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Population dynamics throughout the urban context: A case study in sub-Saharan Africa utilizing remotely sensed imagery and GIS

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by

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ABSTRACT

Population dynamics throughout the urban context: A case study in sub-Saharan Africa utilizing remotely sensed imagery and GIS

by

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The characteristics of places where people live and work play an important role in explaining complex social, political, economic and demographic processes. In sub-Saharan Africa rapid urban growth combined with rising poverty is creating diverse urban environments inhabited by people with a wide variety of lifestyles. This research examines how spatial patterns of land cover in a southern portion of the West African country of Ghana are associated with particular characteristics of family organization and reproduction decisions. Satellite imagery and landscape metrics are used to create an urban context definition based on landscape patterns using a gradient approach. Census data are used to estimate fertility levels and household structure, and the association between urban context, household composition and fertility levels is modeled through OLS regression, spatial autoregressive models and geographically weighted regression. Results indicate that there are significant differences in fertility levels between different urban contexts, with below average

fertility levels found in the most urbanized end of the urban context definition and above average fertility levels found on the opposite end. The spatial patterns identified in the association between urban context and fertility levels indicate that, within the city areas with lower fertility have significant impacts on the reproductive levels of adjacent neighborhoods. Findings also indicate that there are clear patterns that link urban context to living arrangements and fertility levels. Female- and single-headed households are associated with below average fertility levels, a result that connects dropping fertility levels with the spread of smaller nuclear households in developing countries. At the same time, larger extended family households are linked to below average fertility levels for highly clustered areas, a finding that points to the prevalence of extended family housing in the West African city.

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I. Introduction

By altering landscapes, human populations have been able to generate resources that have led to the advancement of societies (DeFries, Asner and Foley 2006). In the process, humans have transformed more than 40% of the ice free land surface. In the coming decades most of the world's land cover and land use change (LCLUC) is predicted to take place in the tropics, where population is growing the fastest (DeFries, Asner and Foley 2006). United Nations' projections estimate that virtually all of the world's population between now and the middle of this century will emerge in cities of the developing world (United Nations Population Division 2011), driven by natural increase in both urban and rural areas, along with continued migration from rural to urban areas as people search for economic opportunity (Lee 2007). Urbanization plays a major role in shaping landscapes in and around cities through densification and sprawl, but also far away from them as increased interactions with cities are pushing diversification in rural livelihoods (Lambin et al. 2001; Seto et al. 2012).

Literature on urbanization of the developing world is mostly focused on large cities and their prevailing slums, while largely ignoring the magnitude of urban growth that is taking place in small and mid-size cities (Montgomery 2008). However, most urban dwellers in Asia, Africa and Latin America live in urban settlements with less than one million people (United Nations Population Division 2011), and it is in those intermediate cities and market towns that we can expect the most rapid rates of population growth with related implications for LCLUC (Cohen 2006). The spread of population into urban places is important because it virtually revolutionizes the way of life. It puts people in the path of becoming "modern" in the sense that they begin to leave behind traditional ways of thinking and behaving and adopt the more western modes of living that characterize urban places everywhere in the world, albeit with considerable spatial variability (Newson and Richerson 2009). One of the most important changes in life associated with urban living is in the way people think about families. "The demographic transition is in essence a transition in family strategies: the reactive, largely biological family-building decision rules appropriate to highly uncertain environments come eventually to be supplanted by more deliberate and forward-looking strategies that require longer time horizons" (Cohen and Montgomery 1998:6). Put another way, the transition is from "family building by fate" to "family building by design" (Lloyd and Ivanov 1988:141). These are changes that are not necessarily dependent upon economic growth, as was once thought, but rather may actually contribute to economic growth in cities of developing countries.

In sub-Saharan Africa, while urban growth is fueled by rising rural-urban migration, it is also largely driven by the urban rate of natural increase as mortality rates continue to fall faster than fertility rates (Montgomery 2008; Weeks 2008). Although research in the region has indicated that urbanization is associated with falling fertility levels (Brockerhoff and Yang 1994), urban fertility remains high compared to the rest of the world (White et al. 2008). This means that, even though places are urbanizing rapidly, the rate of assimilation to the urban lifestyle varies within urban spaces. In sub-Saharan Africa total fertility rates (TFR) are amongst the highest in West Africa, a region that remains largely rural and where fertility is declining at a very slow pace. Within the region, Ghana is leading the fertility transition. With an average TFR of 4 children, it is ahead of neighbors such as Côte D'Ivoire with a TFR of 5 or Burkina Faso with a TFR of 6 (Measure 2008). Ghana is at the same time leading the urbanization trend spreading throughout the region, having become one of the three countries with over 50% of their populations residing in urban areas as of 2010 (United Nations Population Division 2011). Understanding the demographic changes taking place in Ghana will help anticipate the demographic changes that will take place in the rest of the region as West Africa becomes increasingly urban. This study investigates how landscape characteristics associated with urbanization in southern Ghana provide clues to changes in the social context that are associated with fertility declines. The overall objective is to test the general hypothesis that the characteristics of the urban context in a region are associated with the way that family structure is organized and ultimately with fertility outcomes.

Research Questions

This study addresses three major research questions:

1. Does a pattern-based definition of urban context capture the diversity of urban landscapes?

2. How are household composition and fertility levels associated with urban context?

3. How does the association between urban context, household composition and fertility vary through space?

The urban context is defined using satellite imagery and a combination of remote sensing and GIS techniques. The spatial patterns of the urban context are examined through landscape metrics applied to image-derived maps of built and vegetation land cover in order to generate an indicator of degree of urbanization. The resulting definition of degree of urbanization is then compared to household composition, drawing on data from the 2000 census of population and housing, testing the hypothesis that as places become increasingly urban, living arrangements become westernized, which in turn is associated with lower fertility levels.

II. Literature review

A. Portraying urban contexts through satellite imagery and GIS

1. Mapping urban areas with satellite imagery

The United Nations' guidelines for collection of population data identifies urban localities as distinct population clusters with a recognized name, where the population resides in neighboring buildings within an administrative area (Champion 2004). Urban population data collected worldwide following the UN guidelines are constrained to administrative boundaries and thus are unable to delineate the extent of built up areas outside those administrative boundaries (Champion 2004). Settlement mapping is increasingly relying on the use of satellite imagery through the development of objective, automated and replicable methodologies for the detection of artificial land covers (Pumain 2004).

The physical characteristics of urban places generate spatial and spectral signatures that are readily identified with remotely sensed data (Elvidge et al. 2004) and, as a result, detection and monitoring of urban growth at global, regional and local scales is increasingly relying on the use of such data (Ward and Phinn 2000; Small 2005; Lu and Weng 2006; Potere et al. 2009). In developing countries, where urbanization is taking place at the fastest rate (United Nations Population Division 2011), the geographic comprehensiveness of satellite imagery has made it a useful tool for quantifying and monitoring the distribution and growth of human settlements (Harris and Longley 2002; Small 2003; Weeks 2004).

While different urban land uses are composed of different combinations of land covers, a common denominator of cities throughout the world is the predominance of built materials and features. This is why in remote sensing research urban landscapes are generally defined as lands composed mostly of impervious surfaces or built environments (Arnold and Gibbons 1996). The built environment corresponds to artificial structures such as buildings, paved roads, parking lots and sidewalks where cement or asphalt prevail (Weeks 2003; Lu and Weng 2008).

At the global scale, mapping of urban areas has extensively relied on coarse resolution imagery such as 1 km spatial resolution daily data from Systeme Pour L'Observation de la Terre (SPOT-4) Vegetation sensor (Bartholomé and Belward 2005), 300 m data from the Medium Resolution Image Spectrometer (MERIS) (Arino et al. 2007), 1 km and 500 m imagery from the Moderate Resolution Imaging Spectrometer (MODIS) (Schneider et al. 2003; Schneider, Friedl and Potere 2010) and 2.2 km night lights data from the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) (Small, Pozzi and Elvidge 2005; Elvidge et al. 2007). At regional scales the extent of urban areas has been successfully estimated and monitored through time using DMSP-OLS night time lights imagery (Imhoff et al. 1997; Zhang and Seto 2011). Night lights imagery provides an important approximation of the distribution of human activity worldwide by estimating the extent of the electric power grid and intensity of night-time light associated with human activities. However, given its coarse resolution and pervasive blooming effects, night lights imagery is limited in its capacity to define accurate urban extents and precise city locations (Imhoff et al. 1997; Small, Pozzi and Elvidge 2005). At finer scales Landsat MSS, TM and ETM+ satellite systems provide an extensive and accessible worldwide archive of moderate spatial resolution imagery that has proven to be a significant source of imagery for studies monitoring urban areas and settlements in a wide range of environments (Small and Miller 1999; Seto and Fragkias 2005; Small 2005; Lu and Weng 2008). At local scales high spatial resolution airborne and commercial satellite imagery enables identification and mapping of important details about urban features within the city, but its use is limited by its higher costs and its lower frequency of collection compared to moderate or coarse resolution imagery (Potere et al. 2009).

1.1. Spectral mixture analysis of urban environments

Remote sensing scene models are generally classified as either H-resolution (High resolution) or L-resolution (Low resolution) models (Strahler, Woodcock and Smith 1986). In H-resolution models the individual objects are larger than the cell resolution, whereas in L-resolution models objects of interest are smaller than the cell resolution. In order to detect the arrangement of individual objects, the cell resolution has to be smaller than the average object in the scene. In the case of urban landscapes individual objects can only be detected in H-resolution models because of the variability in object sizes and the spectral heterogeneity characteristic of the city (Lu and Weng 2004; Small 2005). However, analysis of the urban environment based on high resolution sensors has proved to be a complex process as higher resolutions significantly increase spectral variance (Barnsley and Barr 1996). Medium spatial resolution optical sensors with spatial resolutions ranging between the 10 and 100 meters are an accessible source of imagery that allows researchers to successfully differentiate built-up areas from other land cover types (Chen, Stow and Gong 2004; Small 2005). Urban applications of Landsat imagery correspond to an L-resolution model, where individual objects cannot be detected and pixels represent a combination of different elements (Lu and Weng 2004). Traditional per-pixel classifiers rely on a hard classification scheme that assigns each pixel to a single class, a methodology that is efficient for H-resolution scene models that are able to detect individual objects. In the case of L-resolution scene models pixels represent combinations of individual objects, departing from the assumption that each pixel belongs to an exclusive class which makes traditional per-pixel classifiers unsuitable (Rashed et al. 2003).

The incompatibility of traditional per pixel classifiers and L-resolution scene models has led to the emergence of fuzzy classification and spectral mixture analysis (SMA) techniques, based on membership levels (Rashed et al. 2003). SMA extracts sub-pixel information by assuming that the spectral reflectance of a pixel is the product of the linear combination of the spectra of pure components or end-members (Lu and Weng 2008). The resulting proportions of end-members correspond to the portion of each pixel that is covered by each pure component (Lu and Weng 2008).

Even though SMA was originally developed to classify natural environments (Adams, Smith and Gillespie 1993; Roberts, Gardner, et al. 1998), the technique was adapted to urban landscapes by Ridd (1995) to represent the land cover of Salt Lake City as a combination of vegetation, impervious surface and soil (VIS). The accuracy of the proportions generated by SMA is highly dependent on the selection of spectral end-members used to represent pure vegetation, impervious or soil patches of land surface in the un-mixing process. End-member spectra can be collected from field or laboratory spectral reflectance measurements (Roberts, Batista, et al. 1998) or from the imagery's extreme spectral-radiometric features using methods such as the minimum noise fraction (Small 2003; Wu and Murray 2003; Lu and Weng 2004; Wu 2004; 2007) or the pixel purity index (PPI) (Phinn et al. 2002; Rashed et al. 2003). PPI assists in the identification of pure class (i.e., end-member) pixels by ranking their values based on how often they are repeated in the extremes of the spectral distribution of the image (Boardman, Kruse and Green 1995). Urban applications of SMA based on Ridd's (1995)VIS mixture model have produced satisfactory results for the detection of built classes in the United States (Wu and Murray 2003; Lu and Weng 2004; Wu 2004), Australia (Ward, Phinn and Murray 2000; Phinn et al. 2002) , Thailand (Madhavan et al. 2001; Song 2005), Brazil (Lu et al. 2004), Germany (Matthias and Martin 2003) and Egypt (Rashed et al. 2001). For regional to global scale observations, Small (2005) showed that SMA is suitable to detect human settlements by comparing cities in different regions.

1.2. Detecting urban areas with Radar imagery

In tropical regions where cloud cover is a common problem for optical remote sensing, radar imagery has become an important source of data (Rogan et al. 2003). The pulse generated by active sensors in the microwave portion of the electromagnetic spectrum is capable of transmitting through clouds providing information about the features below them on the ground (Kasischke, Melack and Dobson 1997; Henderson and Xia 1998). While optical sensors are limited by how short to medium wavelength electromagnetic energy is absorbed by clouds and precipitation in the atmosphere and land surfaces, synthetic aperture radar (SAR) sensors are capable of transmitting and receiving microwave energy that is sensitive to physical characteristics of land surfaces such as roughness, morphology and geometry, in most atmospheric conditions (Soergel 2010). SAR remote sensing applications have been successfully used to estimate tropical forest cover (Grover, Quegan and da Costa Freitas 1999), tropical coastal vegetation (Simard et al. 2002) and human settlements (Henderson and Xia 1997; Stasolla and Gamba 2008). Applications of SAR imagery for urban mapping have proven to be very effective, given the high return characteristic of man-made features (Haack and Bechdol 2000).

The return or backscatter captured by the SAR sensor is determined by the characteristics of the pulse, its wavelength, polarization, incidence angle, look direction and characteristics of the terrain that include dielectric properties and roughness (Xia and Henderson 1997). Shorter wavelengths in SAR systems provide higher spatial resolutions with the tradeoff of more limited transmission in some atmospheric conditions. Urban mapping studies have shown that while shorter wavelengths allow detection of smaller settlements they also increase noise and reduce image contrast (Henderson and Xia 1997). Different polarizations enable capture of different types of signals because of differential backscatter. While cross-polarized radar imagery is sensitive to volume scatter, like-polarized images tends to be sensitive to surface scatter (Xia and Henderson 1997). In urban mapping cross-polarized imagery has traditionally been favored over like-polarized (Haack 1984; Hussin 1995). However, researchers are increasingly finding like-polarized imagery to be effective for urban area mapping and feature detection (Dekker 2003; Dell'Acqua and Gamba 2003). Incidence angle and look direction play important roles in determining the backscatter captured in radar imagery. While large incidence angles generate higher spatial resolutions they tend to produce larger shadows following the look direction of the sensor. The direction the sensor is facing when the pulse is generated creates "cardinal effects" in radar imagery which means that buildings and walls act as dihedral and trihedral reflectors at very specific angles of look direction. In urban mapping cardinal effects explain why urban areas might generate high bright returns in one orientation and medium gray ones in different orientations (Xia and Henderson 1997).

Two main terrain characteristics determine the intensity of the radar backscatter: the complex dielectric constant that defines the capacity of the terrain or material to conduct electric energy; and the surface roughness that describes its texture as smooth, intermediate or rough (Jensen 2000). In urban environments, metallic objects, characteristics of roofs, bridges, utility poles and other urban features have high complex dielectric constants which, combined with the tendency of buildings and walls to create corner reflectors, generates high returns (Xia and Henderson 1997). The complexity of the urban environment tends to be characterized by high heterogeneity in radar returns, due to the polyhedral nature of man-made features which generate both high and low returns at the same time.

A major issue in dealing with radar imagery is the large amount of coherent interference generated by individual scatterers of the monochromatic radiation generated and recorded by the radar antenna, which produces speckle or noise in the imagery (Haack et al. 2002). In order to reduce speckle, different look angles can be combined into a single image that averages backscatter. This process, called multi-looking, reduces speckle but at the same time reduces the spatial resolution of the image (Henderson and Xia 1998; Soergel 2010). Speckle can also be reduced for single look images by applying filters, such as moving window filters that smooth noise by removing outlying extreme pixel values. Filters that are commonly used for speckle reduction in radar imagery are mean, median and root mean square filters (Thomson et al. 1987), adaptive filters (Frost et al. 1982; Rao et al. 1995), multiplicative filters (Lee 1981; Kuan et al. 1985) and K-average filters (Davis and Rosenfeld 1978). The latter have the ability to reduce multiplicative noise that is characteristic of SAR speckle (Lee et al. 1994).

Researchers exploit the ability of radar imagery to detect structures and forms through the use of measures of texture. Measures of texture are calculated using a moving window that estimates the variability in pixel brightness within the frame. Measures of texture provide valuable information about the heterogeneity or homogeneity of pixel values within an area (Weeks et al. 2004). The use of texture extracted from radar imagery allows for the delineation of features and has been found to improve image classification of land cover and land use. Herold, Haack and Solomon (2004) compared the results of classifications of land use/land cover for sites in Kenya, Sudan, and Katmandu using SAR imagery and texture. Their results suggest that the accuracy of the classifications improved noticeably with the use of texture measures. Dell'Acqua and Gamba (2003) used co-occurrence measures of texture to classify building density and found that measures of texture estimated with window sizes corresponding to the average size of a block were able to differentiate the high density center of an Italian city from intermediate density residential and low density suburban areas. Dell'Acqua, Stassolla and Gamba (2006) used co-occurrence, mean, variance, entropy and dissimilarity measures of texture extracted from ENVISAT ASAR imagery to successfully detect formal and informal human settlements in Sudan and Senegal.

Radar images provide information about features on the ground in two and three dimensions but typically with a single narrow waveband, making them hard to use as a single source of information for spectral discrimination of land cover (Herold, Haack and Solomon 2004). Radar applications have been particularly successful in detection of human settlements when combined with optical data (Haack and Slonecker 1994; Haack et al. 2002). In the Katmandu Valley of Nepal, Haack et al. (2002) tested different combinations of radar and Landsat imagery products for urban delineation, finding that the combination of a mean filter and a variance texture applied to RADARSAT imagery produced the most accurate classifications. Haack and Bechdol (2000) found that the combination of radar imagery with optical data produced highly accurate classifications and that the use of filters and textures in the case of radar imagery increased the accuracy of land cover mapping in Tanzania,. In Kenya, Tatem and Hay (2004) combined radar imagery from the Japanese Earth Resources Statellite-1 (JERS-1) with Landsat ETM+ to map settlements and determine populations at risk of exposure to malaria.

2 Examining urban pattern

Research on land cover and land use focuses on the connection between the biophysical characteristics of the earth's surface, depicted as land cover, and the way people make use of the earth's surface, described as land use (Geist and Lambin 2002). Although anthropogenic changes in land cover are increasingly being recognized as major drivers of global change, little is known about the feedbacks connecting environmental pattern and social processes (Nagendra, Munroe and Southworth 2004). Interactions between population and the environment are hard to establish given the complexity and dynamics of their characteristics over spatial and temporal scales (Bian and Walsh 2002). While satellite imagery is an efficient source of data for monitoring land cover characteristics, it is less successful in monitoring the social processes behind changes in land use (Rindfuss and Stern 1998; Longley 2002). From a methodological standpoint the major challenge in studying population-environment interactions comes from the differences in units and scales of analysis (Longley 2002; Rindfuss et al. 2004). Geographical information systems (GIS), with their flexibility in location-based data management, are becoming an important tool bridging studies of spatial pattern and social process and are improving the understanding of land cover and land use change (Nagendra, Munroe and Southworth 2004). The combination of remote sensing and GIS techniques is particularly valuable for environmental modeling where researchers are increasingly taking advantage of the complementarities of the two geospatial technologies (Wilkinson 1996). In urban studies the combination of remote sensing and landscape metrics has become an important approach for understanding urban morphology (Herold, Couclelis and Clarke 2005).

