FoM) provides insights into the number of correct rejections of undeveloped cells and the persistence of developed cells in the reference and simulated maps. The FoM also divides the developed area change into three components: 1) hits represent cells that were correctly simulated; 2) misses indicate cells that were only absent in the simulated map; and 3) false alarms show cells that were only present in the simulated map (Varga et al., 2019).

Additionally, we computed several landscape metrics to evaluate the quantity and pattern of developed area accuracies. For quantity accuracy, we computed the total class area (CA), the number of developed patches (NP), and the percentage of landscape (PLAND) occupied by the developed Area in the simulated and reference maps for 2020. For pattern accuracy, we used the normalized landscape-shaped index (NLSI) to measure the (dis)aggregation of patches, the contiguity index (CONTIG) to measure patch connectedness, and Euclidean Nearest-Neighbor Distance (ENN) to compute the mean distance between patches of the same class within the landscape. We compared these accuracy metrics across each country's small, medium, and large cities.

4.3 Results

4.3.1 Variable importance

The relative importance of the 14 predictor variables varies across large, medium, and small cities. The development pressure from already developed area is the most important variable in each country except Benin, where distance from all cities was highest, followed by distance from primary cities (Figure 15). Across the study area, developed pressure and distance to all cities were consistently significant across small, medium, and large cities in each country, while the other variables varied in importance (Table S3 and S4).

In Benin's large cities, 11 (84.6%) predictors were statistically significant (at 0.1 alpha level) in large cities except for distance from secondary roads, tertiary roads, rivers, and hillshade (Table S3). For medium cities, 7 (50%) predictors were statistically significant: developed pressure, distance from local roads, primary roads, primary cities, all cities, and protected areas. For small cities, 5 (35.7%) predictors were statistically significant: development pressure, distance from all cities, tertiary roads, lakes, and protected areas. Across the cities in Benin, developed pressure and distance from all city centers and protected areas were consistently significant. In contrast, distance from secondary roads, rivers, and hillshade was insignificant.

In Ghana's large cities, 9 (64.3%) predictors were statistically significant, except distance from secondary roads, tertiary roads, rivers, elevation, and hillshade (Table S3). Likewise, 9 predictors were statistically significant in medium cities, except distance to local roads, primary roads, primary cities, rivers, and hillshade. In small cities, 6 (42.9%) predictors were statistically significant: developed pressure, distance from local roads, primary cities, all cities, protected areas, and slope. Development pressure, distance to all cities, protected areas, and slope were significant in all three city types, whereas distance to rivers and hillshade were consistently insignificant.

In Nigeria's large cities, 8 (57.1%) predictors were significant, except distance from local roads, tertiary roads, primary cities, rivers, elevation, hillshade, and slope (Table S4). All variables were significant in medium cities, except distance from secondary roads, all cities, elevation, and hillshade. Most input variables were significant in small cities, excluding distance to all cities, all roads, elevation, hillshade, and slope. In all three city types, developed pressure, distance from all roads, secondary roads, tertiary roads, lakes, and distance from all cities were significant, whereas elevation was consistently insignificant.

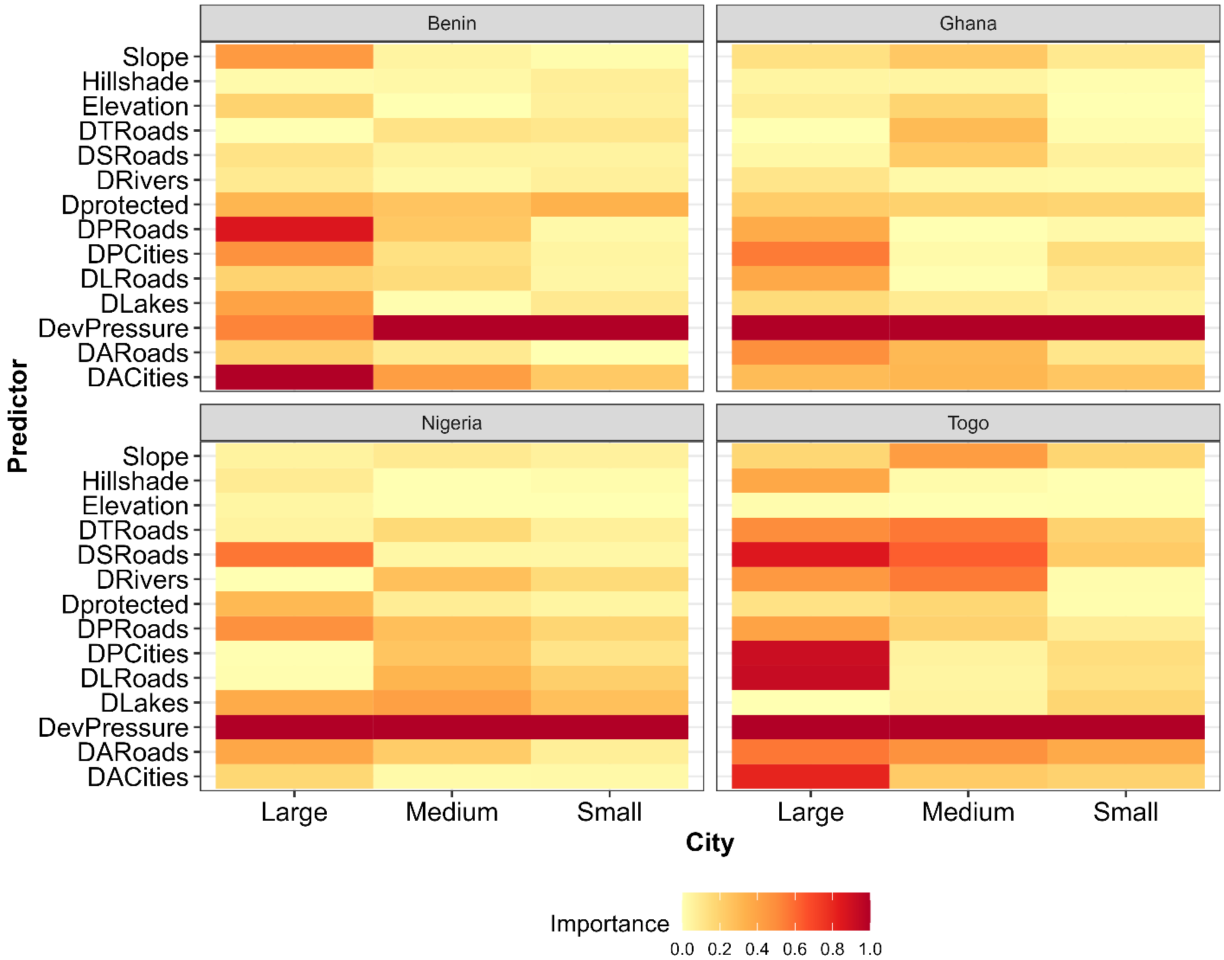

Figure 15: Variable Importance across city types in Ghana, Togo, Benin, and Nigeria. There is a clear variation in the importance of predictors across the four different countries.

In Togo's large cities, 11 (71.4%) predictors were statistically significant, except distance from protected areas, lakes, elevation, and slope (Table S4). In medium cities, all variables were significant, except distance from primary cities, local roads, lakes, elevation, and hillshade. Likewise, all predictors were significant in small cities, excluding distance to roads, rivers, protected areas, elevation, and hillshade. Across all cities, developed pressure, distance from secondary cities, all cities, all roads, and tertiary roads were generally significant, whereas elevation was consistently insignificant.

4.3.2 Accuracy comparison across city types

Under *Status Quo* conditions, the probability of pixel conversion rate varied across the simulated area in each country (Figure 16). Visual comparison of reference maps with the probability of development across all 20 simulation runs found a cut-off of 20% best-simulated future developed area (Figure 17). We arrived at this 20% through visual comparison of different thresholds and comparing them with the 2020 reference map. The FoM, which estimates the intersection between the reference and simulated map, ranges from 0.04 – 0.16. The FoM values across all cities in Nigeria and large cities in Togo were generally over 0.1, while values for cities in Ghana and Benin were below 0.1. The amount of hits, false alarms, and misses varied across cities in each country, with generally higher misses than false alarms, except in cities in Nigeria and Togo. Also, the proportion of hits was generally higher in the large cities than in small and medium cities for each country, except for medium cities in Nigeria (Figure 18).

Additionally, the quantity metrics, including the total developed area and percentage of landscape in the reference map across the cities in each country, were generally higher than in simulated maps, except for large cities in Togo (Table 10). However, the number of patches was consistently higher in the simulated map than in the reference map. The pattern metrics, including the normalized landscape shape index and the contiguous index, were consistently higher in the simulated maps than in the reference maps across all cities in each country. The mean Euclidean nearest neighbor distance, however, was higher in the simulated map than the reference maps across all cities in each country. In short, the patches in the developed area were mostly isolated, irregular, and more dispersed in the simulated map than the reference map for 2020.