Studies in landscape ecology have demonstrated the need to understand the impacts of landscape fragmentation on ecological systems (Gustafson 1998; Hargis, Bissonette and David 1998). Spatial patterns in landscapes are quantified through landscape metrics that permit a close examination of the spatial dimension of ecological processes (Gustafson 1998). By studying the spatial arrangements of ecosystems, researchers have found that landscape patterns have an impact on the spread of disturbance (Franklin and Forman 1987; Turner 1987) and the distribution of habitats (McGarigal and McComb 1995). GIS facilitates the identification and quantification of natural and human managed patches with varying sizes, shapes and arrangements (Turner 1990). A wide range of landscape metrics have been developed into software such as FRAGSTATS (McGarigal and Marks 1995) and a variety of user-generated programs (Turner 1990). Researchers have examined in detail the diversity of landscape metrics used in different fields, finding that they all rely on a very restricted set of common parameters. Patch size, perimeter-area ratio and inter-patch distance play important roles in shaping the bulk of landscape metrics, which suggests the existence of spatial autocorrelation (covariance) between many of them (Li et al. 1993; Li and Wu 2004). Researchers have addressed the matter of spatial autocorrelation by developing simulations that combine different patch sizes and spatial arrangements (Li et al. 1993; Hargis, Bissonette and David 1998) and analyzing the metrics through principal component analysis (McGarigal and McComb 1995; Riitters et al. 1995). McGarigal and McComb (1995) used principal components analysis (PCA) on a set of 25 landscape metrics to create three indicators that described shape and edge contrast, patch density and patch size through which they were able to identify that bird species were more abundant in fragmented habitats. Riitters et al. (1995) used PCA on 55 landscape metrics over a wide variety of landscapes throughout the world and concluded that 26 of them explained most of the variability in five factors: patch compaction, image texture, patch shape, perimeter area scaling and number of attribute classes.

Landscape metrics have become an important tool for researchers to study the effects of fragmentation on the biophysical environment but they are also increasingly being recognized as a useful set of indicators of human activity (Wickham, O'Neill and Jones 2000). Research in human environment interactions indicates that a detailed understanding of landscape characteristics provides important information about context that can shed some light into important social processes (Entwisle et al. 1998). While researchers have found that with urban growth the demand for land conversion has been steadily increasing and driving important habitat fragmentation (Wickham, O'Neill and Jones 2000), little is known about how the urban landscape is changing as cities grow (Liu and Herold 2007; Seto and Shepherd 2009). As the world's population has become predominantly urban, the rapid pace of urbanization is shaping the morphology and function of cities around the world (Longley 2002).

Pesaresi and Bianchin (2003) note that as early as the 1960s urban planners used measures of compactness, porosity and dispersion of built areas to describe the morphology of the city. Nowadays such measures of morphology can be readily extracted from a combination of satellite imagery and spatial analysis in GIS. The study of spatial organization and urban growth patterns is expanding the understanding of increasingly complex urban systems as cities grow (Liu and Herold 2007).

Studies have found that measures of texture and morphology extracted directly from satellite imagery provide important insight into the physical structure of settlement systems. In Italy, Brivio and Zilioli (2003) used geostatistics on Landsat multispectral imagery to depict urban structure for settlements of varying sizes and quantify patterns of anisotropy discovering that patterns identified in the semi-variograms coincided with particular urban characteristics of the area. In northern Italy Pesaresi and Bianchin (2003) used a regional approach to settlement classification from satellite imagery using texture to describe urban patterns finding that through the comparison of multi date measures of structure it is possible to uncover patterns of morphological transition. Gong and Howarth (1990) incorporated a high pass filter and edge detection to generate a structural information band that improved significantly their land cover classification in the rural-urban fringe of Toronto.

In the United States and Europe, researchers studying urban form have found that landscape metrics of multi-class land cover land use maps derived from classified remotely sensed imagery efficiently portrays the complexity of cities (Herold, Scepan and Clarke 2002; Luck and Wu 2002; Herold, Goldstein and Clarke 2003; Pesaresi and Bianchin 2003). In Santa Barbara, Herold, Liu and Clarke (2003) found that landscape metrics and measures of texture contribute to the differentiation of land use classes, and Herold et al. (2002) found that landscape metrics signatures facilitate the quantification of urban growth processes. In the same region, Liu and Herold (2007) found that landscape metrics and geostatistics provide important details about urban patterns that are valuable for land use classifications and also for the analysis of drivers of urban growth. Elsewhere in California, Dietzel et al. (2005) examined changes in urban form in three urban areas and found that edge density, patch density and nearest neighbor Euclidian distance metrics helped identify phases of diffusion and coalescence in urban growth. Researchers have found that measures of fractal dimension capture the complexity of urban form allowing for a detailed characterization of a range of urban land uses (Batty and Longley 1988; Mesev et al. 1995)

Studies of urban form in developed countries are generally focused on the detection and quantification of urban sprawl, typically defined as urban development taking place in suburban areas where land uses are segregated, automobile is the main form of transport, development takes place at the edge of the metropolitan area, densities are lower than within the city and populations tend to be homogeneous (Johnson 2001). A composite measure of urban sprawl is proposed by Galster et al. (2001) based on eight dimensions: density, continuity, concentration, clustering, centrality, nuclearity, mixed use and proximity, confirming that older cities in the north east and Midwest correspond to the most consolidated compact urban areas in the US. Studies combining landscape metrics with demographic data have compared patterns of urbanization between cities worldwide finding clear differences between developing and developed countries where densification characterizes the growth of cities in the developing world while sprawl is identified as a unique feature of developed countries (Huang, Lu and Sellers 2007; Schneider and Woodcock 2008).

For the Washington DC area, Geoghegan, Wainger and Bockstael (1997) found that landscape diversity and fragmentation are correlated with housing and land values. Irwin and Bockstael (2007) discovered that urban fragmentation is increasingly moving farther away from city centers, a sign of the expansion of urban sprawl. Hasse and Lathrop (2003) used an urban atomization approach to measure sprawl characteristics at the housing-unit level, finding that urban sprawl has diverse and significant impacts on natural resources in New Jersey. In Phoenix, studies using landscape metrics have identified an urban gradient pattern that changes with distance to the city (Luck and Wu 2002), where fragmentation is the highest in low density areas on the periphery of the city and urban growth spreads in a contiguous manner (Shrestha et al. 2012).

In the coming years the most important urban transformations of landscapes will take place in Asia and Africa, where urban population is growing at the fastest rate, but little is known about how these demographic changes will impact the urban extent and shape in those regions (Seto and Shepherd 2009). In developing countries, where mapping of urban areas is generally dated and less detailed (Weber 2003), studies of urban morphology rely heavily on simple urban/non-urban classifications. Taubenböck et al. (2009) used landscape metrics to examine patterns of urban growth taking place in the twelve largest cities in India distinguishing monocentric urban agglomerations with laminar spatial growth from cities that are transitioning from monocentric to polycentric through punctual spatial growth and polycentric cities growing in a widespread punctual manner. Oleksandr, Lüdeke and Reckien (2012) found that measures of texture of a built class map extracted from high resolution imagery helped to identify informal settlements and map slums within the city of Hyderabad. In Bangalore, studies have found that urban growth is mostly taking place in the periphery of the city where urban fragmentation is transitioning into larger compact urban patches (Ramachandra, Aithal and Sanna 2012), which are driving increased fragmentation of vegetation land cover (Nagendra et al. 2012). Studies in different urban settings in India have used measures of dispersion and fragmentation to monitor and model the spread of urban sprawl finding that low density fragmented built areas are on the rise (Sudhira, Ramachandra and Jagadish 2004; Mahesh, Garg and Khare 2008).

Seto and Fragkias (2005) examined patterns of urbanization in four Chinese cities using landscape metrics of urban growth and found that built patches tend to converge and coalesce into larger patches as cities grow. Analyzing changes in urban pattern through a series of transects Schneider et al. (2005) detected patterns of dispersion, growth of independent nuclei, densification and infill in Chengdu, western China. In Guangzhou, China, Yu and Ng (2006) found patterns of urban growth that indicate a transition from heterogeneous fragmented landscapes to more aggregated and homogeneous ones.

The selection of spatial metrics for the study of urban environments depends on the research question and the particular characteristics of each specific landscape (Parker and Meretsky 2004). Studies examining patterns of urban form have selected sets of spatial metrics using PCA (Schwarz 2010; Ramachandra, Aithal and Sanna 2012) or based on previous research that identified metrics suitable to describe specific characteristics of the urban context (Herold, Goldstein and Clarke 2003; Sudhira, Ramachandra and Jagadish 2004; Seto and Fragkias 2005).

Studies focusing on capturing the morphological transition between urban and rural places have shown that patch density, mean patch size and patch size variability describe best how fragmented, disperse and heterogeneous the built environment is (Luck and Wu 2002; Herold, Goldstein and Clarke 2003; Seto and Fragkias 2005). While city centers tend to have denser and smaller built patches, the peripheries of the city are more likely to have larger and less dense built patches, characteristic of suburban development. Areas where mixed land uses prevail can be identified within the urban context with the assistance of measures of patch variability, given that they can locate spaces with heterogeneous patches. The complexity of the shape of built patches provides significant information about degree of urbanization. Researchers analyzing transitions of urban form have found that area weighted mean fractal dimension is very efficient in differentiating compact urban core areas from complex patchy areas found in the urban fringe, where urban form is largely shaped by diffusion processes (Longley and Mesev 2000; Herold, Goldstein and Clarke 2003; Dietzel et al. 2005; Seto and Fragkias 2005). Degree of aggregation of urban patches provides further details about the structure of the urban context. Studies have found that the contagion index captures how clumped together different land covers are throughout the landscape providing a broad picture of the spatial arrangement of the different land uses within the urban context (Herold, Goldstein and Clarke 2003; Dietzel et al. 2005; Yeh and Huang 2009).

Urban morphology has been studied through landscape metrics in a variety of scales and geographic domains. The study of urban structure with landscape metrics requires partitioning the city into homogenous units of analysis (Herold, Couclelis and Clarke 2005). Urban studies have found that landscape metrics calculated for small area administrative subdivisions provide important detail about urban composition (Weeks, Larson and Fugate 2005; Mahesh, Garg and Khare 2008). Studies that include peri-urban areas and undeveloped hinterland have defined homogeneous regions based on automated segmentation of satellite imagery (Herold, Couclelis and Clarke 2005), bands of buffers around a core metropolitan area (Dietzel et al. 2005; Seto and Fragkias 2005; Schneider and Woodcock 2008; Nagendra et al. 2012), buffers around individual houses (Geoghegan, Wainger and Bockstael 1997) moving windows or kernels (Luck and Wu 2002; Schneider, Seto and Webster 2005) or regular grid cells as commonly used for urban modeling (Pijanowski et al. 2000; Parker and Meretsky 2004; Song and Knaap 2004; Hahs and McDonnell 2006). The decision of how to subdivide a study area to estimate measures of spatial composition has to consider how the scale of analysis addresses the specific research question but also whether the unit of analysis allows further examination of the resulting metrics (Lausch and Herzog 2002; Herold, Couclelis and Clarke 2005).

Major methodological issues arise when trying to integrate physical and social sciences, as data from each field are collected for different units of analysis and at different scales. Selecting the appropriate aggregation level for studies bridging environment and population fields represents a difficult task (Rindfuss et al. 2004). The use of a gridded unit of analysis was proposed by Tobler et al. (1997) as a solution to the data incompatibility problem, where a uniform unit of analysis permits a direct link between environmental and population variables. Tobler's gridded world population (GWP) method used a five minute quadrangle (9.3 kilometers wide at the Equator); newer versions of the GPW have achieved improved resolutions of two and a half minutes (5 kilometers wide at the Equator) (Deichmann, Balk and Yetman 2001; Balk and Yetman 2004).

3. Pattern-based definition of urban context

Settlements are defined as urban or rural based on a variety of criteria such as population densities, access to basic infrastructure and predominant economic activity (Tacoli 1998). Although these definitions vary widely throughout the world (Bilsborrow 1998) they are all based on the assumption that there are significant differences between rural and urban spaces and their populations (Champion and Hugo 2004; Lacour and Puissant 2007). Urban definitions and delineations are generally based on an arbitrary threshold that is set as the split between rural and urban places (Antrop 2004), without accounting for differences in land use intensity, function or heterogeneity (Seto et al. 2012). However, in urban environments different types and densities of buildings, as well as vegetation, can vary within short distances (Cadenasso, Pickett and Schwarz 2007). By portraying rural and urban areas as autonomous spaces, dichotomous rural/urban classifications are ignoring the importance of flows of people and products that connect these spaces (Hugo, Champion and Lattes 2003; Rain 2007; Seto et al. 2012). With urban growth landscapes are changing within cities as well as in the countryside, where increased connectivity to the city is creating hybrid landscapes in which rural and urban livelihoods overlap (Hugo, Champion and Lattes 2003; Lacour and Puissant 2007; Seto et al. 2012). Rising suburbanization trends are forming edge cities that are increasingly facilitating urban spread into rural areas (Zipperer et al. 2000) and blurring the distinctions between rural and urban places (Hugo, Champion and Lattes 2003). While the ongoing global urbanization trend is widely accepted, there is still much to know about how it is affecting the environment and people within urban areas.

In the mid 1970's, Anderson (1976) proposed a land use and land cover classification scheme for remotely sensed data, using a hierarchical structure that standardizes the system of land use classes at the most general level with a second tier of classes detailing more specific cover and usage characteristics. The urban context is defined at the highest level by Anderson's scheme as urban or built land, expanding in the next level to differentiate between residential, commercial/services, industrial, transportation, communication/utilities, industrial/commercial complexes, mixed built, and other built land uses. Anderson's classification has been adapted for other land use land cover classification schemes such as the National Land cover Data Set (NLCD) (Vogelmann et al. 2001) and the Global Land Cover Database (GLC) (Bartholomé and Belward 2005) by USGS, the Land Cover Classification System

(LCCS) by FAO (Di Gregorio and Jansen 2000) and the Globcover classification (Arino et al. 2007) by ESA. However, classifications based on the Anderson scheme separate natural from human components of systems, largely ignoring how those interact in coupled urban environments (Cadenasso, Pickett and Schwarz 2007). The urban environment being the product of interactions between human and natural mechanisms (McIntyre, Knowles-Yánez and Hope 2000; Naveh 2001) is poorly depicted by traditional classifications of land use land cover.

In the United States cities have been characterized through different classification schemes based on population thresholds, adjacency to a range of city sizes and degree of urbanization (Butler and Beale 1994; Cromartie and Swanson 1996; Ghelfi and Parker 1997). Hugo, Champion and Lattes (2003) proposed a classification of settlements that combines settlement size, population density and accessibility as a way of capturing the multi-dimensional nature of the city.

Research in public health examining the impacts of urbanization on human health has approached classifications of the urban context from a variety of angles. Continuous scales measuring urban-ness have been proposed based on a combination of variables such as population size and density, predominance of economic activity and access to services (Adair, Vanderslice and Zohoori 1993; McDade and Adair 2001; Dahly and Adair 2007; Van de Poel, O'Donnell and Van Doorslaer 2009). Studies have classified the built environment based on details about housing and neighborhood characteristics collected from a variety of surveys (Caughy, O'Campo and Patterson 2001; Weich et al. 2001). Remote sensing applications have been proposed as an efficient alternative to delineate urban areas based on detection of the built environment (Tatem and Hay 2004; Weeks et al. 2004).

Studying urbanization in Europe, Antrop (2004) describes the diffuse transition between urban centers and the countryside as a complex combination of land uses with diverse and fragmented morphology. This heterogeneous transition zone that extends between urban and rural places is not captured by any settlement classification (Hugo, Champion and Lattes 2003) and remains to be further studied.

The transition of urban environments into the countryside has been studied by ecologists who are interested in identifying changes in habitats through an urban gradient (Blair 1996; Blair and Launer 1997; Niemelä et al. 2002; Kühn and Klotz 2006) and also by remote sensing specialists who are interested in capturing spatial patterns of urban growth (Luck and Wu 2002; Weng 2007; Yang et al. 2010). Studies in urban landscape ecology have proposed alternative characterizations of the urban environment that incorporate measures of fragmentation and dispersion with the goal of examining habitat fragmentation and its impacts on ecological function (Alberti 2005; Breuste, Niemelä and Snep 2008).

Studies interested in understanding patterns of urban growth have proposed the use of urban gradients instead of traditional land cover/land use classifications of urban spaces. Continuum classifications of multi-date satellite imagery provide detailed information about environmental changes and their links to urbanization

(Clapham Jr 2003). A continuous urban context can be portrayed through a combination of proportions of land cover and population characteristics (Weeks, Larson and Rashed 2003; Weeks 2003; McDonnell and Hahs 2008) or as a combination of measures of landscape composition and spatial configuration extracted from landscape metrics and socio-economic indicators (Weeks, Larson and Fugate 2005; Hahs and McDonnell 2006; Andersson et al. 2009; Toit and Cilliers 2011).

Fewer studies have extracted measures of degree of urbanization exclusively based on the morphological characteristics of the environment. Hung, Chen and Cheng (2010) combined fractions of built land cover with a normalized vegetation index to create an urbanization index that permitted them to compare degrees of urbanization between Tokyo, Kyoto and Taipei.

Classification of the urban transition into categories is an alternative to the continuous approach to measuring degree of urbanization. Using very high resolution imagery, Cadenasso et al. (2007) proposed a classification that captures the heterogeneity of urban systems by combining details about buildings, vegetation and surface materials to study urban ecosystem's function. The high ecological resolution classification for urban landscapes and environmental systems (HERCULES) defines five classes: coarse textured vegetation, fine textured vegetation, bare soil, pavement and buildings, where buildings are further subdivided into different types.

At regional scales and with less detail about individual features, moderate resolution imagery has been successfully used to identify urban transition patterns and generate meaningful categorical classifications. Van de Voorde, Jacquet and Canters (2011) combined ratios of built land cover with measures of spatial composition through a neural network classifier producing a detailed land use map of Dublin. The resulting land use map allowed them to differentiate the dense urban core from medium and low density residential and activity areas.

Through a decision tree classifier Rashed et al.(2001) used proportions of different land covers to successfully differentiate agricultural areas, recreation areas, newly developed land, central business district, and residential areas of high and low socio-economic status in Cairo. The decision tree classifier is a non-parametric method that deals efficiently with numerical and categorical data, making it a suitable approach to classify urban context based on imagery extracted variables such as land cover and measures of texture and morphology from different data sources.

4. Monitoring urban context in Ghana

One of the major differences between urbanization as it has taken place in the global north compared to how it is taking place now in the global south is that in the south it seems to be happening disjointedly from economic growth (Cohen 2004). This means that in the least developed countries urban growth is not accompanied by the much needed development of infrastructure, particularly in smaller towns and intermediate cities where resources are scarce (Montgomery 2004). This study's hypothesis is that the lack of infrastructure combined with rapid urbanization results in heterogeneous and complex urban landscapes. Such a hypothesis has yet to be explored in detail in Sub-Saharan Africa.

Research on urbanization in Sub-Saharan Africa has mostly focused on portraying the characteristics of urban expansion. Aerial photography was used to quantify urban growth between 1957 and 2009 in the urban fringe of the city of Bahir Dar in Ethiopia, finding that as the city expands it is absorbing large swaths of agricultural areas (Haregeweyn et al. 2012). Landsat imagery was used to monitor urban growth between 1976 and 2000 in Nairobi, Kenya, finding that urbanization and sprawl follow major transportation axes (Mundia and Aniya 2005). Satellite imagery and aerial photography were used to map patterns of urban growth between the mid-fifties and 1998 in Dar es Salam, Tanzania, finding that urban growth followed infill patterns rather than expansion patterns (Briggs and Mwamfupe 2000) and that urban poverty is driving important land use changes in peri-urban areas (Kombe 2005).

In Ghana, urbanization is spreading at fast pace. The 2010 Census of Population and Housing revealed that more than half of the country's population resided in urban areas, a figure that the UN projects to reach three quarters by 2050. Ghana Statistical Service estimates that population in Greater Accra increased from under 1.5 million in 1984 to almost 3 million in 2000, a number that reached the 4 million mark in 2010. However, urbanization is taking place not only in the capital and major cities, but also in smaller settlements both close and far away from cities (Moller-Jensen and Knudsen 2008).