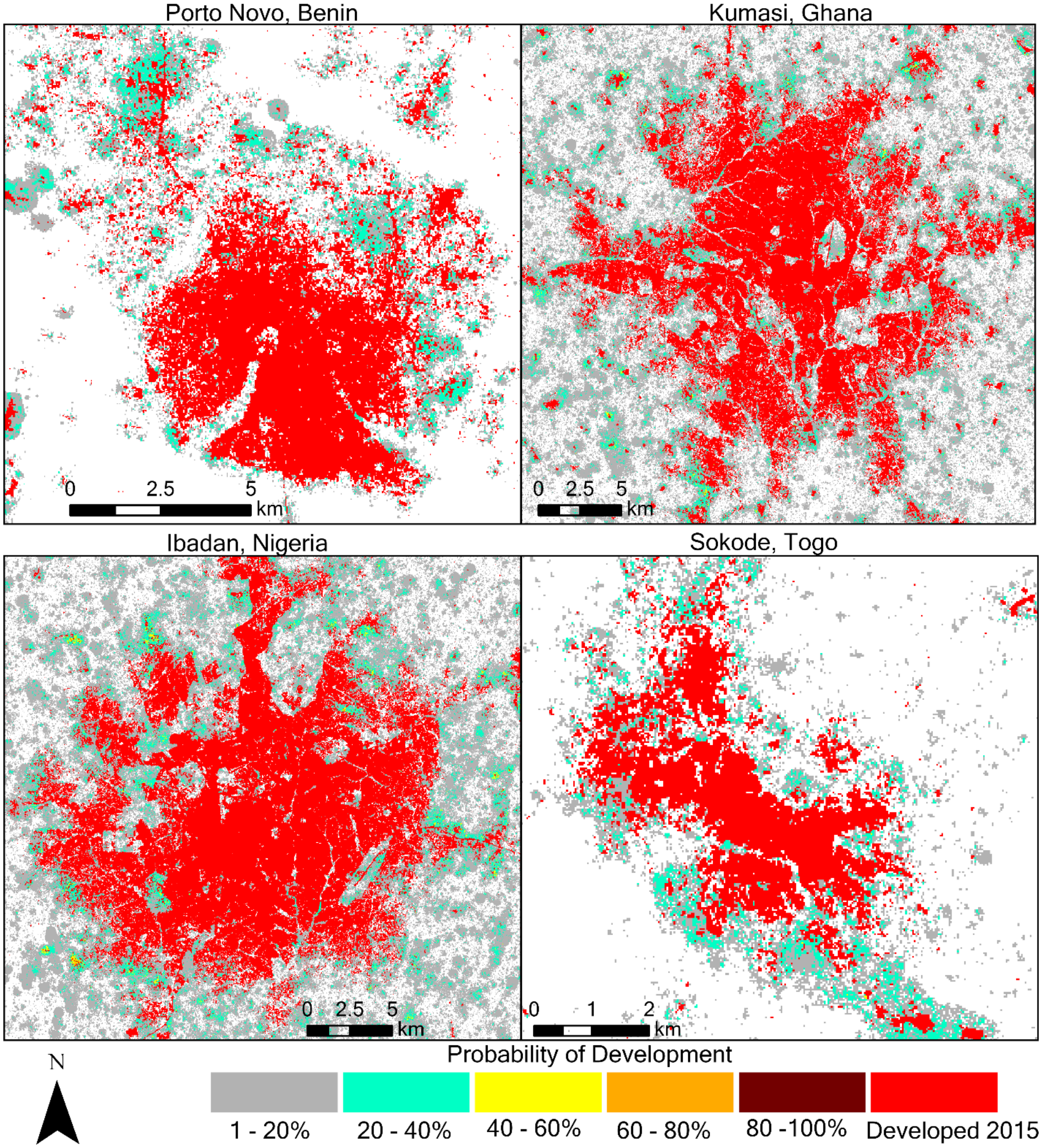

Figure 16: Distribution of development probabilities of pixels selected to develop across 20 simulations.

Table 10: Pattern and quantity metrics of reference and simulated maps in each country.

Country	City	Reference 2020						Simulated 2020					
		PLAND	CA	NP	NLSI	CONTIG	ENN_MN	PLAND	CA	NP	NLSI	CONTIG	ENN_MN
Benin	Small	31.3	143.67	6969	0.243	0.204	89.6	31.1	142.62	8944	0.281	0.166	82.6
	Medium	41.3	178.70	5417	0.178	0.207	89.0	40.8	176.43	7079	0.21	0.164	80.7
	Large	48.5	177.02	3447	0.119	0.193	91.1	46.0	167.77	5488	0.151	0.145	82.8
Togo	Small	18.2	58.79	4013	0.255	0.182	103.0	21.8	69.70	5081	0.291	0.152	87.5
	Medium	21.9	70.56	4482	0.268	0.174	96.2	24.9	83.60	7011	0.335	0.144	80.7
	Large	61.7	218.88	2093	0.127	0.179	85.5	62.5	220.90	3850	0.175	0.145	73.9
Ghana	Small	27.9	286.28	15142	0.247	0.200	89.1	26.5	271.05	16994	0.274	0.158	85.4
	Medium	36.2	353.03	14086	0.218	0.205	83.6	32.4	315.70	15648	0.243	0.164	82.5
	Large	57.5	1019.91	14477	0.141	0.193	79.1	52.7	933.56	23114	0.146	144	76.3
Nigeria	Small	25.6	1011.23	54023	0.350	0.245	NA	24.7	973.85	57309	0.270	0.163	NA
	Medium	38.1	3070.55	82598	0.175	0.193	NA	34.5	2777.68	92389	0.198	0.155	NA
	Large	37.2	3266.60	87416	0.142	0.194	92.79	34.8	3045.53	107009	0.173	0.155	86.87

Note: NA is no data. The quantity metrics consist of the percentage of landscape (PLAND), total class area (CA), and number of developed patches (NP). The pattern metrics comprise the normalized landscape shape index (NLSI), contiguous index (CONTIG), and the mean Euclidean Nearest Neighbor (ENN_MN).

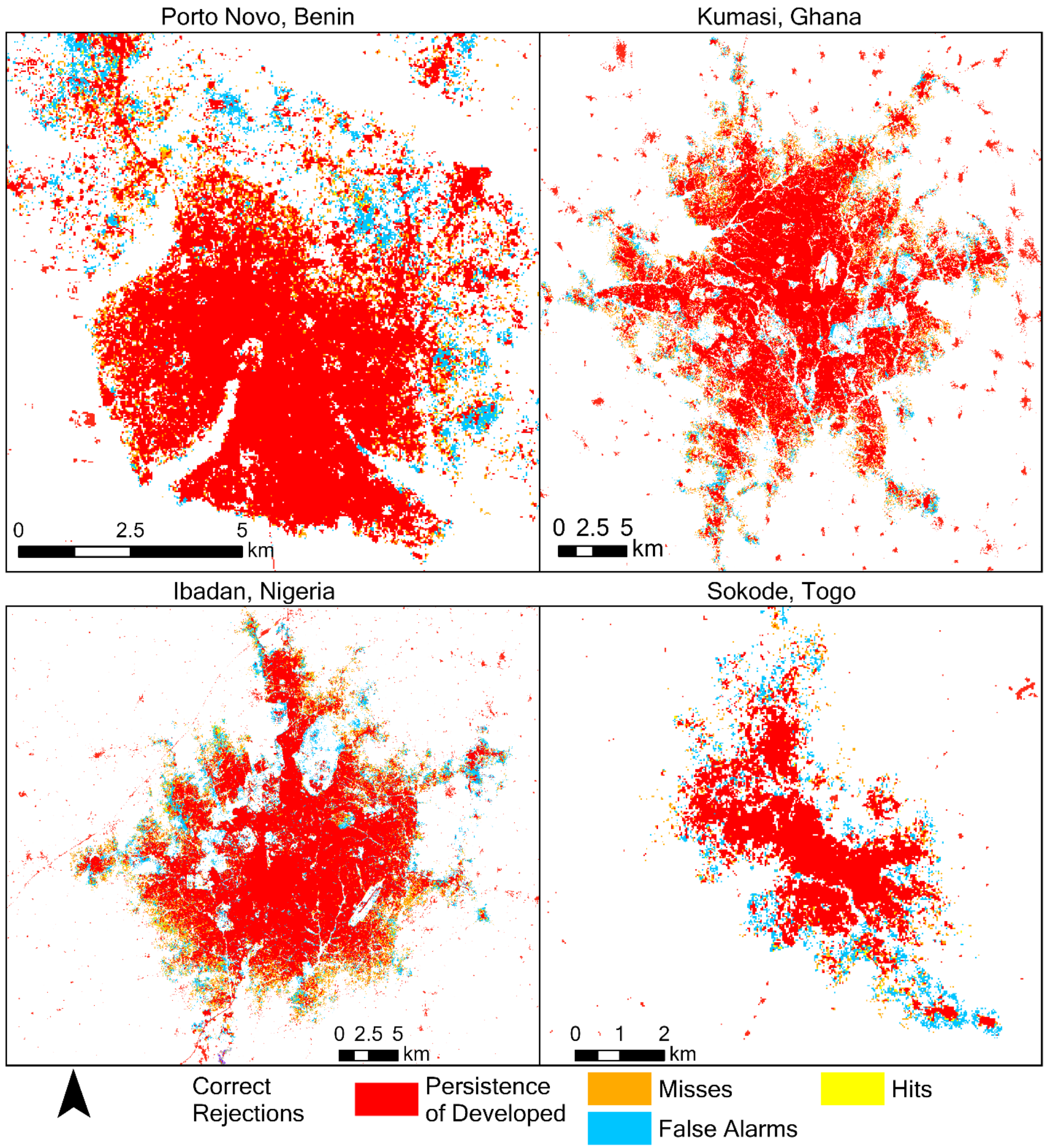

Figure 17: Three-map comparison of the initial development in 2015, reference map for 2020, and simulated map for 2020. Correct rejections are undeveloped cells across all three maps, and persistence of developed are developed cells across all three maps. Misses are reference changes simulated as developed in 2015, and hits are reference changes simulated as change, false alarms are reference persistence simulated as change.

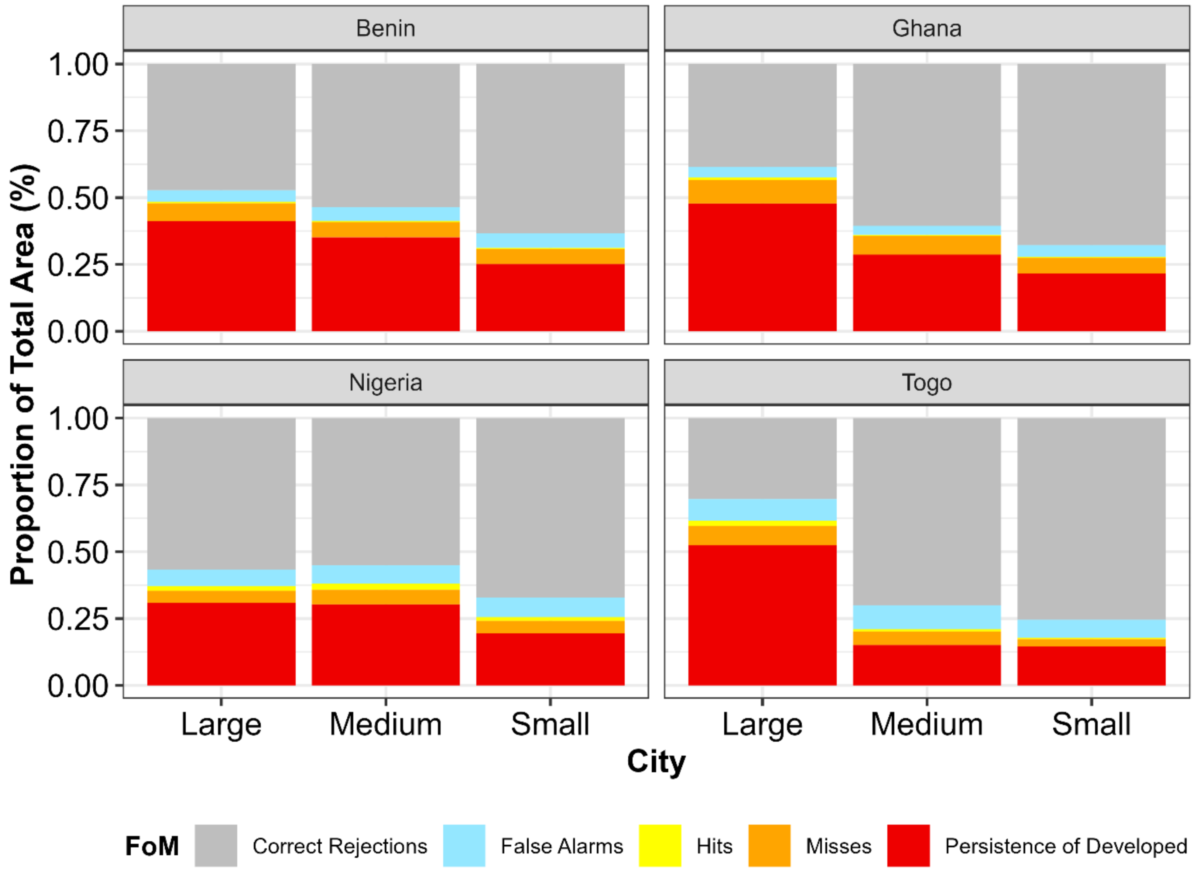

Figure 18: Proportion of total simulated area occupied by various components in the figure of merit (FoM). In Benin, the FoM in large and medium cities was 0.05; in small cities, it was 0.04. In Ghana, FoM in large cities was 0.06; in medium and small cities, it was 0.04. In Nigeria, the FoM in large cities was 0.15; in medium cities, it was 0.16; and in small cities, it was 0.10. In Togo, the FoM in large cities was 0.12; in medium cities, it was 0.05; and in small cities, it was 0.04.

4.3.3 Quantities and rates of expansion across administrative boundaries

Increases in simulated developed area varied across countries in the study area. In Benin, the developed area increased from 788.10 km² in 2020 to 3036.56 km² in 2050. In Ghana, the simulated developed area increased from 2644.20 km² in 2020 to 25361.58 km² in 2050. In Nigeria, the simulated developed area increased from 10828.68 km² in 2020 to 94915.29 km² in 2050, and in Togo, the developed area increased from 681.09 km² in 2020 to 6499.31 km² in 2050 (Table 11). Thus, the simulated developed area between 2020 and 2050 shows a 9.6 times increase in Ghana, a 9.5 times increase in Togo, an 8.7 times increase in Nigeria, and a 3.9 times increase in Benin.

The annual expansion rate varies in each country, with most simulated annual increases occurring in the period 2030 – 2040, except in Benin, where most of the increases were in 2040 – 2050 (Table 11). Also, the simulated distribution of annual expansion rate hotspots was uneven and varied across different time intervals (Figure 19). From 2020-2030, higher annual expansion rates were highest in the southern part of Ghana, the southern and northern parts of Togo and Nigeria, and the central part of Benin. From 2030 – 2040, most of the highest growth was distributed across the entire country, with the lowest expansion rates mostly occurring in the southern parts of each country. Likewise, from 2040 -2050, most of the lowest annual expansion rates were in the southern parts of each country and central parts of Nigeria.

Table 11: Developed area and annual expansion rates across three-time intervals.

Country	Developed Area (km²)				AER (%)		
	2020	2030	2040	2050	2020-2030	2030-2040	2040-2050
Benin	788.10	1091.87	1790.50	3036.56	3.31	5.07	5.42
Ghana	2644.20	6184.06	14627.33	25361.58	8.87	8.99	5.66
Nigeria	10828.68	21729.84	48938.95	94915.29	7.21	8.46	6.85
Togo	681.09	869.16	2434.65	6499.31	2.47	10.8	10.3

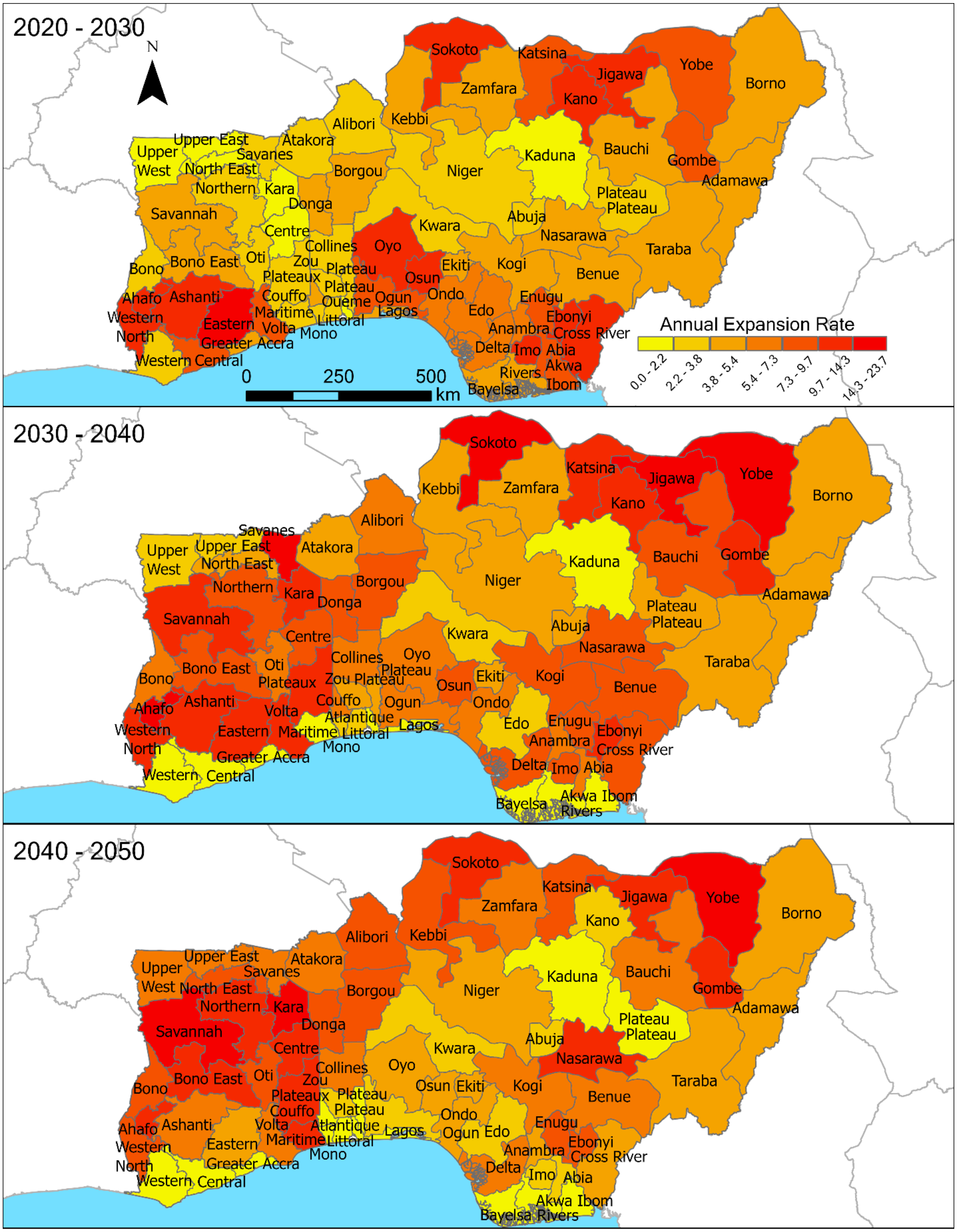

Figure 19: Annual expansion rates across administrative unit level-2 boundaries from 2020 – 2030, 2030 – 2040, and 2040 – 2050.

4.4 Discussion

4.4.1 Importance of input variables

We modeled the relationship between change in developed area from 2001 – 2015 and several spatially explicit predictor variables for each country's small, medium, and large cities. We found that the importance of different input variables varied across city sizes. Development pressure, which is the dynamic mechanism considering the distance from the previously developed areas, was most important across large, medium, and small cities in each country, except large cities in Benin, where the distance to all city centers was most important. Previous urban simulation studies in the region often found that urban developed areas were low at high elevations and in steep terrain and that these topographic variables are important predictors of urban change (Aburas et al., 2016; Enoguanbhor et al., 2022; Kukkonen et al., 2018). In contrast, we found elevation and hillshade were generally insignificant across the various city types. These findings suggest the unique and complex pattern of urban expansion in West Africa, often shaped by a regional cultural background. Although urban expansion (planning) occurs at the local or individual city level, the impacts extend beyond city individual boundaries, necessitating a large-scale understanding of urban expansion across multiple cities (Korah et al., 2024; Tulbure et al., 2022). Our study encompasses all 1603 cities in the study area, consisting of 1305 large, 282 medium, and 16 large cities across the study area. This type of analysis of the variable's importance across an entire system of cities is needed to inform modelers, planners, and the scientific community of unique and diverse predictors of urban expansion across increasingly urbanized and interconnected cities in West Africa.