Studies of land cover and land use change in Ghana have found that migration is linked to decreasing woodlands in northern Ghana (Braimoh 2004; Pabi 2007), that in the Western region the most predominant changes are linked to mining, farming, lumbering, fuel wood collection and urbanization (Kusimi 2008), and that in the Accra region urbanization is the major driver of landscape transformation (Yorke and Margai 2007). In Accra, urban expansion was mapped between 1985 and 2002 with Landsat imagery, showing a fast and unplanned spread of the city into its hinterland (Møller-Jensen and Yankson 1994; Møller-Jensen, Kofie and Yankson 2005). Yeboah (2003) describes the emergence of higher-quality residential sprawl in the peri-urban and rural localities adjacent to Accra's metropolitan area. Even though the region is going through a fast urbanization process, researchers have not yet examined the diversity of spatial patterns that are being brought about by rapid urban growth.

B. Urban context, household composition and fertility

Urban growth is directly the product of population changes, but underlying that are the societal transformations that bring changes in infrastructure, economic, political and cultural activities (Lattes, Rodríguez and Villa 2002). While the morphology of cities can be detected with remote sensing techniques, the complexity of the urban context can only be understood through the combination of landscape and population characteristics (Pumain 2004).

Research linking population dynamics with land cover and land use has mostly focused on deforestation in frontier settings (De Sherbinin et al. 2008).The connection between land cover land use change and household lifecycle was explored in the northern Ecuadorian Amazon by Barbieri, Bilsborrow and Pan (2005) finding that population growth in these rural areas can be directly linked to fragmentation of land holding. In the same region, Carr, Pan and Bilsborrow (2006) found that fertility levels dropped significantly in the frontier setting as migrants settled, diversified their livelihoods and acquired assets. Moran, Siqueira and Brondizio (2003) found a significant association between deforestation and age structure of settlers in the Brazilian Amazon, while Van Wey, D'Antona and Brondizio (2007) examined the relationship between land cover and land use change and household composition discovering that the number of women and children in the household has a significant effect on land use land cover change.

Weeks et al. (2004) examined the variability in fertility levels in Cairo using contextual variables extracted from satellite imagery, finding that much of that variability was explained by a combination of socio-economic and landscape characteristics of the urban environment. In Accra, Weeks et al. (2010) combined satellite imagery with socio-economic indicators to delineate neighborhoods by fertility patterns, finding an important spatial trend in the association between delaying marriage and lower fertility levels. In Sub-Saharan Africa reproductive decisions are highly influenced by the family context (Caldwell and Caldwell 1987; Lesthaeghe 1989), a connection that is less apparent in the city where urban living arrangements are starting to replace traditional household composition (Weeks et al. 2010). However, rapid urban growth combined with rising urban poverty in the region is generating heterogeneous urban environments inhabited by people with a wide variety of lifestyles.

In the early 1970s, Brand (1972) described how even as the city of Accra grew, traditional lifestyles persisted within the city. His paper on spatial organization of residential neighborhoods in Accra classified neighborhoods based on the degree of modernization of enumeration areas, identifying bourgeois migrant communities and urban villagers as the extremes. In his paper, Brand (1972) attributes modernization to education, lower reproductive levels and contact with western culture through non-African in-migration. These characteristics of modernization can be interpreted as demographic characteristics of a population moving through the demographic transition, catching up with both the urban and fertility transitions. Caldwell and Caldwell (1997) described the export of western social systems and the ramification of ideas that accompany it as key triggers of fertility decline.

Industrial societies facing a lower demand for agricultural labor and a higher demand for better education have seen a decline in the economic value of children (Bongaarts and Watkins 1996), and studies in developing countries have established a correlation between higher incomes and lower fertility rates (Bollen, Glanville and Stecklov 2002; Bollen 2007). However, this correlation has not been able to explain the fertility behavior of people in many parts of the developing world (Mason 1997). Research in Sub-Saharan Africa has shown that reproductive decisions are highly influenced by social context, meaning that fertility transitions cannot be purely explained by indicators of socio-economic growth (Lesthaeghe 1989). Kingsley Davis' (1963) theory of demographic change and response emphasizes the importance of social structure in shaping demographic behavior. Fertility decline, as Davis posits, results from changes in lifestyles characterized by marriage postponement, increased use of contraception and migration to the city. These lifestyle changes identified by Davis are embedded in a spreading urban way of life.

As just noted, fertility transitions are influenced by the diffusion of modern methods of birth control, a process that takes place through social networks and communication media (Reed et al. 1999). In developing countries, Bongaarts and Watkins (1996) explain that reproductive decisions are highly influenced by levels of social interaction. Early adopters of fertility control tend to be more educated urban settlers, and this behavior spreads to rural areas through communication networks (Casterline 2001). In rural Egypt, Entwisle et al. (1989) showed that rural fertility rates are highly influenced by the structural characteristics of villages and Weeks et al. (2000) illustrated spatial diffusion effects in the use of contraceptives around rural villages through the study of the spatial distribution of fertility rates. In West Africa, Addai and Trovato (1999) mention the prevalence of a high ethnic fertility characterized by a cultural background that promotes high reproductive expectations. Fertility levels that seem to be strongly influenced by this ethnic component are susceptible to a process of structural assimilation, where assimilation is defined by increasing levels of education, later marriages and a stronger female presence in the labor force (Goldscheider 1971; Weeks et al. 2004). Research in Sub-Saharan Africa has found that universal schooling (Caldwell and Caldwell 1997; Lloyd, Kaufman and Hewett 2000), delaying marriage (Bledsoe and Cohen 1993; Cohen 1998; Garenne and Joseph 2002) and access to family planning (Caldwell and Caldwell 1997; Cohen 1998) are associated with fertility onsets. Nevertheless, studies have found that increasing use of family planning in Sub-Saharan Africa doesn't correspond to a reduction in reproduction expectations as much as it does to an increase in the practice of spacing pregnancies (Caldwell, Orubuloye and Caldwell 1992; Bledsoe and Hill 1998; Cohen 1998).

Even though urbanization has been regularly linked to fertility decline (Mason 1997), the density and diversity of cities in the developing world bring along a diverse set of reproductive strategies that generate a wide range of fertility levels (Montgomery 2003). In Cairo, Weeks et al. (2004) showed that higher fertility levels in the city are comparable to those found in rural Egypt. In Accra, Weeks et al. (2010) found that much of the variability in fertility levels within the city corresponds to the gap between dropping fertility levels of younger women delaying marriage and married women with much higher reproduction levels. Reproductive decisions in Sub-Saharan Africa are highly influenced by religion (Caldwell and Caldwell 1987) and family systems (Caldwell 1996). In Ghana, Gyimah et al. (2008) have shown that there is a connection between a couple's religion and its level of fertility, such that couples belonging to traditional African faiths have higher fertility rates than Muslim and Christian couples. Kinship represents the foundation of the organization of traditional groups in Ghana as it defines clans at the regional scale and lineages at local scale (Nukunya 2003).

In West Africa, lineages are characterized by their reverence for ancestry and lines of descent. Elders in these traditional societies are not only respected by the young, they are supported by them as an obligation to the survival of the lineage. In this region, the connection to the lineage of descent prevails over the conjugal bond as spouses remain part of their lineage of origin even after marriage (Caldwell 1996). Studies in the region have found that the characteristics of the social organization of the family have an impact on reproduction decisions. Takyi and Dodoo (2005) found that in Ghana there is a stronger association between women's reproductive preferences and their effective use of contraception in matrilineal ethnic groups compared to patrilineal ones, a result that indicates important differences in the role females play in household arrangements between matrilineal and patrilineal lines of descent.

The power of the lineage is particularly evident in traditional living arrangements where nuclear families are weakened by the primacy of the kin (Caldwell and Caldwell 1987). The line of descent is particularly important in defining patterns of residence and household composition. In Ghana, as in much of West Africa, living arrangements commonly correspond to extended family units. In the case of kinship families, the definition of a lineage as patrilineal or matrilineal plays a major role in determining where the family members reside. Even though patrilineal lines of descent prevail in the rest of Africa, Ghana is predominantly matrilineal when it comes to descent patterns. The Ashanti or Akan, the largest ethnic group in the country, is a matrilineal society. They are followed in numbers by bilateral descent groups such as the traditional kingdoms of Gonja, Dagomba and Wala. Patrilineal lines of descent are the least common, found in northern tribes such as the Tallensi and southeastern societies such as the Ga and Adangme (Nukunya 2003).

Patrilineal societies tend to be virilocal, meaning that the family settles in the husband's compound. Exceptions are quite common as in the case of the Ga, where men and women live in different compounds with boys moving out of the female's compound at puberty (Nukunya 2003). Matrilineal societies, on the other hand, are generally matrilocal which means that in most cases men and women will also live in different compounds and children are generally not allowed to live with their fathers (Nukunya 2003). In effect, children's residential arrangements are very diverse in this region, compounded by the importance of the practice of fosterage. This common practice allows parents to send their children to be raised in a different household (Caldwell 1996), usually with a lineage/family member. Lineages, as we can see, define a variety of living arrangements, household sizes and structures. Household structure has been linked to fertility from different perspectives. Studies have found that household size correlates positively to fertility (Bongaarts 2001), couple characteristics relate to reproduction rates (Oheneba-Sakyi and Takyi 2001), while polygamy has been associated with lower fertility rates (Bongaarts, Frank and Lesthaeghe 1984; Dodoo 1998). Research focusing on living arrangements has found that parent-child co-residence plays a role in defining reproduction decisions (McDaniel and Zulu 1996) and female co-residence with a family member of the same generation has a negative relationship to birth rates (Moultrie and Timus 2001).

Ruggles and Heggeness (2008) indicate that in developing countries patterns of inter-generational co-residence are among the most common types of living arrangement. In Sub-Saharan Africa Adepoju and Mbugua (1997) classified households as nuclear or extended, further classifying extended as three generation, kinship family or polygamous households.

In developing countries, the social changes brought by urbanization and industrialization are associated with a shift from tribal family patterns to nuclear conjugal families (Goode 1963). With rapid urbanization and the spread of the urban way of life, the ethnic component that has traditionally shaped Sub-Saharan African household composition is subject to a certain degree of assimilation (Lesthaeghe 1989; Weeks et al. 2004). This study investigates the connection between the characteristics of the social organization of the household and the landscape characteristics that define urban spaces. Of particular interest is establishing how the composition of households interacts with heterogeneous urban landscapes and how those in turn correlate with varying fertility levels.

Decreasing mortality levels are considered to be an important precondition for fertility decline (Davis 1963; Reher 2004), a condition that is first met in the city, where infrastructure and services are concentrated. In Ghana, migration to the city and the process of assimilation to its lifestyle has been shown by White et al. (2005) to lower reproduction levels. Moreover, Caldwell (1967) associated regional differences in fertility attitudes to the predominance of rural or urban population. Southern Ghana, with lower rural populations than the north, had a clear tendency for lower fertility, whereas the more traditional and rural north experienced higher fertility levels. Bongaarts and Watkins (1996) explain that communities that are isolated from social interaction see slower fertility declines than those that are integrated through multiple channels. The hypothesis guiding this research posits an association between the physical characteristics of urban areas, family/household structure and fertility outcomes.

III. Study area and Methods

Through the use of remote sensing, image processing techniques and landscape metrics, a detailed indicator of the physical characteristics of the urban context is generated. This measure of urban context was then compared to population characteristics in order to identify the association between degree of urbanization and drivers of fertility decline.

A. Study area

Urbanization is spreading at a fast pace in Ghana. The 2010 census by Ghana Statistical Service (GSS) estimated that more than half of the country's population resided in urban areas, a figure that is projected to reach three quarters in 2050 by the United Nations Population Division. GSS estimated that population in Greater Accra increased from under 1.5 million in 1984 to almost 3 million in 2000. This rapid growth in urban population translates into dramatic changes in LULC.

The study area is located in southern Ghana, consisting of 18 districts covering all of the Greater Accra Region (which comprised 5 districts in 2000) and 13 adjacent districts in the Central, Eastern and Volta regions in the year 2000 (Figure 1). The coastal regions of Ghana have seen a steady increase in population growth and urbanization as Accra's metropolitan area attracts a steady flow of migrants in search of opportunities, but also as smaller intermediate cities such as Cape Coast, Takoradi, and Tema have seen important population expansions. The study area includes Accra and Tema, and their metropolitan fringe, periphery and hinterland. The districts selected for this study stretch over portions of Accra's neighboring regions defined here as the capital's extended area of influence, which is composed of a diverse urban landscape.

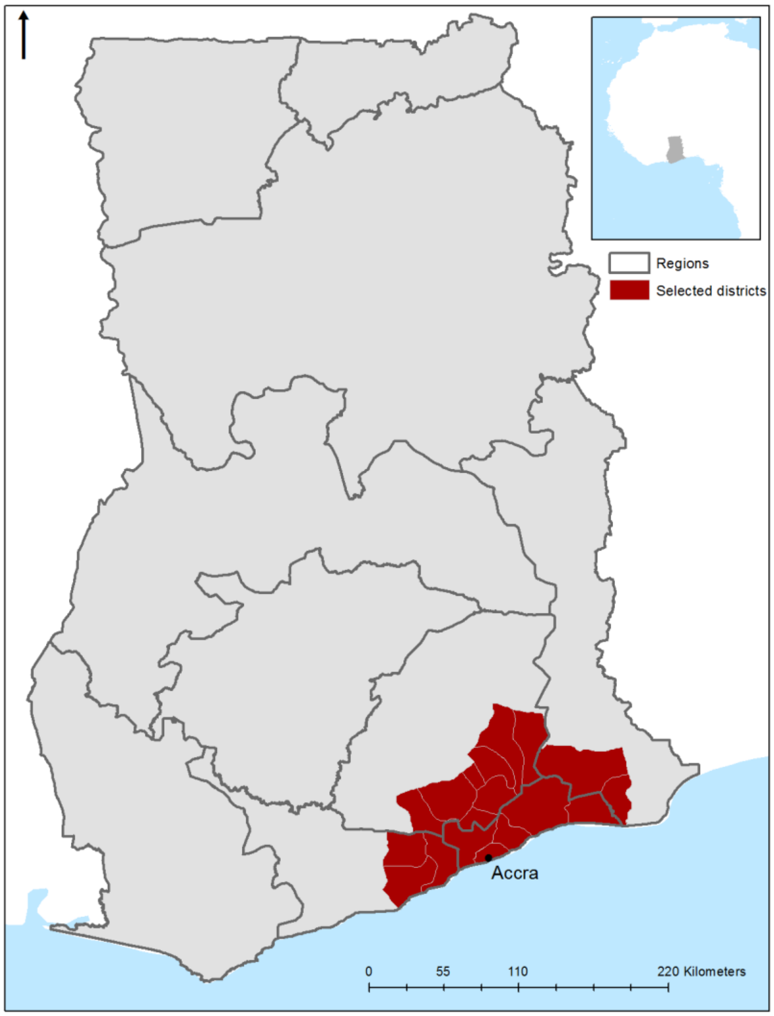


Figure 1: Study area

B. Defining the urban context

1. Identifying built and vegetation land cover

Urban context is characterized using a uniform grid covering the study area through the use of satellite imagery and geographic information system (GIS) techniques (Figure 2). Landsat imagery was used to classify built and vegetation land cover and was combined with ERS-2 radar imagery in order to generate a classification of degree of urbanization.

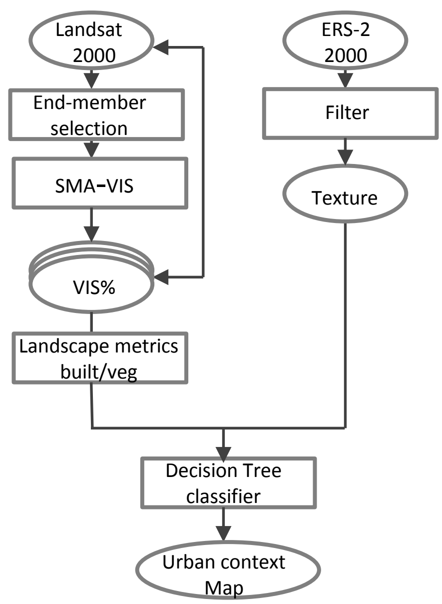


Figure 2: Flow chart for urban context classification

A cloud-free 30 m resolution Landsat ETM+ image captured for path 193 and row 56 in December 26th 2002 was selected (Figure 3). Pre-processing of the image included masking water bodies and sand flats using high resolution imagery from

Google Earth and masking fire scars using a supervised classification of a principal components transform image (Hudak and Brockett 2004).

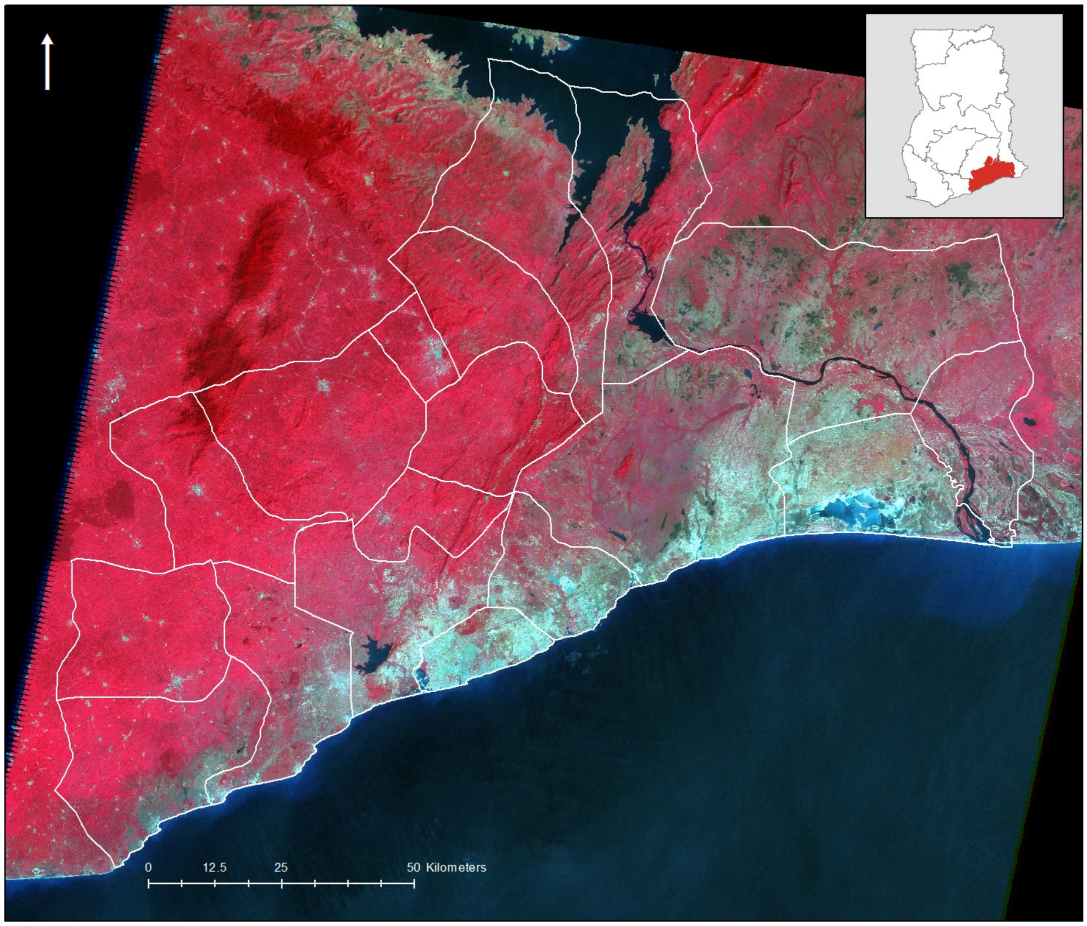


Figure 3: Study area overlaid on false color infrared Landsat ETM+ captured December 26th 2002. Census district boundaries delineated as white polygons.

The resulting pre-processed image with six (all multispectral except thermal infrared) wavebands was analyzed through spectral mixture analysis based on Ridd’s (1995) VIS model. End-members or pure classes were selected from this image with the assistance of a Pixel Purity Index (PPI) to identify the images extreme spectral features. Clusters of pixels with high PPI were identified and visually compared to pan-sharpened and high spatial resolution imagery from Google Earth in order to select end-members. The final group of end-members selected included one pure signature each for green vegetation, non-photosynthetic vegetation, soil, impervious surface and shade.