4.4.2 Accuracy of simulation

Cities and countries are increasingly interconnected, and managing their future expansion requires using urban simulation models. The scenario simulations resulting from applying these simulation models offer planners, decision-makers and other interested parties visualizations of new developments under certain scenario assumptions. These visualizations and the corresponding spatiotemporal information helps to identify unintended consequences (e.g., for biodiversity (Koch et al., 2019) and planning of infrastructure needs.

Using FUTURES, we ran 20 simulations for a *Status Quo* scenario and averaged runs in each country. Running a single simulation covering the entire study area took about 65 hours on an Intel® Xeon® Gold 6126 processor, with 64-bit operating system and 256 gigabytes (GB) installed read-only memory (RAM). Due to time limitations, we decided on 20 simulation runs for the *Status Quo* scenario and the corresponding calibration and validation. We found that pixels with over 20% probability of development closely captured the developed area in each country in 2020. There were higher amounts of misses and false alarms than hits, resulting in 4% - 16% accurate simulations across small, medium, and large cities in the study area. Thus, the FoM values ranged from 10% -16% for large cities in Togo and all city types in Nigeria, which was consistent with 10% – 30% accurate simulation percentage reported from most studies around the globe (Chen et al., 2020; Pickard & Meentemeyer, 2019; Pontius et al., 2008; van Vliet et al., 2016). The lower total developed area and percentage of the city boundary occupied by the developed area class indicate under simulation of future development in the study area. The underpredictions of the developed area were generally lower in small and medium-sized cities than in large cities in each country, except in Togo. This was due to the higher probability of the suitability surface in Togo's large cities. These low FoM values may indicate a dynamic in the underlying approach to development in West African cities, where multiple rationalities and land tenure arrangements shape developments.

Additionally, the higher number of patches in the simulated maps and consistently higher pattern metrics, including the normalized landscape shape index and the contiguous index in the reference maps, show that our simulations resulted in more dispersed urban expansion. This pattern of expansion, however, is consistent with previous urban expansion studies that generally find more sprawl expansion in West Africa, especially in the smaller cities (Enoguanbhor et al., 2022; Korah & Wimberly, 2024c; Linard et al., 2013). Overall, the difference in the number of misses, false alarms, hits, and overall quantity and pattern metrics disagreements between the reference and simulated maps for 2020 in all cities is likely influenced by differences in predictors across individual cities, and our calibration did not account for city level variation in calibration and parameterization.

4.4.3 Future expansion rates

We quantified the total simulated developed area and annual expansion rates across countries from 2020 to 2050. Across the study area, we found that the simulated developed area increased an average of 8.7 times over 30-year intervals, with the highest increase of 9.6 times in Ghana and the lowest being 3.9 times in Benin. The annual expansion rates across countries were highest in Ghana from 2020 – 2030, and this rate was consistently highest in Togo from 2030 – 2040 and 2040 – 2050. Also, the expansion rates across administrative units generally ranged from 3.8% to 14.3%, consistent with rates from previous regional studies (Chen et al., 2020; Korah & Wimberly, 2024c; Seto et al., 2012). The simulation results reveal that annual urban expansion rates increased rapidly, with significantly higher rates from 2030 to 2040 than other intervals. Also, our findings show that the rate of urban expansion varied across and within countries. Most of the highest expansion rates from 2020 – 2030 mostly occurred in the southern and coastal parts of the countries, reflecting the historical concentration of infrastructure in and around large cities. The 2030 – 2040 and 2040 – 2050 intervals show lower expansion rates in the coastal parts, probably because the most suitable areas were developed in preceding intervals, likely resulting in lower allocations of developments.

4.4.4 Policy implications of expansion rates

The simulation results here provide broad national and regional trends in urban expansion, rather than localized application, and the potential of projecting future expansion using FUTURES. To our knowledge, this is the first application of the FUTURES modeling framework in Africa, and the results are not necessarily suitable for individual city or neighborhood-level planning in the study area. However, the results still have broader national and regional implications for people and the environment in West Africa, a global hotspot of current and future urban expansion (Korah & Wimberly, 2024c; Seto et al., 2012).

Globally, previous studies of urban expansion often found that future expansion threatens biodiversity and protected areas and encroaches on croplands (Bren d'Amour et al., 2017; Tu et al., 2021). Some studies found that over 1.4 million square kilometers of urban land are projected to merge within 50 km of protected areas (Güneralp & Seto, 2013; Seto et al., 2012). Also, 50 – 63% of urban land will likely occur on current croplands, resulting in a 3% decline in crop production and impacting the food needs of about 755 million people annually (Chen et al., 2020). Across the four West African countries, most of the simulated future expansions are likely to deplete ecosystem services, especially in areas with substantially high expansion rates (Güneralp et al., 2017; Liu et al., 2019). Also, urban expansion impacts urban populations, including urban heat islands and flood risk, especially the dispersed or sprawl expansion pattern increases the cost of extending water, sewage, electricity, and transportation (Muis et al., 2015; Tu et al., 2021; Yiran et al., 2020).

Additionally, national planning policies in the four West African countries are mostly ineffective, and central and city authorities have limited infrastructure and resources to sustainably manage urban expansion (Abass et al., 2020; Cobbinah et al., 2020; Cobbinah & Aboagye, 2017). The simulation results show the pattern of expansion is mostly dispersed, and this type of expansion largely impacts people and the environment more than compact urban expansion. There is a need to provide housing to accommodate the increasing urban population across the region; however, horizontal development patterns will likely cost more to manage than vertical developments with multiple land uses.

4.4.5 Limitations of study and recommendations

The calibration and parameterizing of FUTURES were done at the broader national level rather than at a finer scale because of a lack of consistent population data and future population estimates at subnational scales, which is required by FUTURES DEMAND submodel to extrapolate future development (Meentemeyer et al., 2013). The historical population data and future population projections are not available at finer spatial scales, likely introducing errors and influencing future land demand patterns and suitability surfaces used in the simulations.

We classified simulation over the 20 runs as developed if the probability of a cell converting into developed was greater than 20%. This classification threshold may not consistently capture the developed areas and will likely change as we project into the future. However, the 20% threshold best captures the developed patterns in 2020, the latest year we have regionally consistent data to validate the simulations.

Urban expansion modelers in the region and the scientific community can make concerted efforts to provide good-quality road network data and consistent population data at multiple levels (Korah et al., 2024). Additionally, more qualitative information such as locational choices, source of income, income level, cultural affiliations, and education level for urban land agents can support consistent and more reliable projections of urban expansion across large, medium, and small cities in the study area. This research was the first application of FUTURES in West Africa, and future studies need to repeat similar simulations over the study area or other rapidly urbanizing regions in Africa. Future urban expansions are expected to impact people and influence global environmental change. There is a need to incorporate policy-relevant and environmental management scenarios to support decision-making better and help countries assess their progress toward realizing United Nations Sustainable Development goals.

4.5 Conclusion

We used FUTURES to simulate urban expansion across Ghana, Togo, Benin, and Nigeria. We found that the relative importance of input variables varies in small, medium, and large cities. However, there is no consistent city population, and most of the local roads in the global road inventory project are biased toward larger cities, offering limited opportunities for finer-scale calibration to account for the difference in variable importance across the study area. This likely resulted in higher misses and false alarms than hits, potentially contributing to the quantity and pattern metrics differences in the reference and simulated maps. However, the FoM for all cities in Nigeria and large cities in Togo was consistent with 10% - 30% reported in previous urban simulations globally. The higher annual expansion rates (3.8% - 14.3%) across the study area highlight the need for repeated regional urban simulation studies in West Africa to better support sustainable urban land expansion. Future urban expansion mostly depends on land demand from populations and the successful implementation of appropriate planning and scenarios, and such information needs to be integrated into urban expansion models to improve their practical applications in West Africa. The availability of consistent road network data across cities and good-quality populations at finer scales will allow modelers to account for differences in variables' importance and assess possible future developments under different planning and urban management scenarios.

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Chapter 5: Synthesis, Conclusion, and Future Work

Globally, urban expansion increases impervious surfaces through sprawl that expands the urban footprint and infill that compact previously developed areas (Angel et al., 2021). Urban expansion contributes to economic growth and innovation centers in high and low-income countries (Mahtta et al., 2022). Multiple studies found that urban expansion leads to tree cover and cropland loss, habitat fragmentation and biodiversity loss, frequent heatwaves, urban fires, and floods (Abass et al., 2020; Güneralp et al., 2017; Marcotullio et al., 2022; Seto et al., 2012; Zhao, 2011). Thus, urban expansion is an important component of global environmental change; however, governments in many low-income countries in Africa have limited resources and infrastructure, making them more vulnerable to the negative impacts of unplanned urban expansion (Cobbinah & Aboagye, 2017; Güneralp et al., 2017).

The West Africa urban system (WAUS) is a global hotspot of rapid urbanization, with 51% of the population living in urban areas, and projections are that this number will increase to 70% by 2050 (OECD/SWAC, 2020). The WAUS also comprises a wide range of city sizes that are interconnected; and the impacts of urban changes are much broader than localized. However, previous global studies and studies in West Africa have often overlooked the many secondary cities with less than a million population and focused on few individual primary cities with over a million urban populations (Güneralp et al., 2020; Mahtta et al., 2022). Although some studies have focused on multiple primary and secondary cities, until this dissertation, no study has analyzed patterns of urban expansion for an entire urban system in West Africa, including all cities down to a minimum population size of 10,000. The overall purpose of this dissertation was to improve understanding of historical, current, and future infill and sprawl expansion and their causes across primary and secondary cities in West Africa, an urban expansion hotpot. This dissertation does so in three folds: 1) quantify rates of urban expansion from 2001 – 2020 across all cities in Ghana, Togo, Benin, and Nigeria; 2) investigates the causes of sprawl and infill expansion in rapidly expanding secondary and primary cities in Ghana; and 3) simulate future urban expansion from 2020 – 2050 in Ghana, Togo, Benin, and Nigeria.