SMA models estimated different combinations of proportions of the selected end-members for each pixel. The algorithm constrains the resulting fractions to sum to 1 for each pixel, while each individual fraction has to be in the 0 to 1 interval (Roberts, Batista, et al. 1998). Root mean square errors for the resulting SMA models were assessed in order to determine the most efficient combination of end-members for the detection of impervious surfaces and vegetation cover. The resulting proportions were classified into vegetation and built land covers using threshold classifiers. Pixels with more than fifty percent impervious surfaces were automatically classified as built.

Resulting SMA proportions showed that within urban areas shade played an important role in capturing building shadows and dark pavement. Large settlements were delineated through visual inspection of a pan-sharpened Landsat ETM+ image, and pixels found within those areas with proportions of over fifty percent shade and twenty five percent impervious were classified as built. Pixels modeled as having more than fifty percent vegetation were classified as vegetation cover. Results from SMA indicated that shade is also associated with vegetated areas where trees create substantial amounts of shade. A normalized difference vegetation index (NDVI) was calculated and compared to the proportions of vegetation and shade produced by the

SMA confirming the overlap of vegetation and shade in heavily vegetated areas. In order to capture the portion of shade found within the vegetation cover pixels with more than fifty percent shade and twenty five percent vegetation cover were classified as vegetation. The resulting product is a 30 m resolution raster land cover map of the study area containing built, vegetation and other categories.

Errors in the SMA-based land cover map were assessed relative to a land cover and land use map created by the Center for Remote Sensing and GIS applications (CERSGIS) at the University of Ghana, Legon. The land cover map created by CERSGIS is a product of heads-up digitizing (i.e., visual interpretation and manual digitizing) of Landsat 7 ETM+ imagery from 2000. The classes in the LCLU map generated by CERSGIS were aggregated in order to have two comparable built and vegetation classes. A stratified random sample of two thousand and five hundred points was generated over the study area and the corresponding land cover types from the SMA classification were compared to the CERSGIS land cover map. Given the relatively small proportion of the study area that is covered by impervious surfaces, the built land cover class was oversampled in order to produce a representative measure of accuracy. Five hundred points were collected for the built class, 1200 were collected over the vegetation class and 800 were collected for the other class. Given the scarcity of high resolution reliable reference data we should note that our error assessment corresponds more to an assessment of agreement between two independent land cover and land use classifications than to a rigorous accuracy assessment. We assume that by combining visual interpretation and field work validation the CERSGIS classification represents a valid reference of the characteristics of land cover and land use. However we don't have access to any measures of accuracy that would validate our assumption. Results from the error assessment are discussed in the results section.

2. Extracting settlement texture from radar imagery

ERS-2 radar imagery is collected in the C microwave band (5.6 cm) with vertical transmission and vertical received polarization, yielding 12.5 m resolution images. ERS-2 imagery covering the study site was requested from the European Space Agency for three orbits: 18370 collected in October 1998, 19601 collected on January 1999 and 41373 collected on March 2003 (Figure 4).

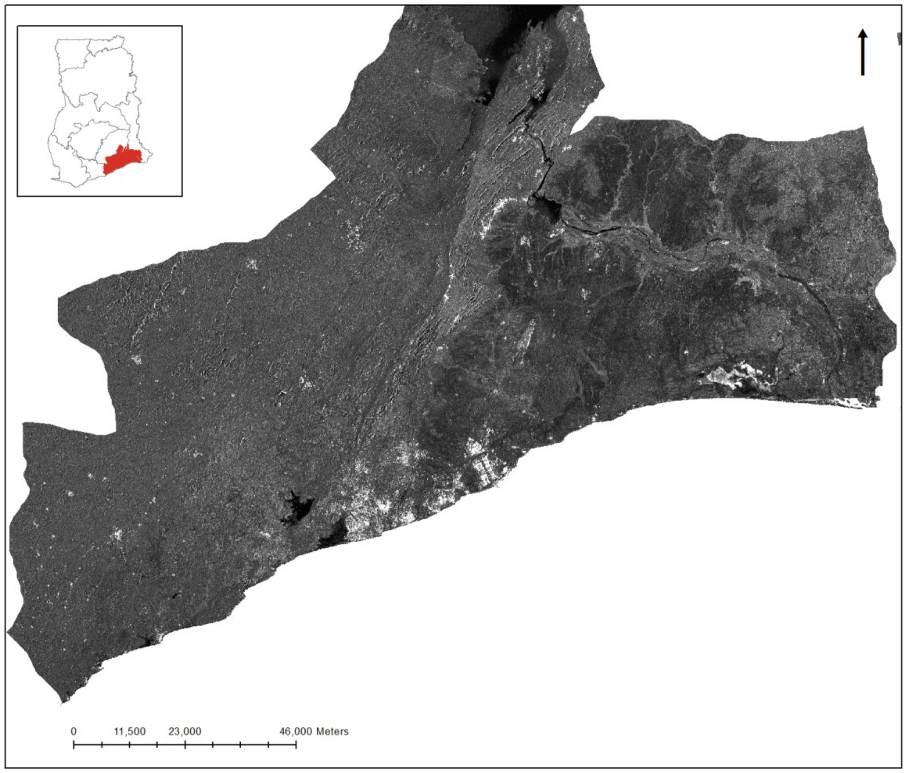


Figure 4: ERS-2 SAR image captured October 25th 1998, January 19th 1999 and March 20th 2003 for the Ghana study area.

Ground range images were pre-processed using the NEST toolbox developed by the European Space Agency. Pre-processing of the radar imagery included: terrain correction, radiometric normalization and speckle reduction filtering. A range Doppler terrain correction algorithm was used for terrain correction and radiometric normalization using 30 m resolution Global Digital Elevation Model (GDEM V2) derived from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite sensor and DELFT precise orbit files. A SAR simulation terrain correction was created using the same digital elevation model in order to generate a layover mask. The terrain corrected SAR image and the layover mask were closely inspected against high resolution imagery (Google Earth) and a DEM in order to verify that areas with terrain distortion were excluded from the imagery.

Research in settlement mapping has shown that radar imagery is particularly useful in areas with little terrain where background classes can be defined as flat undeveloped surfaces with low radar returns against which artificial structures with high returns easily stand up (Haack and Slonecker 1994). Through visual inspection areas located at higher elevations were identified as irregular bare rock formations generating mixed returns and foreshortening distortions which appeared to be missed by the terrain correction. After close examination of the radar backscatter against optical imagery the decision was made to expand the layover mask in areas located above 200 m of elevation using a 200 m buffer to remove any remaining foreshortening distortions. The expanded mask helps to ensure that the radar backscatter captured by the sensor is minimally influenced by the radar beam interacting with the terrain, but rather is a product of its interaction with man-made structures. Given that the study area is mostly flat the masked sections of the imagery are limited to scattered ridges in the northern portion of the study site. Examination of optical imagery indicates that the masked sections do not coincide with major settlements.

A refined Lee filter was used to reduce speckle noise generated by interference of individual scatterers. The refined Lee filter examines variance in a seven by seven window and establishes a threshold that detects edges. A measure of texture was extracted from the filtered radar images using a 9 x 9 moving window to estimate the standard deviation of the radar backscatter. The standard deviation texture image was then smoothed using a 3 x 3 moving window in order to remove outliers. The smoothed image was then rescaled from 32 to 16 bit to reduce pixel range. The resulting variance of radar backscatter was used as an indicator of spatial composition of the built environment, where heterogeneous returns are associated with complex artificial landscapes such as man-made features characteristic of settlements. The rescaled SAR texture is then visually compared against a range of settlement sizes throughout the study area in Google earth in order to define a threshold of texture that matches to populated areas The threshold used to classify the radar texture as built or non-built classes was selected following a supervised classification approach. Areas of interest (AOI) were digitized over high resolution imagery on Google Earth for a sample of varying size settlements and the corresponding measures of texture were examined selecting the minimum texture value matching the reference settlements of 200.

Errors in the radar based built land cover map were assessed relative to the land cover and land use map created by the Center for Remote Sensing and GIS applications (CERSGIS) at the University of Ghana, Legon. The built class extracted from radar texture was compared to the aggregated built classes (non-biotic constructed surfaces) from the CERSGIS land use land cover map for an independent stratified random sample of 2500 points, oversampling the built class given its limited coverage. 1600 points were drawn from the non-built class and 900 points were drawn from the built class and the agreement-disagreement of the two classifications was assessed for the points.

3. Landscape metrics of urban and vegetation patches

Built and vegetation land covers extracted from SMA (section 3.2.1) were overlaid on a series of uniform grid cells and class and landscape metrics were calculated for the two land cover classes at the cell level in order to evaluate land cover fragmentation. Six different grid cell sizes were used to estimate land cover fragmentation generating six different measures of urban context, which were then compared. Landscape metrics were estimated for cell sizes of 14400 meters (480 by 480, 30 m pixels), 7200 meters (240 by 240, 30 m pixels), 3600 meters (120 by 120, 30 m pixels), 1800 meters (60 by 60, 30 m pixels), 900 meters (30 by 30, 30 m pixels) and 450 meters (15 by 15, 30 m pixels) (see Figure 5).

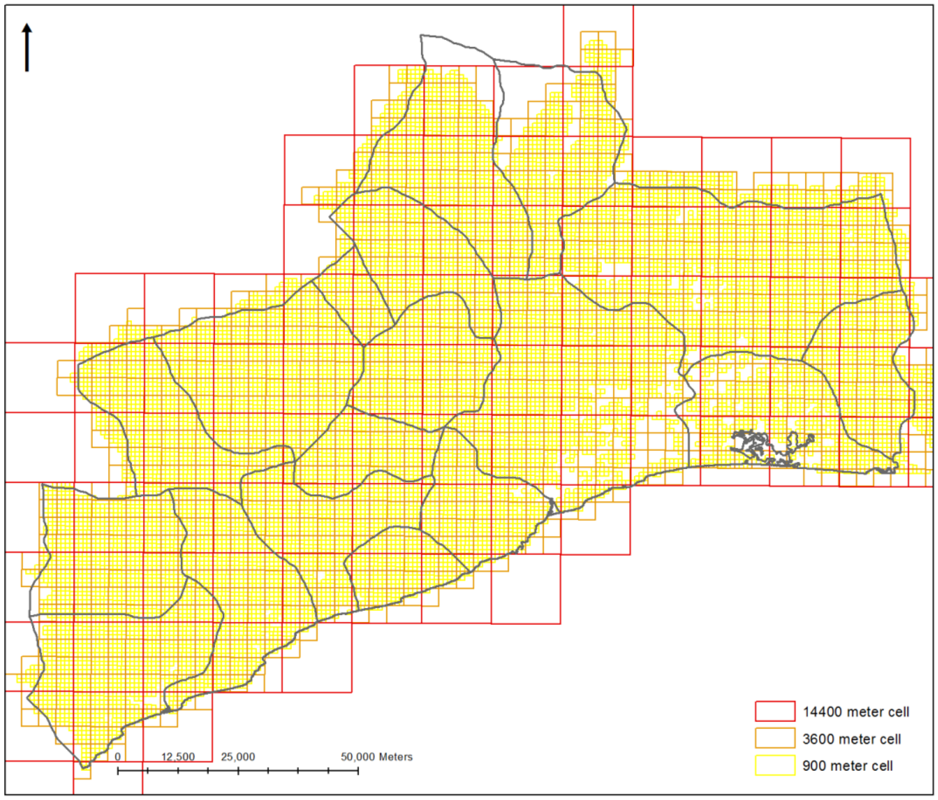


Figure 5: Three different grid cell sizes overlaid on a map of district boundaries

Built and vegetation patches were analyzed for each cell (at each grid cell size) with the goal of examining degree of fragmentation, dispersal and complexity throughout the urban transition. The metrics were calculated using FRAGSTATS software (McGarigal and Marks 1995), in combination with the R statistical package. Heterogeneity of the urban context was quantified using percentage of built land cover and density of built and vegetation patches. The complexity of urban patches was assessed through estimates of area weighted mean patch fractal dimension:

$$area\ weighted\ mean\ patch\ fractal\ dimension = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{2ln(0.25p_{ij})}{lna_{ij}}\ \frac{a_{ij}}{A}\right) \quad \text{Eq. 1}$$

where m is the number of patch types, n is the number of patches of a class, p_{ij} is the perimeter of the patch *ij,* a_{ij} is the area of patch *ij* and *A* is the total landscape area (Herold, Scepan and Clarke 2002)

In addition to the previously described metrics, an index of contagion was used to evaluate adjacency and compactness in the urban landscape:

$$Index\ of\ contagion = \left\{1 + \frac{1}{2lnm}\left[\left(\sum_{i=1}^{m}\sum_{k=1}^{m} p_i \frac{g_i}{\sum_{k=1}^{m} g_{ik}}\right) - lnp_i \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right]\right\}100 \quad \text{Eq. 2}$$

where m is the number of patch types (classes), p_i is the proportion of the landscape occupied by patch type (class i) and g_{ik} is the number of adjacencies (joins) between pixels of classes I and k (O'neill et al. 1988; Herold, Scepan and Clarke 2002).

Class and landscape metrics estimated for each cell size unit of analysis were then converted into raster files with the same resolution as the size of the unit of analysis. Each cell size had one raster file for percent built land cover, built patch density, built area weighed mean fractal dimension, contagion index, vegetation patch density and vegetation area weighed mean fractal dimension (Figure 6).

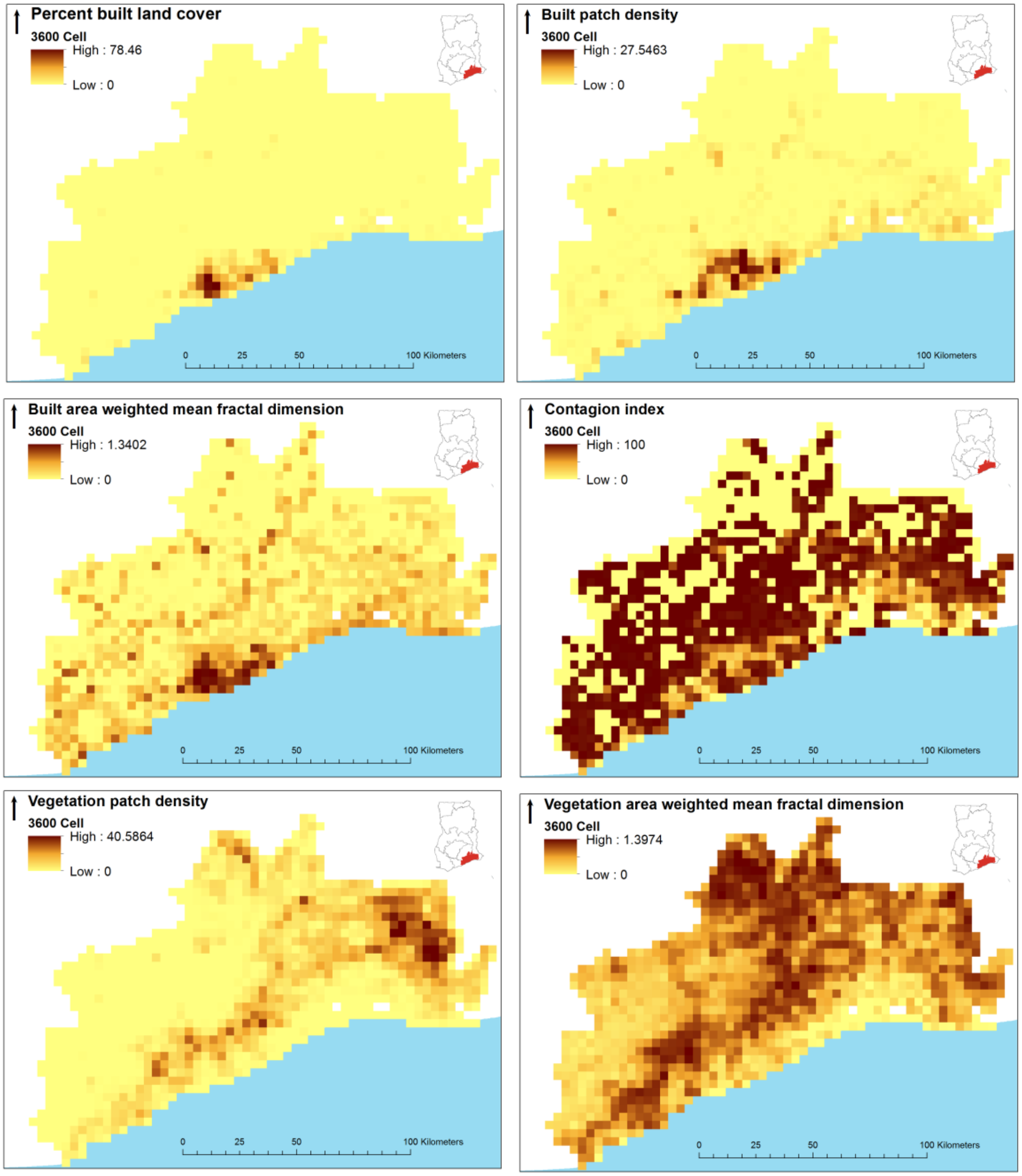


Figure 6: Measures of class and landscape fragmentation for 3600 m cell

4. Decision tree classifier

Decision tree classifiers allow the combination of different input layers into a single classified product by recursively splitting the data until every leaf is assigned to an independent class (Figure 7). Decision tree classifiers were used to combine landscape metrics calculated on the SMA-based classification of built and vegetation land covers with texture extracted from the SAR imagery for the six different units of analysis. This classification technique takes advantage of the spectral characteristics of the optical imagery, the pattern characteristics of the landscape metrics and the structural characteristics of the radar imagery to generate a range of urban context classes that describe the physical characteristics of the landscape.

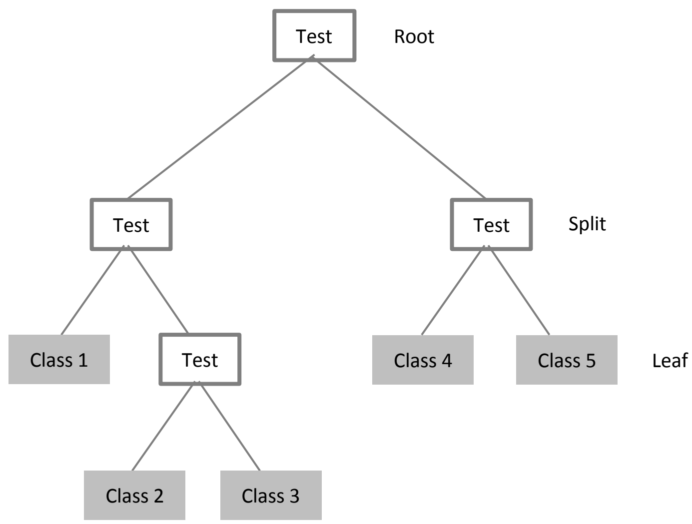


Figure 7: Recursive splitting in the decision tree classifier defined by test rules that partition the data into individual leafs or classes

The radar based texture measure detailed in section 3.2.2 was overlaid onto each one of the grid cell units of analysis and an aggregated measure of standard deviation was extracted for each cell (Figure 8).Cell level measures of landscape fragmentation and cell level aggregated radar texture were used as inputs for the decision tree classifier to generate a pattern based classification of the urban context.