5.1 Smaller Cities Have Large Impacts on West Africa's Expanding Urban System

Previous urban expansion studies have often used global impervious datasets, including Global Human Settlement Layers (Pesaresi et al., 2015), Global Human Built-up and Settlement Extent (Wang et al., 2017), Global Man-Made Impervious Surface (Brown de Colstoun et al., 2017), and the Global Impervious Area (Gong et al., 2020). These globally calibrated datasets are not necessarily suitable for regional analysis of entire urban systems since they overestimate or underestimate urban extent in some study areas and mostly provide data for relatively larger cities (Tulbure et al., 2022). This study combined LandTrendr and Random Forest algorithms and developed the first regionally calibrated 30 m resolution impervious dataset for rapidly urbanizing West African countries. The name is WADISC: annual impervious surface data for Ghana, Togo, Benin, and Nigeria from 2001-2020 (Korah & Wimberly, 2024a, 2024b). This regional impervious data generation was necessary as it allows for consistent analysis of urban expansion across cities of varying sizes. These data can support large-scale analysis and projection of urban growth and its impacts and help decision-making and regional planning efforts in West Africa.

Chapter two uses WADISC and quantifies the rates of urban expansion from 2001 - 2020 across all the 1603 cities, including 16 large, 282 medium, and 1305 small cities in the study area. I found that developed areas more than doubled across the study area, with over 54% of the increase in small and medium cities (Korah & Wimberly, 2024c). The annual urban expansion rates decreased in the large cities but increased or were stable in the smaller cities, and the sprawl-to-infill ratio was also higher in the smaller cities. A global synthesis of urban expansion and a study of 130 cities in China found that cities with populations below 1 million have faster growth rates than more populous cities (Güneralp et al., 2020; Schneider & Mertes, 2014). In contrast, a study of 200 global cities, including 25 African cities, found larger cities grew faster between 1990 and 2014 than smaller cities (Xu et al., 2019). This dissertation research is distinctive from these previous studies in that it focused on urbanization hotpots in four West African countries with a high density of cities and included all cities down to a minimum population size of 10,000. This research also explored how changes in one or more cities influence the expansion of other cities. I found that smaller cities near large cities grew faster in Nigeria, while more remote cities expanded faster in Ghana, Togo, and Benin. These comprehensive analyses of urban expansion are needed to capture the numerous smaller cities and their networks that contribute substantially to national and regional urban expansion trends. Overall, this chapter lays the foundation for improving our understanding of urban expansion, and chapter three draws from it to explain the causes of expansion, while chapter four uses WADISC data as the dependent variable to simulate future expansion.

5.2 Understanding the Causes of Urban Expansion Across Primary and Secondary Cities in Ghana

Several studies in West Africa have investigated the causes of urban expansion and found that rising income levels, global real estate investment, individual preferences, crime rates, land accessibility, and speculation generally influence expansion (Bibri et al., 2020; Mbiba, 2017;

Tagnan et al., 2022; Yang et al., 2021). These causes are similar to findings from multiple studies in Ghana's primary cities: Accra and Kumasi (Cobbinah & Aboagye, 2017; Korah, 2020; Korah et al., 2019; Yeboah et al., 2020). These studies in Ghana and other West African countries provide a broad understanding of the socio-economic and cultural causes of urban expansion in cities of different sizes.

Chapter three is distinct from previous studies because it explored the causes of sprawl and infill expansion across multiple secondary cities compared with primary cities. The relevance of this research to the current and future urban development in Ghana and most West African countries cannot be overstated, as it provides a solid foundation for understanding and managing the socio-economic and cultural processes of urban expansion across multiple cities growing under similar conditions. This research used a mixed-method approach involving urban expansion rates and was complemented by semi-structured interviews with knowledge-rich urban stakeholders. This approach enabled me to understand the differences in patterns of urban expansion and how multiple factors and actors influence urban expansion across primary and secondary cities. In primary cities, the high cost of land and rent, travel costs, and fewer land allocation regimes were important considerations, whereas, in secondary cities, lower land, rent, and transportation costs and more diverse land allocation were important concerns among participants. Most of the new developments in primary cities reflected the aims of the powerful urban stakeholders, especially the landowners (the chiefs in particular), who mostly dictated the allocation regimes, and the political elite used their connections to access lands. Access to lands for urban development was less difficult in the periphery of secondary cities due to lands mostly owned and allocated by multiple individuals.

In the previous chapter (two), I found smaller cities expanded faster, with a higher sprawl-to-infill ratio compared to the larger ones (Korah & Wimberly, 2024c). The results of the mixed-method analysis in chapter three helped to explain the socio-economic and cultural factors and urban stakeholders that shaped the differences in urban expansion patterns across cities of varying populations that I observed in chapter two. This context-specific understanding of urban expansion and associated actors is helpful for decision-making and implementing regulatory policies such as taxes, subsidies, and penalties to control unplanned expansion. Thus, chapters two and three improved historical and current understanding of urban expansion using satellite data and qualitative interviews. Given that cities in West Africa are expected to grow rapidly, it is important to stimulate their future expansion using models.

5.3 Projecting Urban Expansion Across the West Africa's Urban System

Most urban simulation models are developed and implemented in Europe, North America and recently in Asia (Clarke, 2018; Liu et al., 2017; Meentemeyer et al., 2013). There are also multiple applications of urban simulation models in Africa, and a scoping review of urban growth models across Africa reveals that 87.5% of the studies focused on individual cities (Addae & Oppelt, 2019; Goncalves et al., 2019; Korah et al., 2024; Mahmoud et al., 2016). Urban simulation models are mostly cellular automata based using regular cells; however, urban landscapes are irregular, necessitating the need to use models that better simulate urban landscape patterns over large scales (Agyemang & Silva, 2019; Dorning et al., 2015; Meentemeyer et al., 2013; Van Berkel et al., 2019).

Chapter four builds on the previous chapters and simulates future expansion using FUTURES, a stochastic model that employs a random seed, allowing for different possible locations of new developments. FUTURES combine cell and patch-based algorithms, making it more suitable for capturing urban landscape patterns (Meentemeyer et al., 2013). This research is the first to apply FUTURES to an African landscape. I found that variables used to simulate future expansion vary in importance across small, medium, and large cities. New developments emerged in close proximity to previous developments, which was expected and consistent with previous studies (Korah et al., 2024; Linard et al., 2013; Pickard et al., 2017). Also, some previous urban simulations for individual cities mostly found a significant negative relationship between elevation, slope, and urban expansion; I found an insignificant relationship when modeled across multiple cities. The quantity and pattern metrics were similar in the reference and simulated maps in smaller cities than in larger cities. I found high annual expansion rates across the study area, and most of the simulated expansion occurred between 2030 and 2040. Most of the high expansion rates from 2020 – 2030 were in the coastal areas but shifted inland across most parts of the study area from 2030 to 2050. The simulations in this research are not necessarily suitable for neighborhood or city-level applications, as that require planning and policy-relevant scenarios, and this information is mostly lacking and inconsistent in the study area. However, the simulations in this chapter provide a broad understanding of the expected future expansion rates across multiple administrative boundaries in West Africa.

In chapter two, I developed better historical urban land cover change data that I used to extrapolate into the future, but the results in chapter four suggest that there are other data needs that need to be addressed. For example, population data are not available at finer scales (e.g., city level), and local road networks are biased towards larger cities (Meijer et al., 2018). In chapter three, I found that several actors and socio-economic factors shape urban expansion patterns. These qualitative data are costly to collect and consistently analyze over large scales, and privacy and national sovereignty guidelines also limit sharing (Alexander et al., 2020; Carroll et al., 2021; Plassin et al., 2020). Also, without integration with agent-based models, a phenomenological model like FUTURES cannot directly model the differences in urban stakeholder behavior, which I documented in chapter three. However, the results from FUTURE simulations show rapid expansion and governments in the study area need to pay particular attention to the expansion patterns to maximize the positives and limit the negative impacts on people and the environment.

5.4 Limitations and Possible Directions for Future Work

I developed historical impervious cover data from the Landsat archive using Landsat 7 and 8 images from 2001 to 2020 (Korah & Wimberly, 2024a, 2024b). Landsat 7 data collected after May 31, 2003, have data gaps resulting from the scan line corrector (SLC) failure. Although most SLC gaps are filled in the process of generating the annual temporal metrics using LandTrendr, the process sometimes results in different values in the SLC gaps, particularly between 2003 and 2013 when only Landsat 7 images are available. Also, the WADISC classification allowed only positive changes, possibly omitting negative changes in submerging coastal areas and declining urban centers. However, the impervious cover mapping is consistent over time with high overall accuracy. The data covered four rapidly urbanizing West African countries and captured only horizontal expansion and possibly underestimated urban extents in locations with vertical expansion.

The limitations of WADISC, as highlighted in the preceding paragraph, do not diminish the dissertation's research contributions. WADISC is the first regionally optimized 30-m spatial resolution impervious cover data in West Africa, with higher accuracy than global datasets such as global artificial impervious area (GAIA) and global impervious surface area (Korah & Wimberly, 2024). It allowed me to compare the urban expansion dynamics for the entire national and regional urban systems in Ghana, Togo, Benin, and Nigeria from 2001 -2020 in chapter two. Combining WADISC with qualitative data in chapter three helped me to explain the causes of expansion in primary compared with secondary cities. Such a comparative understanding of socio-economic and cultural factors influencing infill and sprawl expansion in different-sized cities is often lacking in previous studies. WADISC was further used in chapter four to calibrate and validate the first application of FUTURES urban expansion simulation in West Africa, offering opportunities for national and regional level decision-making and improving the models' applicability over multiple scales.