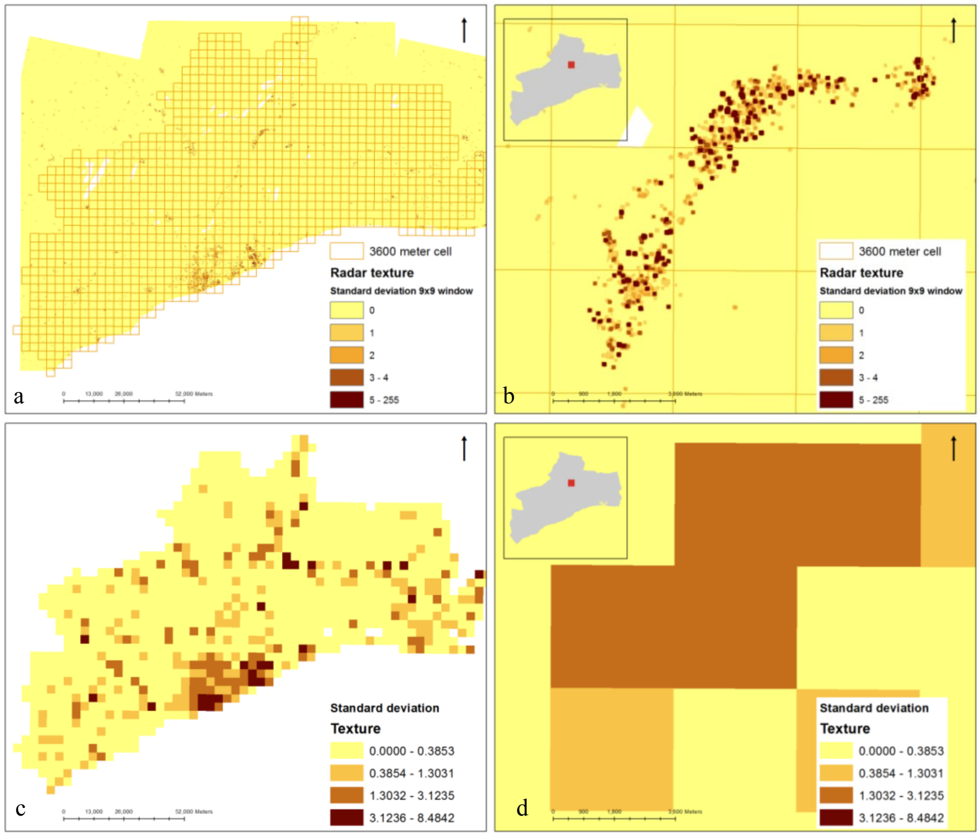


Figure 8: a) 3600 meter cell overlaid onto radar texture (9x9 SD) b) Zoom to 3600 meter cell overlaid onto radar texture (9x9 SD) c) Standard deviation of radar texture for 3600 meter cells d) zoom to standard deviation of radar texture for 3600 meter cells

The frequency distributions of the aggregated measures of fragmentation and radar texture were examined for each one of the scales of analysis (i.e., grid cell sizes) and were split in two (high and low values) using a natural breaks classification scheme that minimizes within-class variance and maximizes between-class variance. The natural break split for each variable was used to define the rules for the decision tree classifier and the resulting subclasses were named and validated by examining the land cover characteristics of a set of representative cells for each one the classes in the urban context scheme. Decisions rules were defined for each one of the scales of analysis with the breaks being determined by the characteristics of each frequency distribution.

Urban context classifications were created for the six different units of analysis using two different classification schemes. Larger cell sizes (14400 and 7200 m) with fewer cells were divided into six urban context classes: compact urban core, fragmented sub-urban, scattered settlement, sparsely populated, fragmented transition and unsettled land (Figure 9). The six class classification scheme is based on the four more basic pattern variables: percent impervious land cover, impervious land cover patch density, radar texture and vegetation land cover patch density. Given that the units of analysis are large enough to capture big sub-metropolitan areas measures of shape complexity and dispersion/interspersion were not used at these two scales.

Smaller cell sizes (450 to 3600 m) with more numerous cells were divided into nine urban context classes: compact urban core, fragmented large urban patches, dense and dispersed small urban patches, fragmented sub-urban, scattered settlements, sparsely populated, fragmented transition, fragmented unsettled and unsettled land (Figure 10).

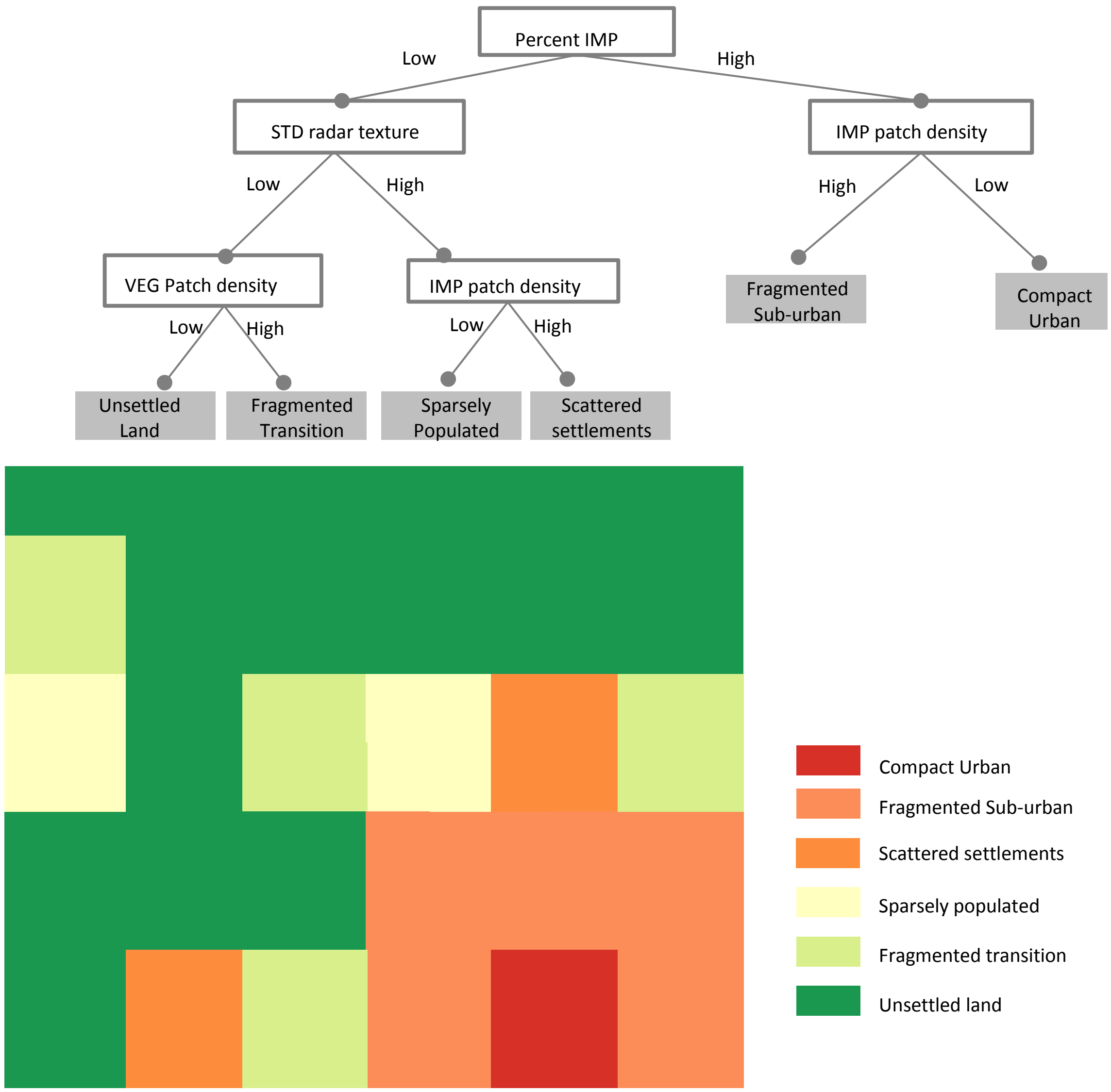


Figure 9: Model of urban context classification scheme for 14400 and 7200 m cells

In the case of cell sizes of 3600, 1800, 900 and 450 m, urban context was defined using all seven pattern variables including the measures of shape complexity and dispersion/interspersion. Smaller units of analysis, with more numerous cells, allowed increasing the number of classes, widening the diversity of urban contexts identified by the classification scheme. Measures of shape complexity and dispersion/interspersion for these units of analysis differentiate small homogeneous sub-zones that can be attributed to different neighborhoods within cities. The classification scheme for the 450 to 3600 m cells expands on the one defined for 7200 and 14400 m cells by subdividing both ends of the classification scheme based on shape complexity and dispersion/interspersion of built and vegetation patches. Based on a larger number of variables the classification scheme for the smaller cells identifies a wider range of transitional classes between the two ends of the urban context classification.

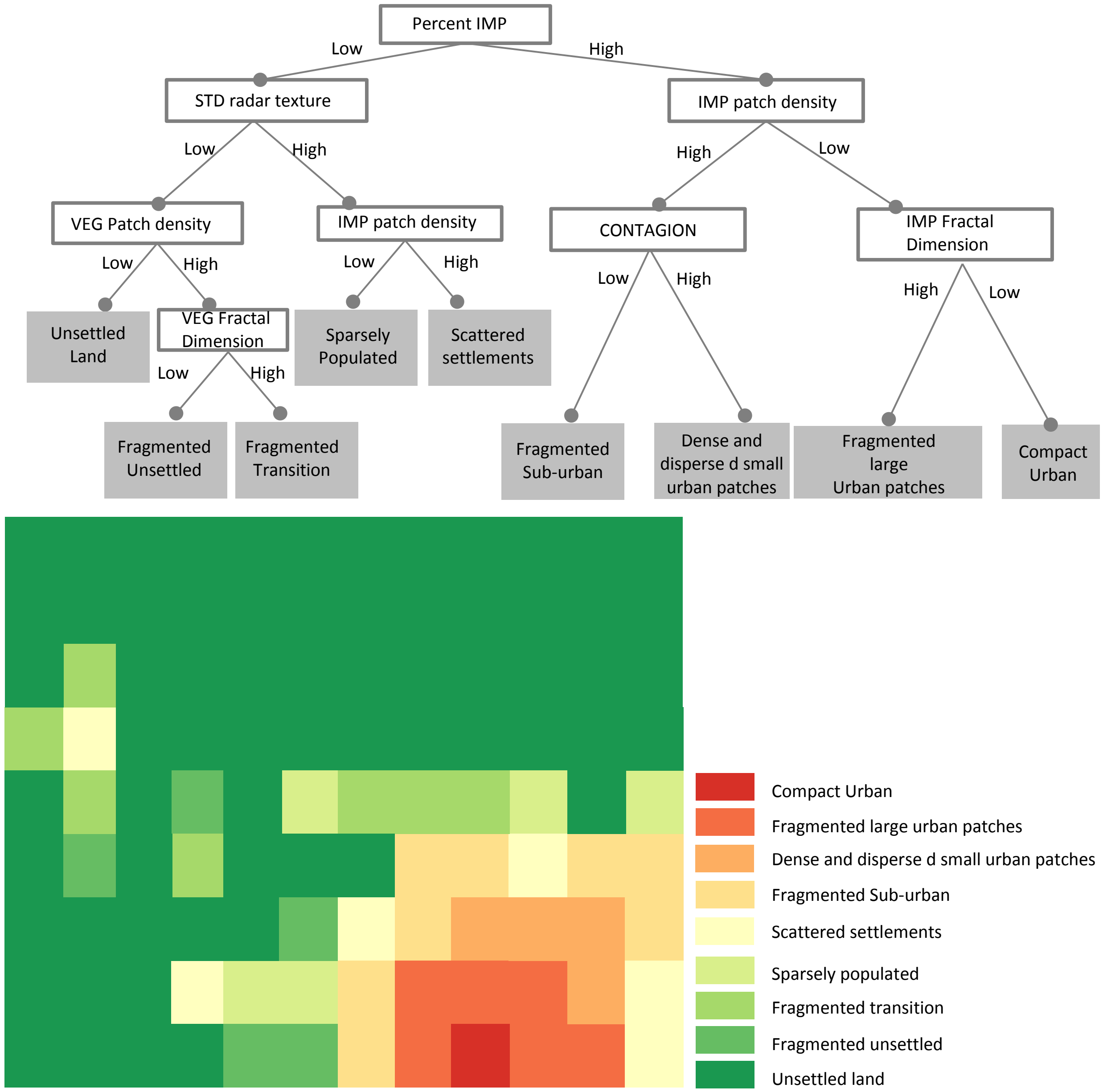


Figure 10: Model of urban context classes for 3600, 1800, 900 and 450 m cells

It is important to mention that the rules used in the decision tree classifier were defined *a priori* from the analysis of each one of the relative measures of pattern. Given the lack of reference data pertaining to degree of landscape fragmentation, it was impossible to rely on an iterative process of training, pruning and validating the decision tree. The validation of the classes consisted of examining in detail all measures of fragmentation for a sample of cells representing each of the urban context classes, then naming and ordering them according to their land cover and pattern characteristics. The resulting urban context maps for the six different scales of analysis were compared and the smallest cell size was selected for further spatial analysis.

Errors of the urban context map for the 450 m cell map were assessed relative to the land cover and land use map created by CERSGIS at the University of Ghana, Legon. The two classification schemes had to be aggregated in order to make them comparable. The top five urban classes in the urban context map: Compact urban, fragmented large urban patches, dense and dispersed small urban patches, fragmented sub-urban and scattered settlements were aggregated into a single built class with the rest of the urban context classes defined as non-built and the non-biotic constructed surfaces from the CERSGIS map were aggregated into a single built class. All other classes were aggregated into a non-built class.

C. Examining drivers of fertility throughout diverse urban contexts

1. Census variables

Data from the 2000 census at the enumeration area (EA) level (Figure 11ca) was assigned to towns outside of Accra (Figure 11 b) and EA centroids within the city of

Accra. The census data were then aggregated to the cell level used as units of analysis for the urban context maps from section 3.2.

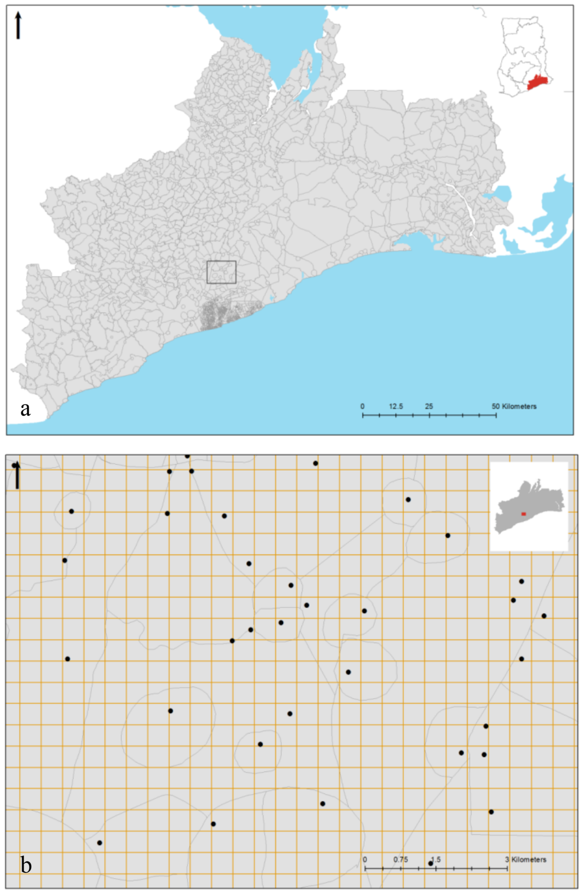


Figure 11: a) Enumeration areas from the 2000 census b) 450 m grid overlaid onto towns that were assigned EA level data

Enumeration area boundaries defined by Ghana Statistical Service have very heterogeneous shapes and sizes, and are heavily influenced by the presence of settlements. Converting the census data from the EA level into a continuous grid allows generating units of analysis of comparable size and incorporates both rural and urban areas as a means for representing the entire rural-urban gradient. Variables measuring population characteristics, fertility levels and household composition were aggregated to the cell level in order to model the association between household composition, fertility levels and urban context.

2. Ordinary least square (OLS) regression

Fertility levels were modeled through ordinary least squares (OLS) regression using household composition variables and urban context as explanatory variables of interest:

$$y_i = \beta_0 + \sum_k \beta_k x_{ki} + \varepsilon_i \qquad \text{Eq. 3}$$

where the dependent variable y is defined as an age standardized measure of children ever born to women of reproductive age (CEBz) at location i, β_0 is a constant and β_k are the coefficients measuring the association between y and each independent variable x_k at location i.

$$CEBz = \frac{CEB_{individual} - avgCEB_{agegroup}}{standard\ deviationCEB_{agegroup}} \qquad \text{Eq. 4}$$

Living arrangement variables were created at the household level based on individual responses to the 2000 census and then aggregated to the cell unit. In order to identify different types of living arrangements, household members were assigned to different generations based on age thresholds and relationship to the head of household, allowing the identification of households with inter-generational co-residence. Household composition is also affected by high levels of long- and mid-term mobility of household members, where the absence of members is fairly common. Thus, in addition to inter-generational co-residence, households were classified according to whether they were headed by women; whether a member's usual residence was in a different district and whether the residence held foster children. The association between fertility, living arrangements and urban context was evaluated for the six different units of analysis and results were compared. The smallest unit of analysis (450 m cell) was chosen for further analysis given the detail captured for small area urban context and given that its size is closest to the median size of the enumeration areas. Within the study area EA sizes range between 2000 m^2 and 260 km^2, with 45% of the EA's areas falling below the 0.2 km^2 represented by a 450 by 450 m cell size.

Regression analysis establishes unbiased linear estimations when the data meet assumptions of normality, homoscedasticity, linear associations and uncorrelated errors. In geographical analysis, the existence of spatial dependence deviates from the assumption of non-correlated errors in the data. The resulting residuals were analyzed for spatial autocorrelation in order to identify whether there is a spatial component unaccounted for in the regression analysis. Spatial autocorrelation was estimated through a global Moran's I:

$$I = {}^{n}/_{s_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} {z_i}^2} \qquad \text{Eq. 5}$$

where z_i is the deviation of an attribute for feature i from its mean$(x_i - \bar{X})$, w_{ij} is the spatial weight between features i and j, n is the total number of features and

$s_{0}=\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}$ is the aggregate of all spatial weights. The spatial weights matrix was created using a K-neighbors approach where the five closest neighboring cells were defined as adjacent.

Given that the residuals were found to be spatially autocorrelated, individual variables were tested for spatial dependence using both Global Moran's I_i and the Getis and Ord G_i^* spatial autocorrelation statistic (Getis and Ord 1996).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}} \qquad \text{Eq. 6}$$

Where x_j is the attribute value for the feature j, w_{ij} is the spatial weight between feature i and j, n is equal to the total number of features $\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$ and $S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$

Variables showing significant spatial dependence were then filtered using the Getis spatial filter (Getis and Griffith 2002), which isolates the spatial component from the variable. The spatially filtered variable x_i^* is based on the Getis and Ord G_i^* statistic and is defined as:

$$x_i^* = \frac{x_i\left[\frac{w_i}{n-1}\right]}{G_i^*(d)} \qquad \text{Eq. 7}$$

The filtered variable is the result of the comparison of the G_i^* observed with its expected value given no spatial autocorrelation. The distance d is determined by estimating the G_i^* statistic at a series of increasing distances until spatial autocorrelation starts to decrease.

An OLS regression is then run with the spatially filtered variables. Once again, the residuals are evaluated for the presence of spatial autocorrelation.

3. Spatial lag and spatial error models

Given that spatial autocorrelation was still found in the residuals of the spatially filtered variables OLS a spatial error autoregressive model was used to specify the spatial component within the regression analysis. In a spatial autoregressive model the spatial dependence found in the dependent variable can be formally modeled through either a spatial lag model or a spatial error model (Chi and Zhu 2008). The spatial lag model is defined as:

$$y = x\beta + \rho wy + \varepsilon \qquad \text{Eq. 8}$$

Where *y* is the vector of response variables, *x* is the matrix of explanatory variables, *w* is the spatial weights matrix and *ε* is the vector of independent, not identically distributed error terms. The spatial error model on the other hand is defined as:

$$y = x\beta + u \qquad \text{Eq. 9}$$

$$u = \rho wy + \varepsilon \quad \text{Eq. 10}$$

In the spatial lag model spatial autocorrelation is modeled through the association between the dependent variable and the spatially lagged independent variables, whereas the spatial error model incorporates spatial autocorrelation through the error term. The advantage of the spatial lag model is that it allows for the specification of spatial dependence in the variables included in the model, while the spatial error model assumes that spatial autocorrelation accounts for key explanatory variables not included in the model (Chi and Zhu 2008). A spatial error model is selected based on the diagnostics for spatial dependence estimated on the GEODA package, where the Lagrange Multiplier for the error model shows higher statistical significance than the one for the spatial lag model (Anselin 2004). The spatial error regression is used to model fertility as a function of household structure and urban gradient.