I have provided open access to the code and data used to generate WADISC (Korah & Wimberly, 2024a, 2024b). Future studies can use the methods and processes in this research to extend the impervious cover data to other countries and regions in Africa. Some studies can improve the impervious cover data quality by correcting the few locations with noticeable effects of Landsat 7 SLC off or fusion with light detection and ranging (LiDAR), synthetic aperture radar (SAR), Google Earth 3D, and OpenStreetMap 3D to capture vertical expansion. Urban impervious surface cover consists of diverse neighborhoods (e.g., formal and informal, planned and unplanned, gated and ungated communities) and multiple land uses (e.g., residential, commercial, educational, and industrial) that need to be consistently mapped across cities. Also, cities have heterogeneous land cover, including forest, cropland, water, and soil surfaces; however, urban land cover classifications are inconsistent across study areas (Korah et al., 2024). Developing urban land cover that consistently captures the heterogeneous morphologies of cities over time in West Africa is needed.

Future studies need to explicitly analyze the current and future impacts of different-sized city expansions on economic growth, food production, carbon emission, biodiversity, ecosystem services, and heat stress. Human behavior influences sprawl and infill patterns, but data on individual decisions across the landscape are challenging to collect and analyze over multiple scales due to cost, time, and privacy issues. Researchers can make a concerted and collaborative effort to develop a comprehensive database of urban stakeholders' decisions and choices, following privacy and national sovereignty guidelines (Alexander et al., 2020; Carroll et al., 2021; Plassin et al., 2020). Also, WorldPop provides consistent gridded population data across countries at 100 m spatial resolution, and the United Nations provides population estimates at the country level. Although national censuses provide city-level population data, they are inconsistently collected over different time points, and the definitions of cities vary across countries. There is a need for consistent city-level population data that researchers and modelers can use to parameterize urban simulation models across cities. In addition, road network data, especially local roads from the global road inventory project, are mostly biased toward the larger cities in the study area, potentially introducing errors in the urban simulation processes. There is a need for more collaboration among urban expansion stakeholders, including researchers, users, modelers, and decision-makers, to provide consistent population, road network, and individual-level data. These initiatives can further improve urban expansion simulations across multiple scales.

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Supplemental Material

Chapter Two

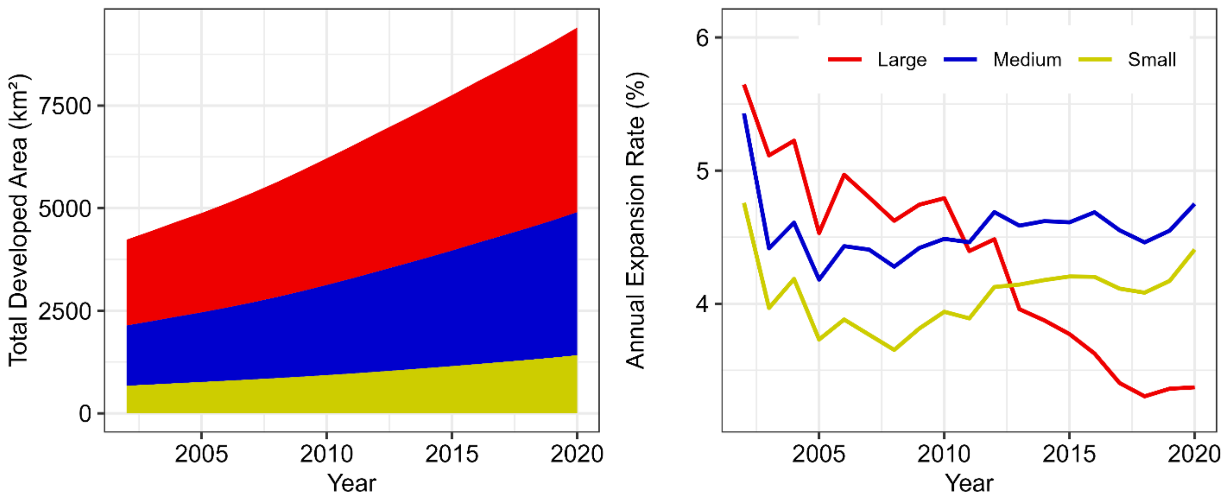

Figure S1: Developed area and expansion rates summarized across the study area. The area graphs on the left represent the proportion of total developed area for each city type, and the line graphs on the right represent the corresponding growth rates.

Table S1: Mann-Kendall and Sen's slope test of annual expansion rates trend from 2001 – 2020 at a 0.05 alpha value. The bolded numbers are the statistics for the entire study area or country.

City Type	P-Value	Confidence Interval (95%)	Sen's Slope
Benin	**0.0000**	**[-0.1181, -0.0782]**	**-0.0999**
Large	0.0000	[-0.2051, -0.1521]	-0.1814
Medium	0.0000	[-0.1126, -0.0705]	-0.0806
Small	0.0589	[-0.0436, 0.0010]	-0.0227
Ghana	**0.0118**	**[-0.0527, -0.0076]**	**-0.0311**
Large	0.0008	[-0.0782, -0.0351]	-0.0594
Medium	0.1237	[0.0108, 0.0379]	0.0159
Small	0.0209	[0.0040, 0.0568]	0.0365
Nigeria	**0.0000**	**[-0.1399, -0.0729]**	**-0.1033**
Large	0.0000	[-0.1704, -0.1107]	-0.1403
Medium	0.0026	[-0.1390, -0.0398]	-0.0793
Small	0.5756	[-0.0392, 0.0154]	-0.0100
Togo	**0.1837**	**[-0.0522, 0.0110]**	**-0.0209**
Large	0.0000	[-0.1358, -0.0812]	-0.1111
Medium	0.0000	[0.1561, 0.2667]	0.2040
Small	0.0005	[0.0376, 0.1138]	0.0768

Table S2: Mann-Kendall and Sen's slope test of ratio of sprawl-to-infill growth trend from 2001 – 2020 at a 0.05 alpha value. The bolded numbers are the statistics for the entire study area or country.

City Type	P-Value	Confidence Interval (95%)	Sen's Slope
Benin	**0.0000**	**[0.0424, 0.075]**	**0.0575**
Large	0.0179	[0.0028, 0.0339]	0.0168
Medium	0.0000	[0.0414, 0.0797]	0.0624
Small	0.0150	[0.0322, 0.2307]	0.1327
Ghana	**0.0003**	**[0.0471, 0.1210]**	**0.0810**
Large	0.0026	[0.0155, 0.0907]	0.0453
Medium	0.0001	[0.0858, 01820]	0.1401
Small	0.0001	[0.1600, 0.3048]	0.2483
Nigeria	**0.2561**	**[-0.0260, 0.0645]**	**0.0209**
Large	0.7212	[-0.0257, 0.0220]	-0.0047
Medium	0.2300	[-0.0284, 0.8034]	0.0284
Small	0.0000	[0.1471, 0.3280]	0.2235
Togo	**0.0000**	**[0.0672, 0.1128]**	**0.0842**
Large	0.0644	[-0.0015, 0.0508]	0.0179
Medium	0.0000	[0.2195, 0.4150]	0.3422
Small	0.0000	[0.4570, 0.6060]	0.5319

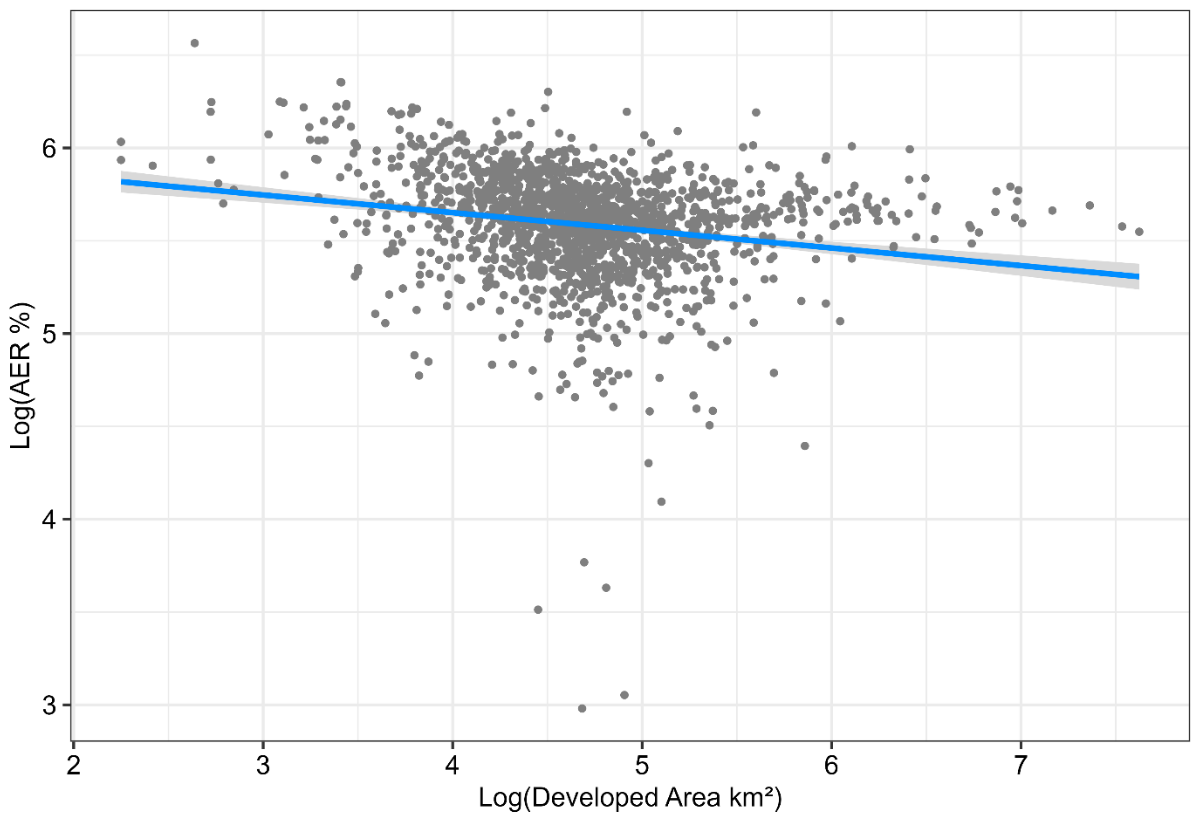

Figure S2: Relationship between annual expansion rate (2001-2020) and initial developed area (2001) across the study area. The blue line shows the smooth curve, and the gray portion is the 95% confidence bounds.