4. Geographically weighted regression

Finally the association between fertility, household structure and urban context is evaluated for spatial heterogeneity through geographically weighted regression (GWR). Local parameters were generated through GWR incorporating spatial heterogeneity within the regression analysis as an added term in the equation (Fotheringham, Charlton and Brunsdon 2009).

$$y_i = \beta_0(u_i, v_i) + \sum k\beta_k(u_i, v_i)x_{ik} + \varepsilon \quad \text{Eq. 11}$$

Where (u_i, v_i) correspond to the coordinates of the ith point and k denotes the number of independent variables. GWR generates as many models as points included in the regression and the strength of the relationship between dependent and independent variables is affected by its neighbors, with:

$$\beta(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y \qquad \text{Eq. 12}$$

Where W corresponds to the weight assigned in each model to neighboring points, at the same time that neighboring points are defined by a kernel-based distance decay function. GWR is used to estimate the spatially varying strength of relationship between fertility, household structure and the urban gradient.

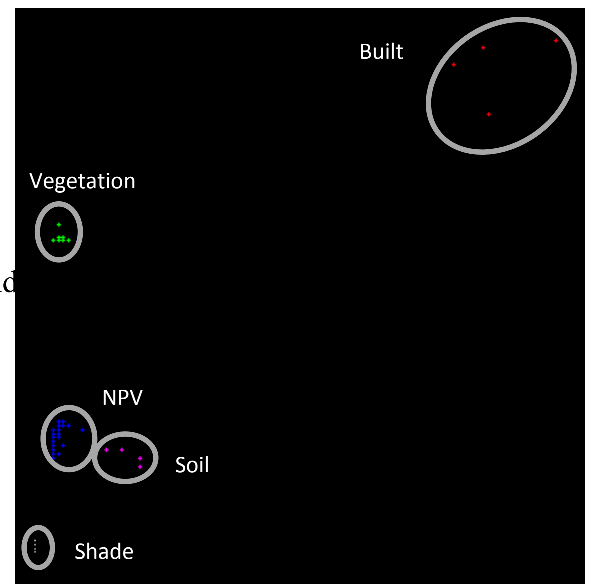
The spatial analysis of the association between fertility, degree of urbanization and household composition was used to identify major spatial trends guiding the diffusion of fertility and urban transitions.

IV. Results: Defining the urban context

A. Identifying built and vegetation land cover

Built and vegetation land covers were mapped through spectral mixture analysis using five image end-members: green vegetation, non-photosynthetic vegetation, shade, soil and built environment. Image end-member selection was aided by a Pixel Purity Index that identified the image's spectral features extremes as illustrated in figure 12.

Band



Band 3

Figure 12: PPI and example of End-members

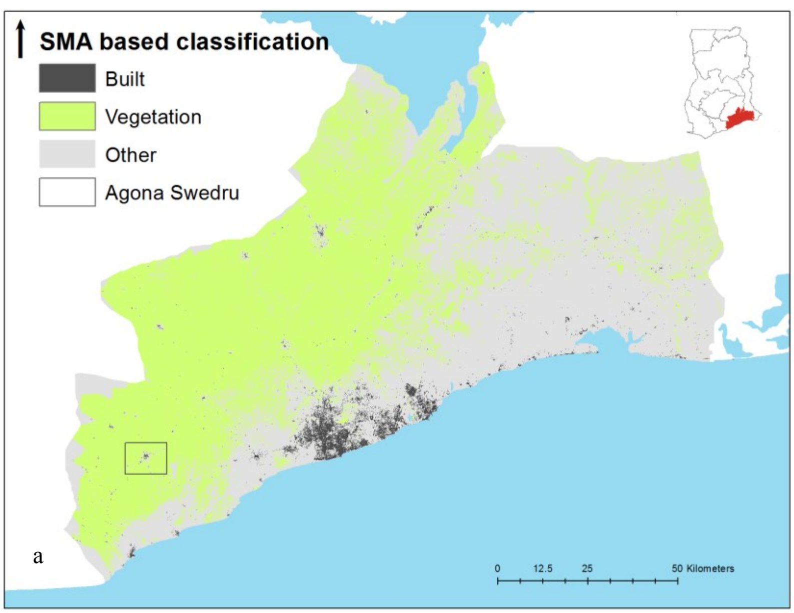
Extreme features were then visually inspected and a series of end-member combinations were tested in un-mixing models. Through model testing, sources of land cover confusion were identified such as fire scars and dry bright soil or sand bars. The dark features of recent fire scars were consistently associated with shade end-members whereas bright soils and sand bars were associated with built environment end-members. In order to improve the accuracy of the SMA model areas with both fire scars and bright sand flats or soils were masked out. Fire scars were identified with a supervised classification using the three first principal components of the Landsat ETM+ image and then masked out. High spatial resolution imagery (Google Earth) was used to visually isolate problematic areas with bright soils and sand flats, those areas were manually digitized and masked out as well.

Results from the final SMA model show that distinguishing soil and built land cover classes remain problematic given the similarity of both classes, but also given the high prevalence of mixing that occurs in cities of the developing world where a large share of the streets remains unpaved (Ridd 1995). Close examination of the spectral characteristics of end-members and resulting proportions indicate that multiple end-member spectral mixture analysis (MESMA) could improve the distinction of soil and built proportions.

The resulting land cover proportions were classified based on thresholds, identifying pixels with a majority of proportion of impervious surfaces and vegetation as built and vegetation land cover. The resultant shade proportions image was visually inspected in order to assess shade in association with built features and vegetation. Results showed that within the urban context the shade class plays an important role in revealing building shadows and dark pavement features. Major settlements were visually delineated on high spatial resolution imagery and pixels having high proportions of both shade and impervious surfaces were classified as built. SMA results pointed also to a connection between vegetation land cover and the predominance of shade, a link that suggests the significance of mixing of vegetation and shade in vegetated areas (Lu, Moran and Batistella 2003). Normalized Difference Vegetation Index (NDVI) was calculated and compared to the SMA-derived proportions and used in the identification of pixels having high proportions of shade and vegetation, which were classified as vegetation land cover. The final land cover map produced through SMA shows that Accra and Tema are merging into a single metropolitan area that dominates the urban context in the region. A network of smaller settlements can be seen spreading east-west following the coastline (Figure 13a) and scattered mid-size towns, such as the town of Agona Swedru, extend inland following major roads (Figure 13 b and c).

Errors in the SMA based classification of built and vegetation land covers was assessed by comparing them to the corresponding classes in the CERSGIS land cover map for a stratified random sample of points. As noted above, the non-biotic constructed classes in the CERSGIS map, which include rural and urban settlements and transportation ways, were all aggregated into a single built class. The aggregated vegetation class from the CERSGIS map included agricultural land, forest, savanna and shrub thicket plus a range of combinations of mixed land use. A comparison of the maps shows that there is a fair amount of disagreement (primarily apparent omissions) relative to the CERSGIS map, for both the built and the vegetation classes, with the biggest discrepancy for vegetation (Figure 14). The differences found in vegetation extent can be linked to the fact that all vegetation types from the CERSGIS map were aggregated into a single class that includes large patches of savanna and mixed land use with dispersed fallow and shrub lands where dry scattered grassland were identified by the SMA as mostly bare soils. This discrepancy is particularly noticeable in the area that expands east of Accra towards the border with Togo.

An examination of the agreement-disagreement tables in Tables 1 and 2 shows that the built and vegetation classification generated through SMA has fair agreement with the CERSGIS map with producer's accuracies of over 60%. In the case of the built class we can see that the magnitudes of omission and commission errors are comparable between 13% and 15% (Table 1).



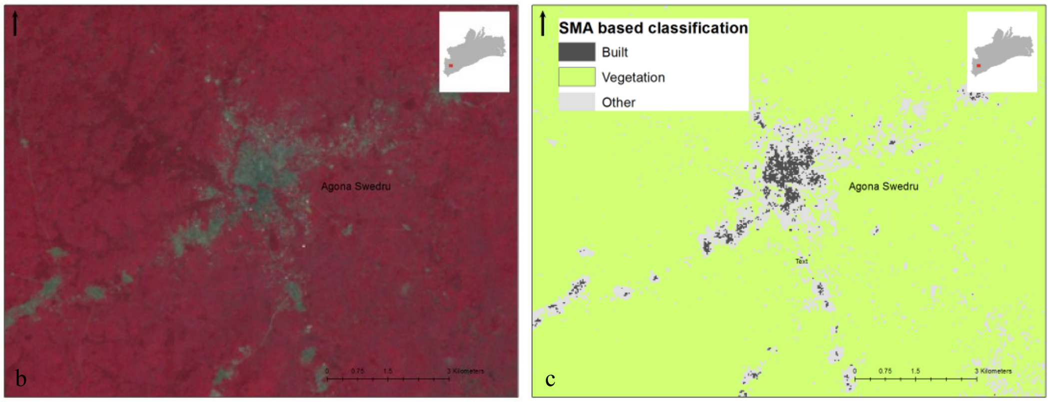


Figure 13: a) Built (>50% impervious & >25% impervious+>50% shade) and Vegetation (>50% vegetation & >25% vegetation+>50% shade) land cover extracted from SMA b) Landsat ETM+ false color infrared zoom on the town of Agona Swedru c) Built and Vegetation land cover extracted from SMA zoom on the town of Agona Swedru.

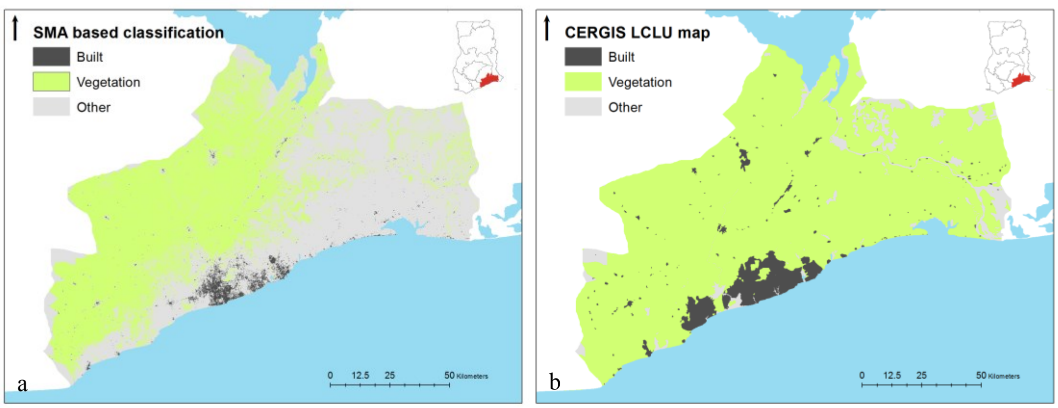


Figure 14: a) Built and vegetation land cover classified from SMA proportions b) Built and vegetation land cover aggregated from CERSGIS classes

Table 1: Agreement-disagreement table for the SMA based Built class

		CERSGIS classification			
		Non Built	Built	Total	Users accuracy
SMA Class	Non built	1933	67	2000	96.7
	Built	75	425	500	85
	Total	2008	492	2500	
	Producers accuracy	96.3	86.4		

The vegetation class on the other hand has a much higher omission of roughly 40% that contrasts with a very low commission of 3% (Table 2). As it was mentioned earlier the magnitude of the omission indicates the prevalence of mixed pixels in areas where vegetation and other land covers such as bare soil are highly intermixed.

Table 2: Agreement-disagreement table for the SMA based Vegetation class

		CERSGIS classification			
		Non-vegetation	Vegetation	Total	Users accuracy
SMA Class	Non-vegetation	553	747	1300	42.5
	Vegetation	38	1162	1200	96.8
	Total	591	1909	2500	
	Producers accuracy	93.6	60.9		

B. Extracting surface texture from radar imagery

ERS-2 synthetic aperture radar imagery was used to generate a measure of surface texture and used as a proxy measure for the presence of built artifacts. Pre-processing of the radar imagery included terrain correction, radiometric normalization and the generation of a layover mask to exclude areas with topographic distortion. A 9 by 9 moving window was used to estimate the standard deviation of the radar backscatter in order to identify areas with heterogeneous returns which are associated with the built environment. Given that the radar imagery has a spatial resolution of 12.5 m single pixel spikes in the measure of texture could be associated with scattered individual buildings or artifacts which wouldn't necessarily indicate the presence of a settlement. By using a 3 by 3 average window the effects of single pixel outliers are minimized, enhancing the identification of built areas that are large enough to be associated with a human settlement. Figures 15 b-c and d-e illustrate for the two towns of Agona Swedru and Agona Nyakrom the correspondence of the smoothed radar texture with the false color infrared Landsat image for 2002.

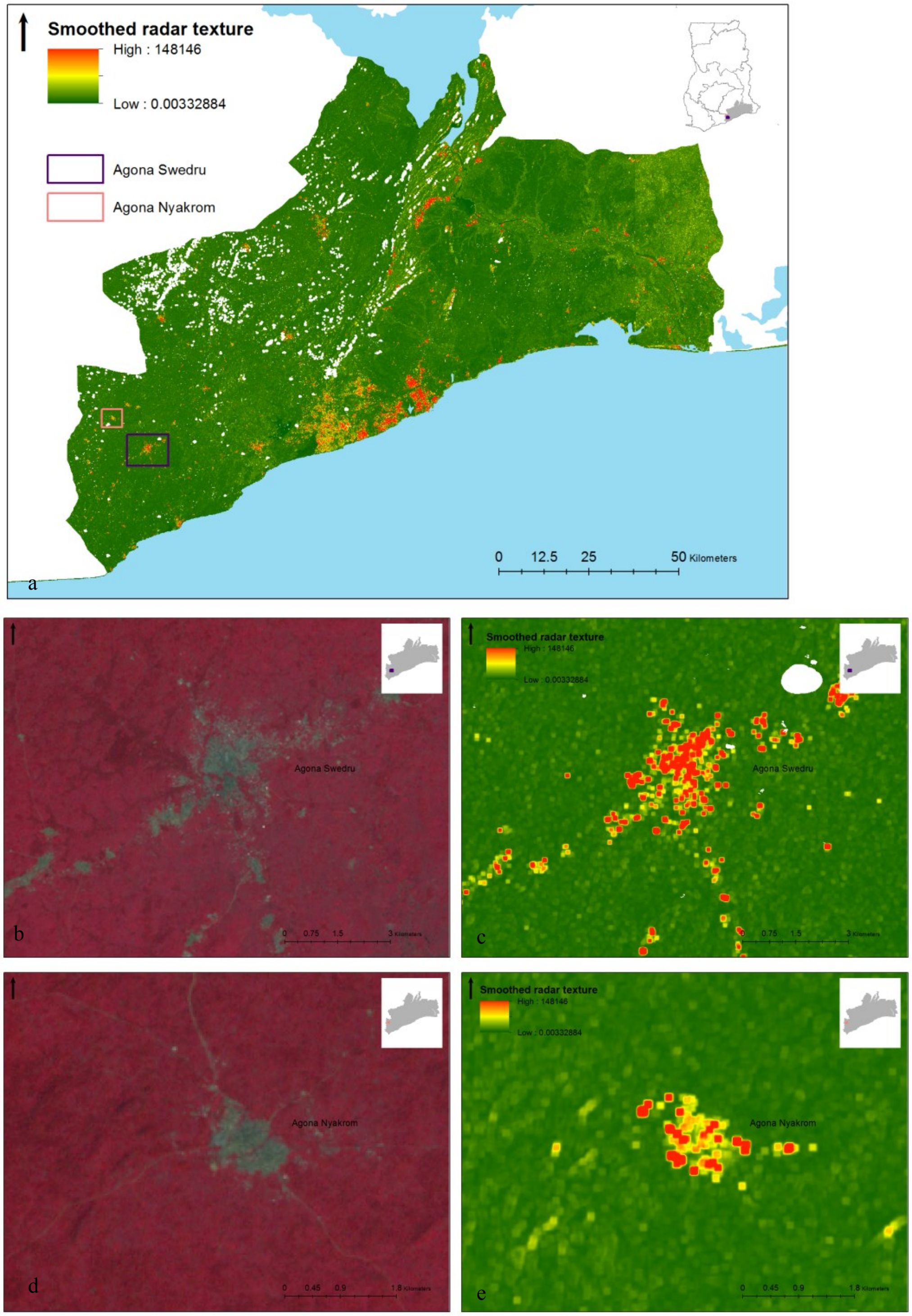


Figure 15: a) 3 by 3 average of radar texture (Standard deviation 9x9) b) Landsat ETM+ false color infrared zoom on the town of Agona Swedru c) 3 by 3

average of radar texture zoom on the town of Agona Swedru d) Landsat ETM+ false color infrared zoom on the town of Agona Nyakrom e) 2 by 3 average of radar texture zoom on the town of Agona Nyakrom

The final radar texture was rescaled to 16 bit images and the rescaled images were classified into built and non-built classes (Figure 16a) based on a threshold defined through comparison with high resolution imagery from Google Earth.

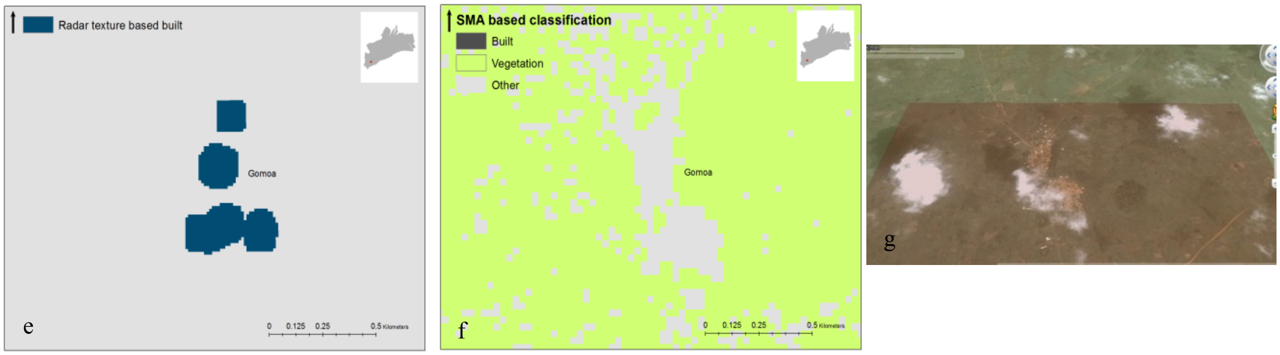


Figure 16: a) Radar based built class b) Radar based built class zoom on the town of Kwame Adewe c) SMA based land cover classification zoom on the town of Kwame Adewe d) Google Earth image from the town of Kwame Adewe 2003 e) Radar based built class zoom on the town of Gomoa f) SMA based land cover classification zoom on the town of Gomoa e) Google Earth image from the town of Gomoa 2000

Close inspection of the SMA based and radar texture based built land cover classes against Google Earth imagery indicates that the radar texture based class captures a wider range of settlement sizes in the study area (Figure 16b-g). The small towns of Gomoa and Kwame Adewe on figure 16 b-d and e-g illustrate the propensity of the radar based built class to detect small towns that are missed by the SMA based classification of the built class. While the built map extracted from SMA seems to have a fair amount of omission, the radar texture extracted built class, given its finer spatial resolution, is capable of identifying much smaller towns

The resulting agreement-disagreement table (Table 3) shows that while the radar extracted built class has a user's accuracy of 64.4 % it has a much higher producer's accuracy of 91%. These results are not surprising since the radar imagery's single band provides a limited picture of land cover characteristics.

Table 3: Agreement-disagreement table for radar-based built class relative to CERGIS 2000 LCLU map

		CERSGIS classification			
		Non-built	Built	Total	Users accuracy
Radar Class	Non-built	1544	56	1600	96.7
	Built	320	580	900	64.4
	Total	1864	636	2500	
	Producers accuracy	82.9	91.2		

C. Measures of landscape structure

Measures of landscape fragmentation were derived using the SMA-based vegetation and built land cover classes for a series of uniform grid cells. Given the wide range in size of enumeration areas an alternative uniform grid cell approach is proposed in this study to estimate landscape fragmentation. Landscape and class metrics were calculated for six different size units of analysis, 450 m, 900 m, 1800 m, 3600 m 7200 m and 14400 m. A first look at the resulting class and landscape metrics shows that larger cells capture higher variances for most of the estimated metrics, a result that was expected. However in the case of the measures of built fractal dimension and index of contagion cells with the highest variance correspond to two intermediate cell sizes, 1800 and 3600 m and not the larger ones (Figure 17).

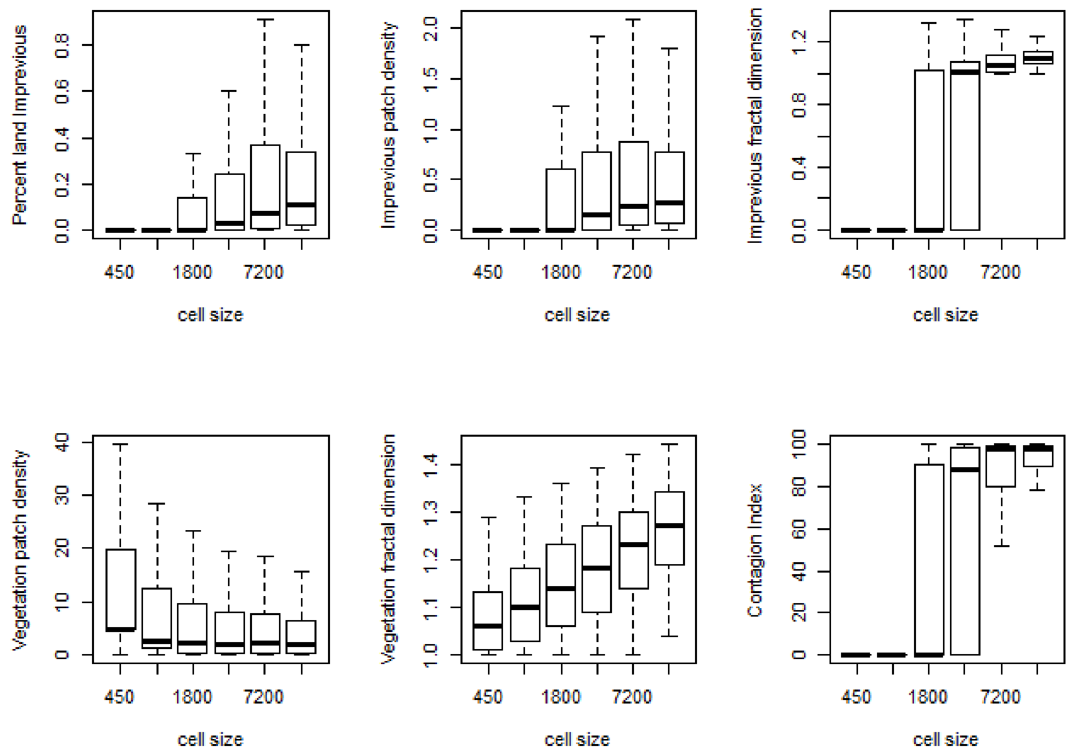


Figure 17: Comparing landscape metrics variance for different size units of analysis for the entire study area

This result indicates that when it comes to measuring shape complexity and dispersion intermediate units of analysis fail to capture homogeneous regions while small and large units of analysis succeeded. When comparing the resulting spatial distributions of the measures of landscape fragmentation it is evident that a smaller unit of analysis (450 m) captures greater detail about structural arrangement than the intermediate and large size units of analysis (Figure 18, 19, 20 and appendix 1).

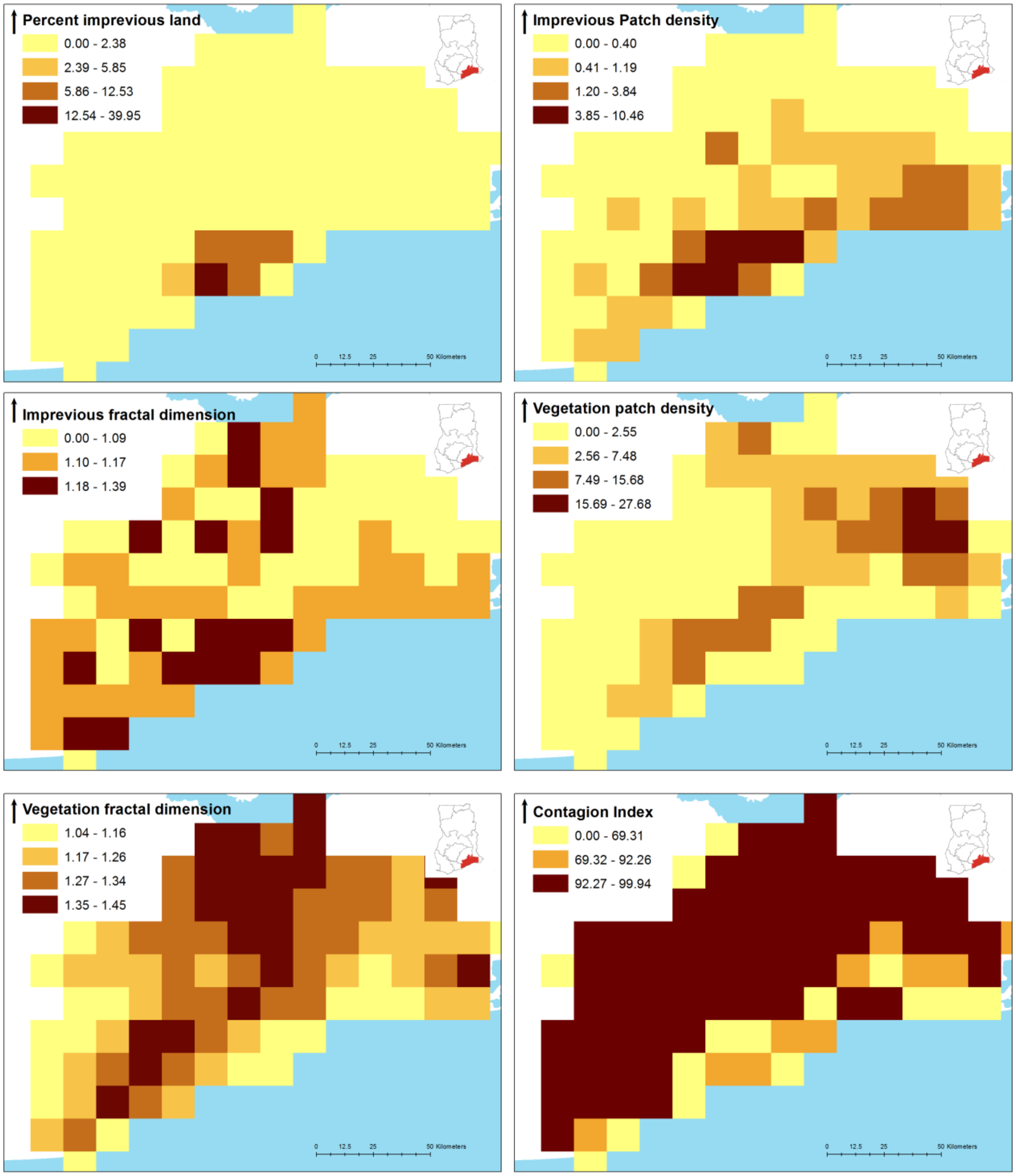


Figure 18: Landscape and class metrics for 14400 m cell unit of analysis

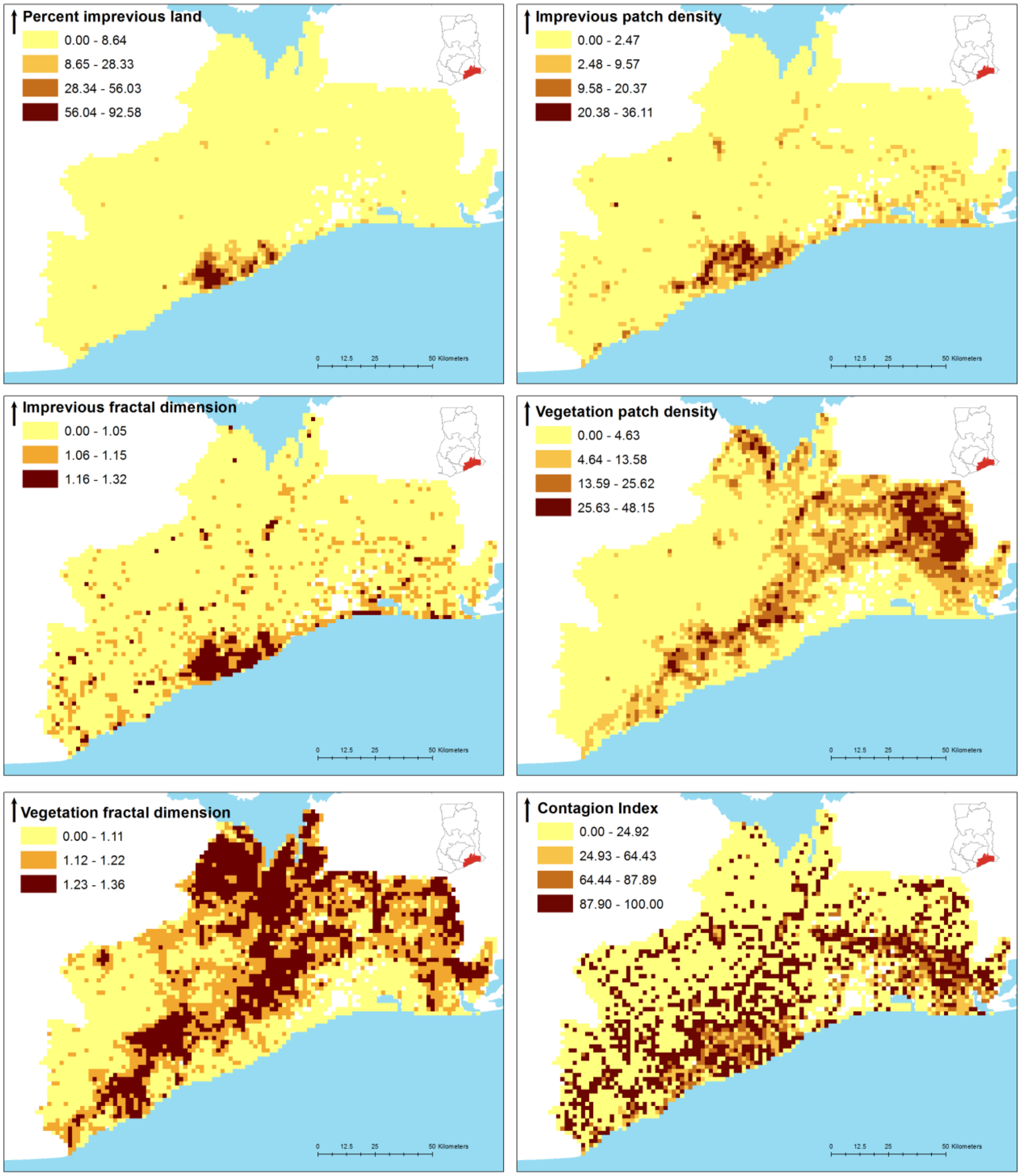


Figure 19: Landscape and class metrics for 1800 m cell unit of analysis

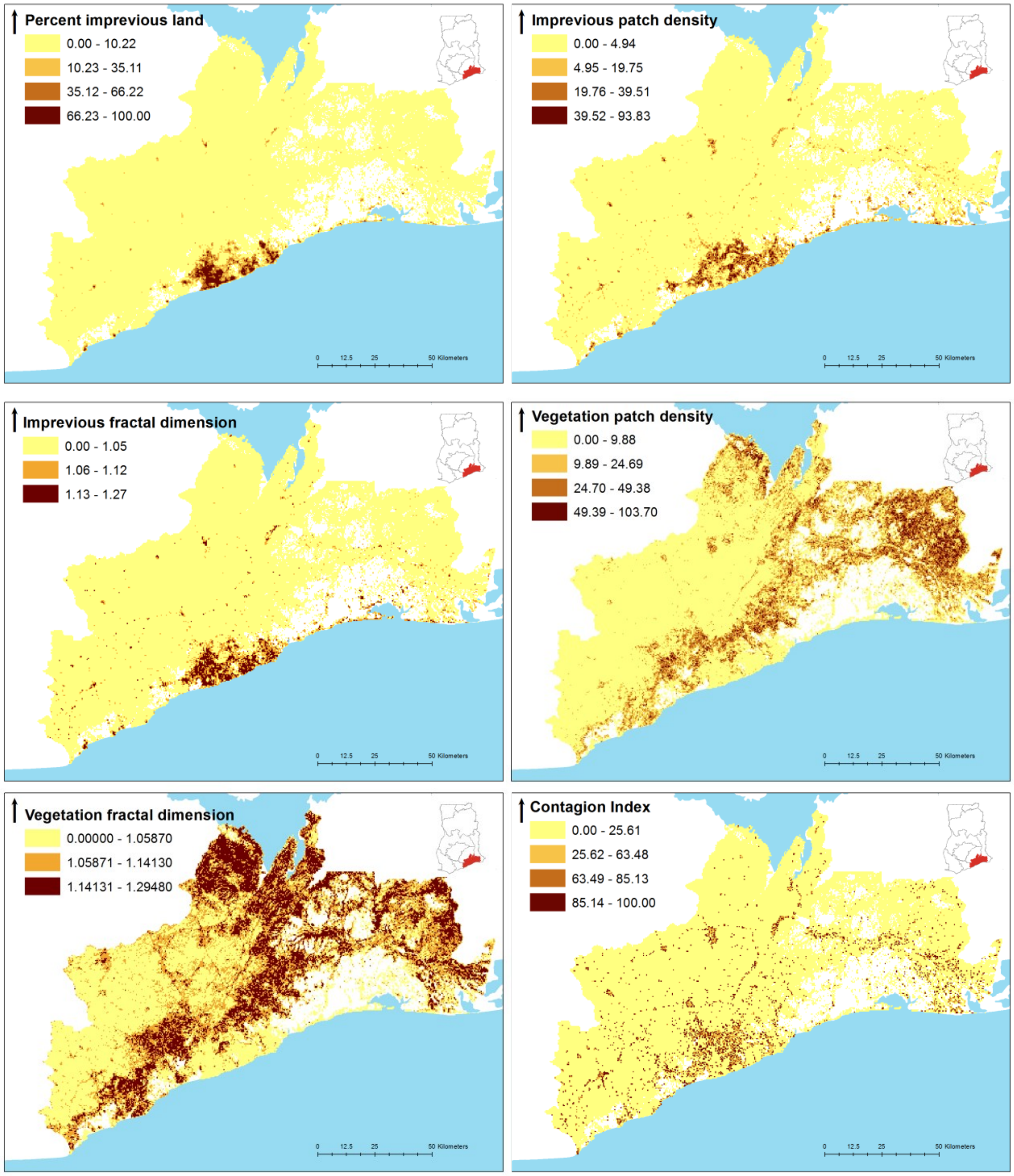


Figure 20: Landscape and class metrics for 450 cell unit of analysis

D. Urban context definition

Measures of landscape fragmentation were combined with the measure of radar texture using a decision tree classifier in order to generate a pattern-based classification of urban context. Radar texture was aggregated to each one of the six units of analysis by estimating the standard deviation of the radar texture for each cell. The frequency distributions of each one of the seven variables were evaluated in order to determine a set of decision rules for the decision tree classifier. Given that the larger units of analysis have fewer cells in comparison to the smaller ones, two different sets of classifications schemes were selected. For 14400 and 7200 m cells, totaling 90 and 313 cells respectively, a six class urban context scheme was defined using four variables: percent of impervious land, impervious patch density, standard deviation of the radar texture and vegetation patch density (Figure 21).

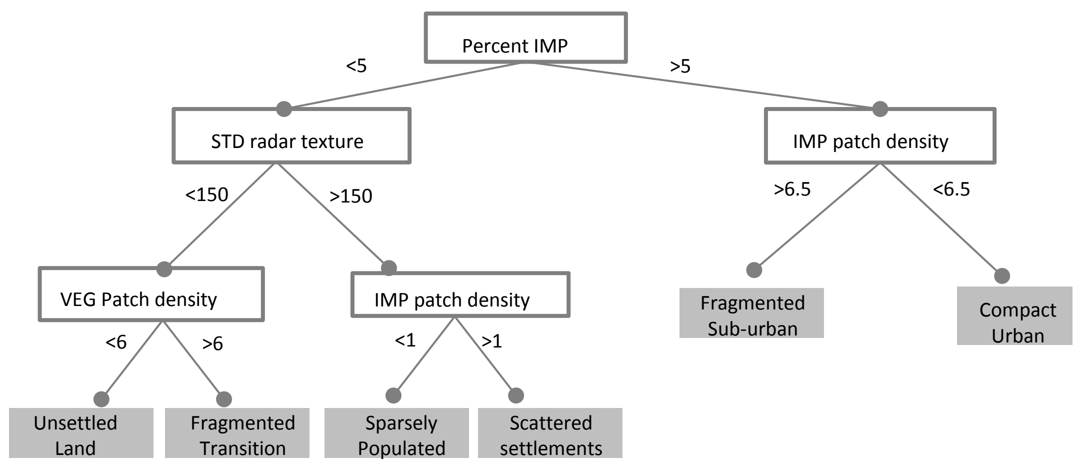


Figure 21: Decision rules for 14400 m cell units of analysis

The first split in the decision tree was defined at 5% impervious land cover. A low threshold was selected for percent impervious land cover because of the relatively small portion of the study area that is covered by built surfaces (around 2% of the study area was classified as built based on the SMA proportions). The frequency distribution of the landscape metric variables were inspected and partitioned in two (high and low values) using natural breaks for each distribution (Figure 22). Once cells went through the first split those above 5% built were further divided using a threshold of impervious patch density. Cells with higher percentages of impervious land cover and lower densities of impervious patches denote lower levels of urban fragmentation, where lower densities are the result of fewer larger impervious patches. On the other hand, higher densities of impervious patches for cells with significant proportions of built land cover indicate the prevalence of numerous small size patches associated with fragmented urban contexts.

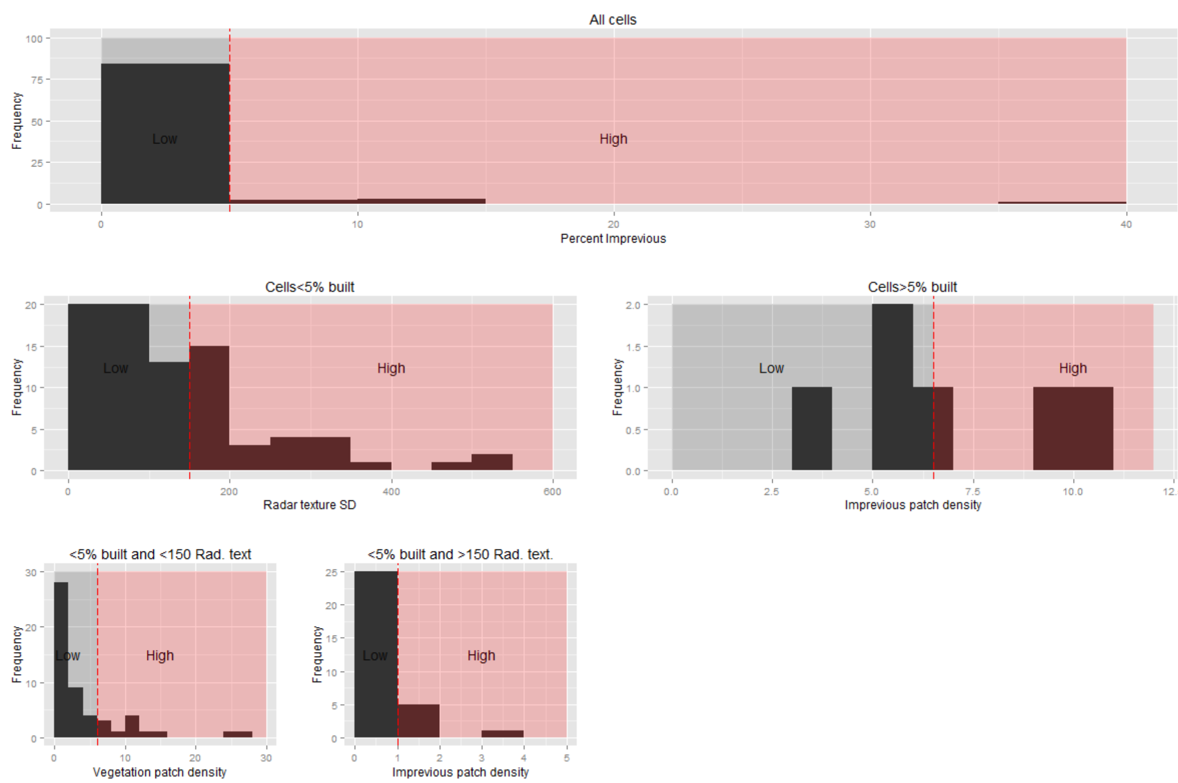


Figure 22: Partitioning of variables with natural breaks for 14400 m cells.