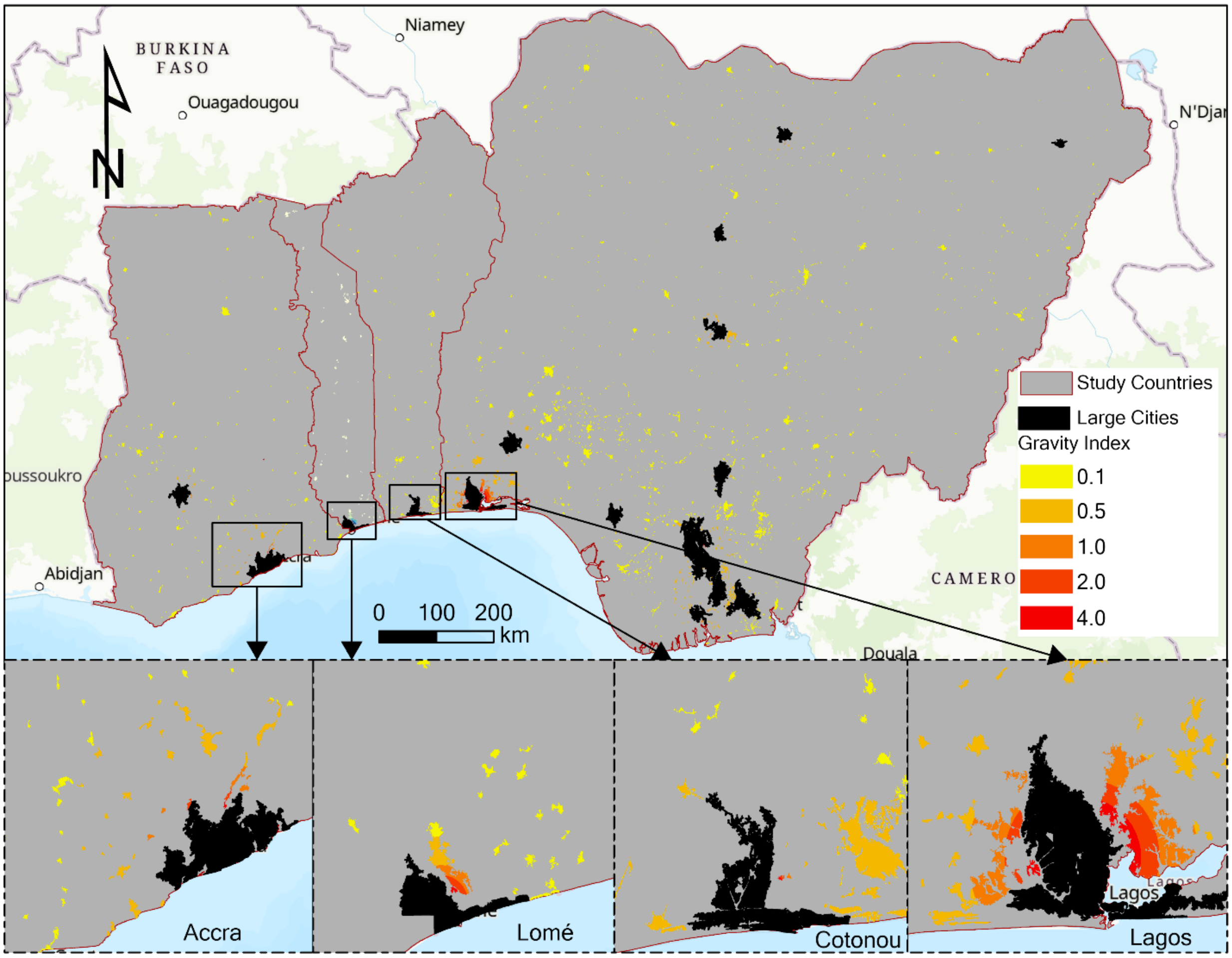

Figure S3: Gravity index for small and medium cities near large cities across the study area. Higher indexes are located close to the large cities.

Chapter Four

Table S3: Summaries of generalized linear modes across large, medium, and small cities in Benin and Ghana.

Benin		**Estimate**			**Std. Error**			**Z Value**			**Pr(>|z|)**	
Predictor	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Intercept	**-1.286**	**-0.995**	**-0.943**	**0.389**	**0.701**	**1.462**	**-3.309**	**-1.420**	**-0.645**	**0.0009*****	**0.1556**	**0.5191**
DevPressure	0.445	0.367	0.191	0.028	0.025	0.036	15.990	14.808	5.307	0.0000***	0.0000***	0.0000 ***
DLRoads	-0.011	0.030	-0.071	0.013	0.013	0.033	-0.807	2.251	-2.119	0.4197	0.0244*	0.0341
DPCities	0.012	-0.026	-0.082	0.013	0.013	0.017	0.936	-1.97	-4.864	0.3493	0.0488*	0.0000 ***
DSRoads	0.011	-0.016	0.054	0.011	0.020	0.037	1.017	-0.778	1.443	0.3092	0.4366	0.149
DACities	-0.187	-0.165	-0.240	0.048	0.026	0.025	-3.925	-6.27	-9.825	0.0000***	0.0000***	0.0000 ***
DARoads	-0.020	-0.114	-0.220	0.089	0.084	0.098	-0.221	-1.348	-2.233	0.8253	0.1776	0.0255 *
DTRoads	0.045	0.069	0.019	0.024	0.038	0.067	1.893	1.825	0.287	0.0584.	0.0679.	0.7742
DRivers	-0.004	0.003	-0.035	0.003	0.008	0.030	-1.249	0.363	-1.164	0.2117	0.7165	0.2446
DPRoads	0.002	0.092	-0.351	0.004	0.026	0.041	0.618	-3.578	-8.491	0.5368	0.0003***	0.0000 ***
Hillshade	-0.003	0.002	0.001	0.002	0.005	0.002	-1.365	0.437	0.485	0.1722	0.6618	0.6280
Slope	0.003	-0.008	-0.019	0.006	0.011	0.004	0.451	-0.695	-4.527	0.6518	0.4868	0.0000 ***
DProtected	0.017	0.029	0.089	0.003	0.008	0.027	5.455	3.784	3.302	0.0000***	0.0001***	0.0009 ***
Elevation	-0.000	0.000	0.000	0.000	0.000	0.000	-1.227	0.004	-2.125	0.2198	0.9967	0.0336 *
DLakes	-0.005	0.001	0.110	0.003	0.007	0.027	1.725	0.115	4.124	0.0846.	0.9086	0.0000 ***
Ghana		**Estimate**			**Std. Error**			**Z Value**			**Pr(>|z|)**	
Predictor	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Intercept	**-0.388**	**0.299**	**0.337**	**0.336**	**0.362**	**0.447**	**-1.154**	**0.825**	**0.754**	**0.2483**	**0.4093**	**0.4509**
DevPressure	0.576	0.403	0.2401	0.028	0.023	0.019	20.250	17.485	12.357	0.0000***	0.0000***	0.0000***
DLRoads	0.002	-0.000	-0.113	0.001	0.001	0.024	2.350	-0.364	-4.7	0.0188*	0.7162	0.0000***
DPCities	-0.002	0.000	-0.065	0.001	0.001	0.010	-3.371	0.695	-6.868	0.0007***	0.4872	0.0000***
DSRoads	-0.007	0.032	-0.009	0.004	0.008	0.018	-1.601	4.247	-0.497	0.1094	0.0000***	0.6193
DACities	-0.240	-0.117	0.047	0.045	0.021	0.013	-5.282	-5.678	3.672	0000***	0.0000***	0.0002***
DARoads	-0.166	-0.338	-0.656	0.065	0.061	0.108	-2.545	-5.507	-6.048	0.0109	0.0000***	0.0000***
DTRoads	-0.005	-0.037	0.004	0.007	0.007	0.041	-0.696	-5.416	0.102	0.4867	0.0000***	0.9185
DRivers	0.001	0.001	0.014	0.001	0.001	0.010	0.838	0.803	1.479	0.4021	0.4221	0.139
DPRoads	-0.001	-0.000	-0.089	0.001	0.001	0.020	-0.887	-0.32	-4.565	0.3751	0.7491	0.0000***
Hillshade	0.001	-0.003	0.002	0.002	0.003	0.003	0.543	-1.102	0.641	0.5874	0.2703	0.5218
Slope	-0.021	-0.061	-0.030	0.009	0.014	0.017	-2.300	-4.419	-1.734	0.0214*	0000***	0.083.
DProtected	0.015	0.028	0.030	0.004	0.008	0.011	4.034	3.714	2.758	0.0000***	0.0002***	0.0058**
Elevation	0.000	0.000	-0.000	0.000	0.000	0.001	0.395	3.513	-1.010	0.693	0.0004***	0.3127
DLakes	0.002	0.003	-0.022	0.001	0.001	0.011	1.540	1.850	-2.004	0.1236	0.0643.	0.0451*

Note: The input variables consist of slope, hillshade, elevation, distance from tertiary roads (DTRoads), distance from secondary roads (DSRoads), distance from rivers (Drivers), distance from primary roads (DPRoads), distance from primary cities center (DPCities), distance from local roads (DLRoads). Distance from lakes (DLakes), development pressure (DevPressure), distance to all roads (DARoads), and distance from all cities center (DACities).

Table S4: Summaries of generalized linear modes across large, medium, and small cities in Nigeria and Togo.

Nigeria	Estimate			Std. Error			Z Value			Pr(>|z|)		
Predictor	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Intercept	**-0.120**	**0.379**	**1.772**	**0.203**	**0.212**	**0.192**	**-0.982**	**1.785**	**9.253**	**0.3262**	**0.0743.**	**0.0000*** **
DevPressure	0.564	0.385	0.418	0.015	0.013	0.016	38.042	30.444	26.736	0.0000***	0.0000***	0.0000***
DLRoads	-0.003	-0.004	-0.000	0.000	0.000	0.001	-6.346	-10.02	-0.33	0.0000***	0.0000***	0.7413
DPCities	-0002	-0.003	-0.001	0.000	0.000	0.002	-7.049	-7.993	-0.211	0.0000***	0.0000***	0.8328
DSRoads	0.004	-0.001	-0.059	0.001	0.001	0.004	4.748	-1.459	-15.203	0.0000***	0.1446	0.0000***
DACities	-0.027	-0.009	-0.025	0.017	0.008	0.002	-1.607	-1.081	-4.702	0.1081	0.2796	0.0000***
DARoads	-0.023	-0.110	-0.185	0.008	0.016	0.018	-3.047	-7.106	-10.39	0.0023	0.0000***	0.0000***
DTRoads	0.017	0.032	0.015	0.006	0.006	0.010	2.866	5.299	1.497	0.0042**	0.0000***	0.1344
DRivers	0.001	0.002	0.000	0.000	0.000	0.000	8.23	8.61	-0.102	0.0000***	0.0000***	0.9185
DPRoads	0.002	0.006	-0.018	0.001	0.001	0.001	2.562	8.749	-12.925	0.0104*	0.0000***	0.0000***
Hillshade	-0.001	-0.001	-0.003	0.002	0.002	0.001	-0.895	-0.396	-2.434	0.3709	0.692	0.0149 *
Slope	0.002	-0.017	-0.006	0.004	0.006	0.004	0.336	-3.083	-1.504	0.737	0.0021**	0.1325
DProtected	0.004	-0.006	-0.025	0.002	0.002	0.003	2.034	-2.794	-8.223	0.0419*	0.0052**	0.0000***
Elevation	0.000	0.000	0.000	0.000	0.000	0.000	-1.37	0.365	-1.200	0.1708	0.7148	0.2301
DLakes	-0.012	-0.014	-0.012	0.001	0.001	0.001	-10.677	-12.868	-9.836	0.0000***	0.0000***	0.0000***

Togo	Estimate			Std. Error			Z Value			Pr(>|z|)		
Predictor	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Intercept	**-1.466**	**0.761**	**-0.425**	**0.854**	**0.676**	**0.511**	**-1.716**	**1.126**	**-0.832**	**0.0861.**	**0.2602**	**0.4054**
DevPressure	0.607	0.428	0.199	0.040	0.042	0.034	15.036	10.271	5.858	0.0000***	0.00 ***	0.0000 ***
DLRoads	-0.038	0.009	-1.483	0.016	0.015	0.272	-2.314	0.592	-5.449	0.0207 *	0.5536	0.0000 ***
DPCities	0.040	-0.011	-0.185	0.016	0.016	0.035	2.497	-0.685	-5.371	0.0125 *	0.4936	0.0000 ***
DSRoads	-0.015	-0.238	0.258	0.004	0.036	0.051	-3.714	-6.541	5.016	0.0002 ***	0.0000 ***	0.0000 ***
DACities	-0.177	0.054	0.211	0.055	0.022	0.044	-3.226	-2.444	4.778	0.0013 **	0.0145 *	0.0000 ***
DARoads	-0.220	-0.481	-1.263	0.038	0.097	0.376	-5.760	-4.977	-3.358	0000***	0.0000 ***	0.0008 ***
DTRoads	0.029	-0.099	-0.214	0.009	0.017	0.071	3.225	-5.841	-3.001	0.0012 **	0.0000 ***	0.0027 **
DRivers	-0.001	0.036	0.109	0.003	0.006	0.040	-0.541	5.737	2.695	0.5883	0.0000 ***	0.0070 **
DPRoads	-0.007	-0.011	-0.122	0.004	0.005	0.050	-1.514	-2.177	2.442	0.1300	0.0295 *	0.0146 *
Hillshade	-0.002	0.002	0.005	0.005	0.005	0.002	-0.357	0.332	2.304	0.7212	0.7396	0.0212 *
Slope	-0.080	-0.128	0.007	0.026	0.028	0.007	-3.018	-4.514	1.128	0.0025**	0.0000 ***	0.2593
DProtected	0.004	0.058	0.039	0.008	0.023	0.046	0.514	1.933	-0.848	0.6072	0.0533.	0.3966
Elevation	-0.000	-0.000	0.000	0.001	0.002	0.000	-0.387	-0.147	-0.210	0.6985	0.8831	0.8338
DLakes	0.008	0.002	0.006	0.003	0.004	0.048	3.023	0.684	0.131	0.0025 **	0.4937	0.8957

Note: The input variables consist of slope, hillshade, elevation, distance from tertiary roads (DTRoads), distance from secondary roads (DSRoads), distance from rivers (Drivers), distance from primary roads (DPRoads), distance from primary cities center (DPCities), distance from local roads (DLRoads). Distance from lakes (DLakes), development pressure (DevPressure), distance to all roads (DARoads), and distance from all cities center (DACities).

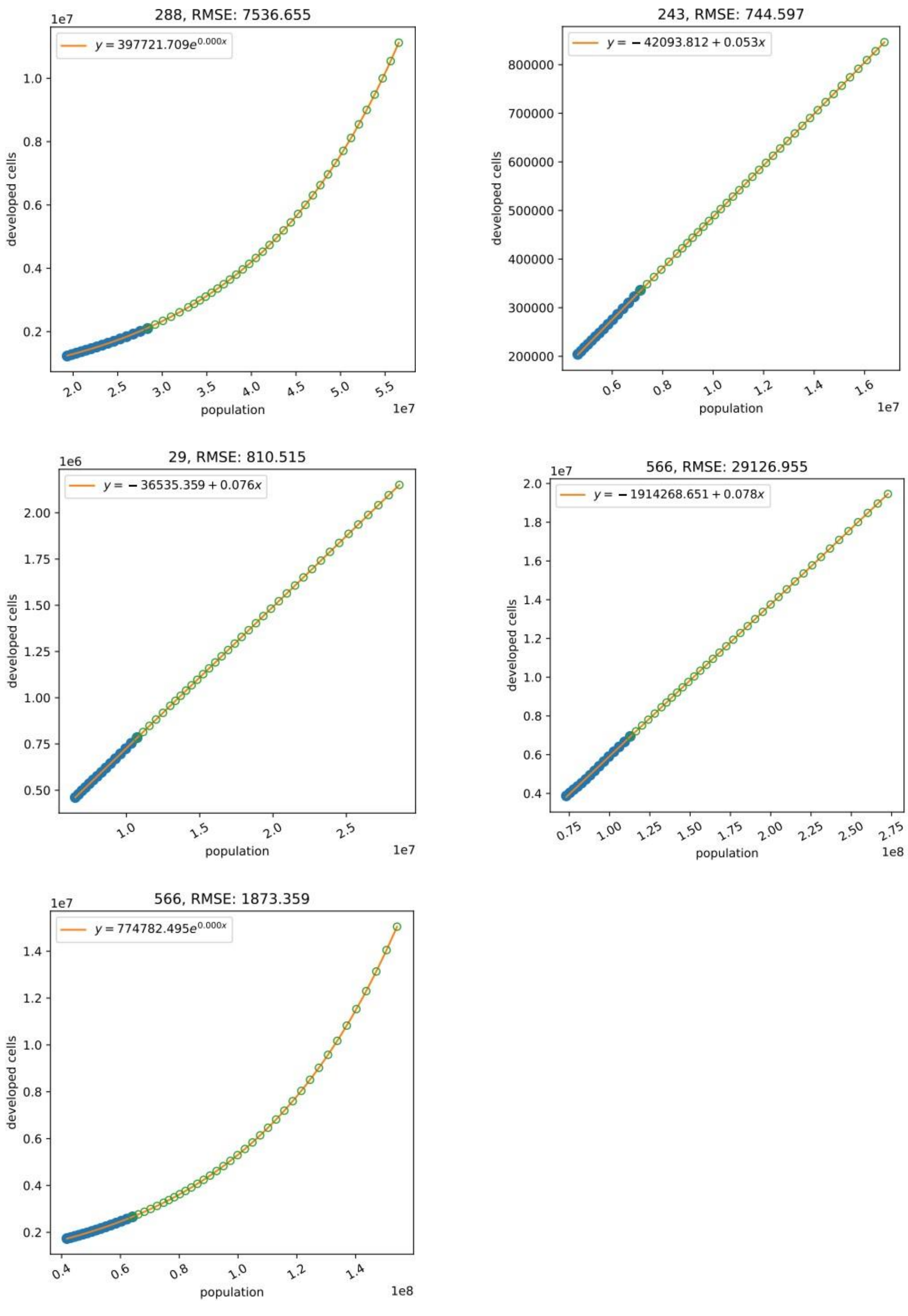

Figure S4: Relationship between developed cells and historical population trends and projections. The blue dots show the historical urban land demand, whereas the green dots show the future land demand into 2050. Each parameterization level is represented by code. Ghana has code 288, Togo has 243, Benin has 29, and Nigeria has 566. The 566 on the left represents the Southern part of Nigeria, and the right represents the Northern part of Nigeria.