Cells with built land cover below 5% were further split using the standard deviation of the measure of radar texture, where high values indicate incidence of built structures. Cells with higher radar textures were further split based on their densities of built patches, classifying them into higher density scattered settlements and lower density sparsely populated areas. The last two categories correspond to cells with the lowest proportions of impervious land cover and the lowest values of radar texture, these cells were in turn split based on their vegetation patch densities. Cells with higher densities of vegetation patches were identified as fragmented transitional land cover where higher density is the product of a large number of smaller vegetation patches. On the other hand cells with lower densities of vegetation were identified as unsettled land where fewer large vegetation patches prevail.

The final urban context classification for cells of 14400 m identified three out of the 87 cells as compact urban covering the most urban areas of Greater Accra and Tema, an additional three cells are classified as fragmented sub-urban in the outskirts of Greater Accra (Figure 23). Six cells are identified as scattered settlements on the banks of the Volta River, outskirts of Tema and an inland area covering the city of Koforidua in the eastern region. Areas classified as sparsely populated spread inland from the outskirts of Greater Accra and cover roughly 30% of the study area (25 cells).

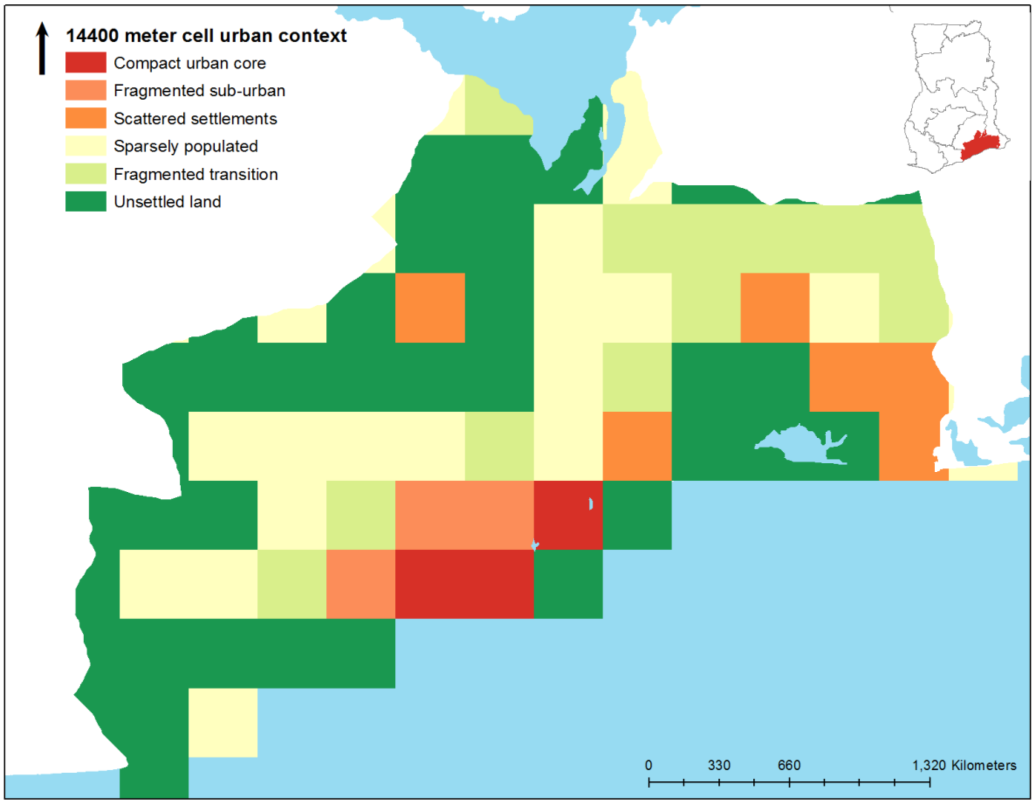


Figure 23: 14400 cell size urban context classification

For the four smaller units of analysis (450 m to 3600 m) a nine class urban context classification scheme was defined using all seven analyzed variables: percent impervious cover, impervious patch density, fractal dimension of impervious surfaces, index of contagion, standard deviation of the radar texture, vegetation patch density and fractal dimension of vegetation patches (Figure 24). The variables were partitioned into high and low values using the natural breaks in each frequency distribution (Figure 25).

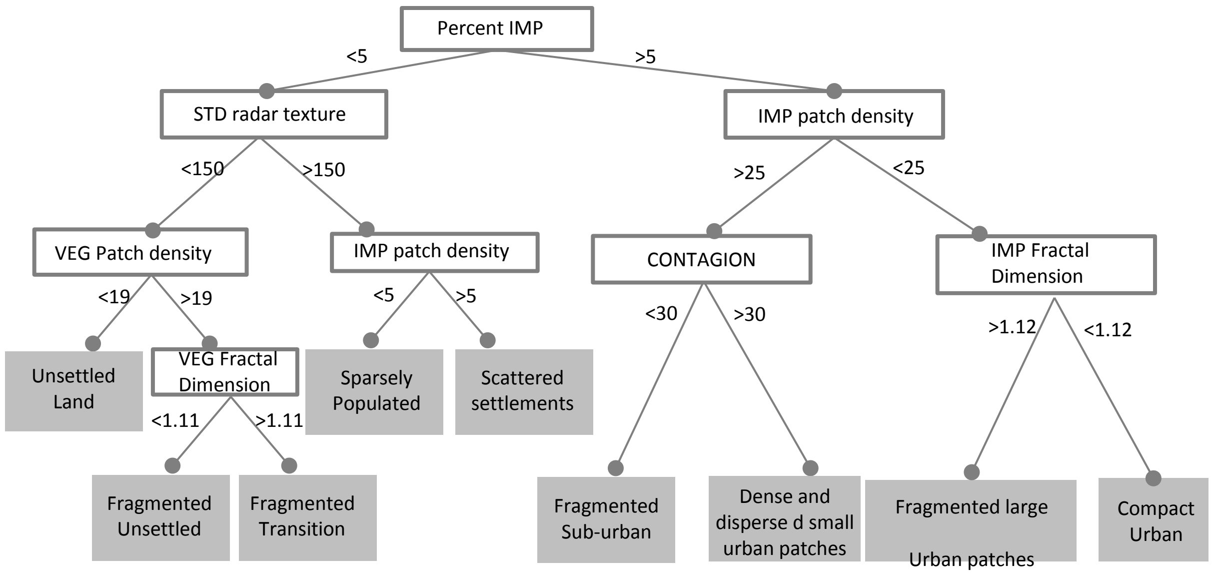


Figure 24: Decision rules for 450 m cell units of analysis

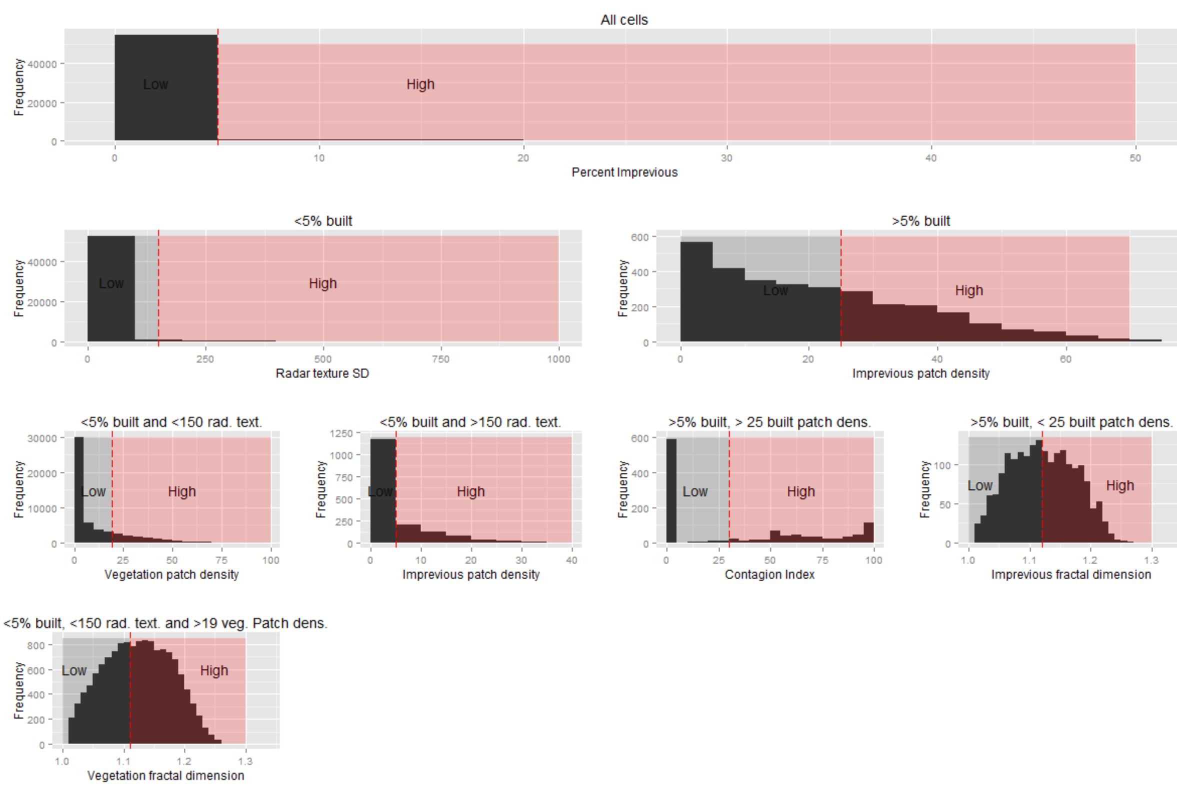


Figure 25: Partitioning of variables with natural breaks for 450 m cells.

Even though the proportions of built land cover are higher for smaller units of analysis the share of cells with predominant built land cover remains low because of the relatively small area it covers in the study area. For that reason the same threshold of 5% impervious land cover was used as the first split in the decision trees created for 450 to 3600 m cells. Once cells were partitioned into lower and higher proportions of built land cover the latter ones were further partitioned based on the density of built patches. Cells with lower densities of impervious patches were identified as less fragmented urban areas where fewer large size built patches prevailed whereas higher densities were identified as areas with more numerous smaller size built patches. The less fragmented lower density urban patches were further split into compact urban and fragmented large urban patches based on the shape complexity described by the fractal dimension of built patches. Cells with lower built fractal dimensions indicate the predominance of simple shapes in the built environment, a sign of higher compactness. On the other hand higher fractal dimensions are associated with higher complexity in shapes, a feature that indicates fragmentation of the urban environment. The more fragmented higher density urban cells were further split into dense and dispersed small urban patches and fragmented sub-urban classes based on their contagion index. Higher contagion indices indicate that urban cells have larger size impervious patches, highly clumped together and with low levels of interspersion. In contrast lower contagion indices indicate that urban cells have smaller size impervious patches, highly dispersed with higher levels of interspersion, representative of fragmented sub-urban areas.

Cells with higher radar texture were identified from within the group of cells with low proportions of built land cover and those were further split into higher density built scattered settlements and low density sparsely populated areas. Cells with low proportions of impervious cover and lower values of radar texture were further split based on the density of vegetation patches. Cells with higher densities of vegetation patches are associated with higher fragmentation in vegetation with more numerous small size vegetation patches, while lower densities are associated with fewer larger vegetation patches characteristic of non-fragmented unsettled land. Finally the cells identified with fragmented vegetation were further split into fragmented transition and fragmented unsettled land based on the fractal dimension of vegetation patches. Cells with higher fractal dimensions indicate the predominance of complex shape vegetation patches pointing to higher levels of vegetation fragmentation while those with lower fractal dimensions indicate vegetation patches with simple shapes a sign of relatively low vegetation fragmentation.

The 450 m cell classification of the urban context identifies almost 1000 out of the 58 000 cells as compact urban areas; these cells are located in Greater Accra and Tema, but also in the centers of major cities such as Koforidua and Winneba and major coastal and inland settlements (Figure 26).A similar number of cells are classified as fragmented large urban patches with most of those cells located within the central areas of major cities and settlements. Around 500 cells are identified as dense and dispersed small urban patches found closer to the outskirts of larger cities such as the area located between Accra and Tema. The fragmented sub-urban class is restricted to the outskirts of large cities found almost entirely in coastal areas, where urbanization is spreading at a fast pace. Scattered settlements on the other hand spread around the periphery of intermediate towns, most of them inland. Cells classified as sparsely populated areas cover around 1200 cells and are scattered throughout the study area extending beyond the peripheries of consolidated towns. Finally, cells identified as transitional classes spread into unsettled land following a band pattern that expands beyond the periphery of settled areas.

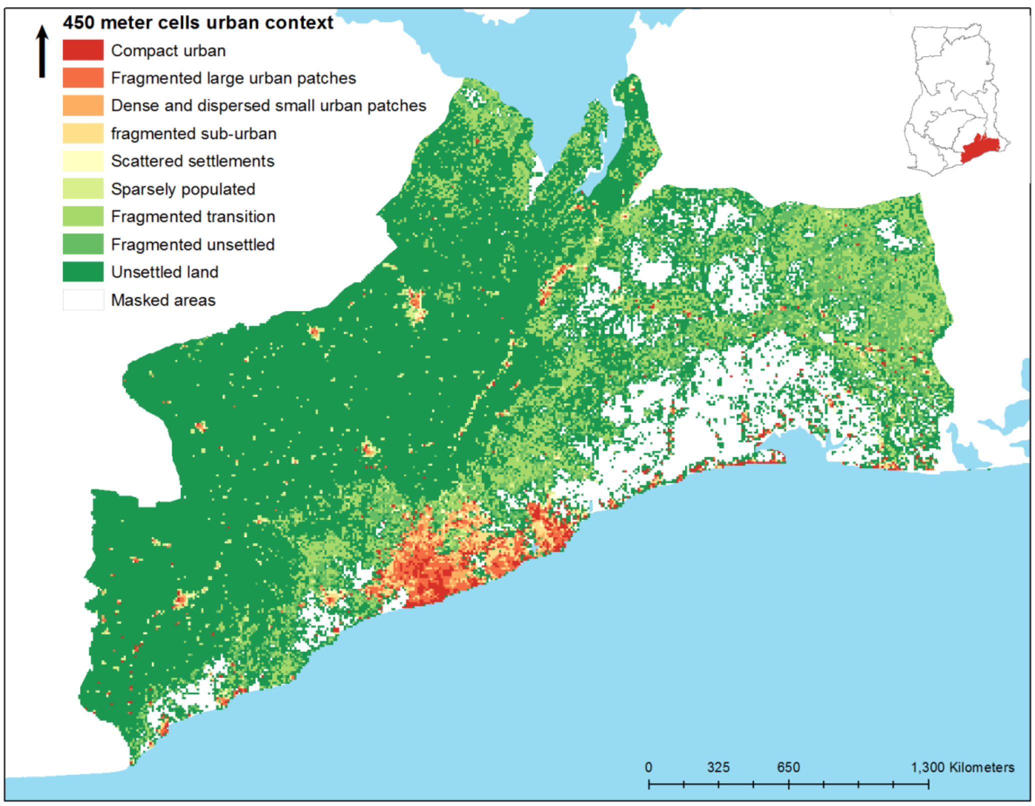


Figure 26: 450 m cells urban context classification

Comparing landscape metrics throughout the six different scales (appendix 2) we can conclude that smaller cell sizes capture more detail in terms of landscape structure. At the same time smaller units of analysis tend to have lower variances in measures of pattern which means that they tend to capture more homogeneous regions. The urban context map for 450 m cells was compared to the CERSGIS land use land cover map in order to assess the level of agreement between the two independent classifications. The five most urbanized classes in the urban context map were aggregated to represent a single built land cover class and compared to the aggregated non biotic constructed surfaces classes from the CERSGIS land use land cover map. An agreement-disagreement table was created by matching the land cover classes assigned to the random points from the urban context map and the CERSGIS classification (Table 4). Results show that the overall accuracy is over 65% with an omission error of only 5%. The higher commission error can be interpreted as a product of the discrepancy of scale in the data sources for the two maps and as a product of the difference in classes mapped. While the aggregated urban context classes represent a wide range of urban environments that include different combinations of mixed land use, the CERSGIS map is restricted to only capturing built surfaces. The prevalence of commission disagreement can be attributed in part to the differences in classification schemes used by the two independent classifications.

Table 4: Agreement-disagreement table for top five urban classes in urban context map relative to CERGIS 2000 LCLU map

		CERSGIS classification			
		Non-built	Built	Total	Users accuracy
Urban context Classes 1-5	Non-built	1564	36	1600	97.8
	Built	290	610	900	67.8
	Total	1854	646	2500	
	Producers accuracy	84.4	94.4		

The pattern-based urban context map integrates radar and optical imagery with measures of landscape metrics through the use of a decision tree classifier. This map is based on a nuanced definition of urban spaces based on landscape characteristics and provides a gradient-like approach to defining urban spaces. Results from the error assessments show that the SMA based built land cover classification alone does not capture the entire built environment in the study area. Differentiating land covers for mixed pixels combining soils and impervious surfaces with moderate resolution optical imagery has shown to be a difficult task, a problem that is very prevalent in urban environments of the developing world. Radar imagery provides a valuable complementary source of data for detection of man-made features; however as a single data source it fails to detect the full extent of the urban environment. Combining both sources of data allowed generating a more complete map of the built environment that captured a wider range of urban features. Finally, through the use of landscape metrics this approach was able to capture in detail the diversity of urban patterns that characterize different urban contexts. To create this pattern-based urban context map required the definition of a uniform unit of analysis that represented homogeneous urban spaces. Comparing different size units of analysis allowed recognizing that smaller units tend to capture more homogeneous spaces while providing at the same time the maximum detail about spatial patterns.

V. Results: Fertility, living arrangements and diverse urban contexts

The goal of this study is to determine the degree of association between urban context and demographic characteristics in the study area, and more specifically to examine the role played by the urban context in shaping drivers of fertility levels in southern Ghana. The uniform cell unit of analysis was defined as a solution to the problem of linking population and land cover data collected at different scales and for different areal zones. The demographic data collected for enumeration areas were aggregated in order to create variables using cells as the spatial unit of analysis. Variables were created at the individual and household levels and then aggregated to the EA level. In rural areas the EA level data were split between the towns located within each EA, while in urban areas the data were assigned to the centroid of the EA polygon. Having the census data assigned to towns and EA centroids allowed overlaying uniform grid cells onto the point layer and aggregate the data for all points falling within a cell.

A. Census variables

Individual level census data were used to create indicators of fertility (the dependent variable) and household structure (independent variables of interest). As discussed above, an age standardized children ever born variable was created and used as an individual level measure of fertility (Weeks et al. 2013). Household structure variables were created to identify different types of extended family co-residence. Households where grandchildren of the head of household reside were identified, as were households where parents of the head of household reside and those with foster children. Households with children that have the two parents residing in the household were differentiated from those with single parents and those practicing polygamy. Lastly, households with a woman head of household were identified. Variables were created to characterize the head of the household using religion, ethnicity, usual residence and migration within the last five years. Variables were created to summarize housing characteristics including having permanent walls, a permanent roof, access to piped water and own toilet, variables were also created to characterize women's education, employment and marriage status.

Examining the distribution of the different living arrangements identified through the household structure variables it is apparent that the most common living arrangements in the study area include households that host foster children, households where the head is a female and households where the children have a single parent residing with them. In contrast, the least common living arrangements include households that practice polygamy and households where the parents of the head reside (Figure 27).

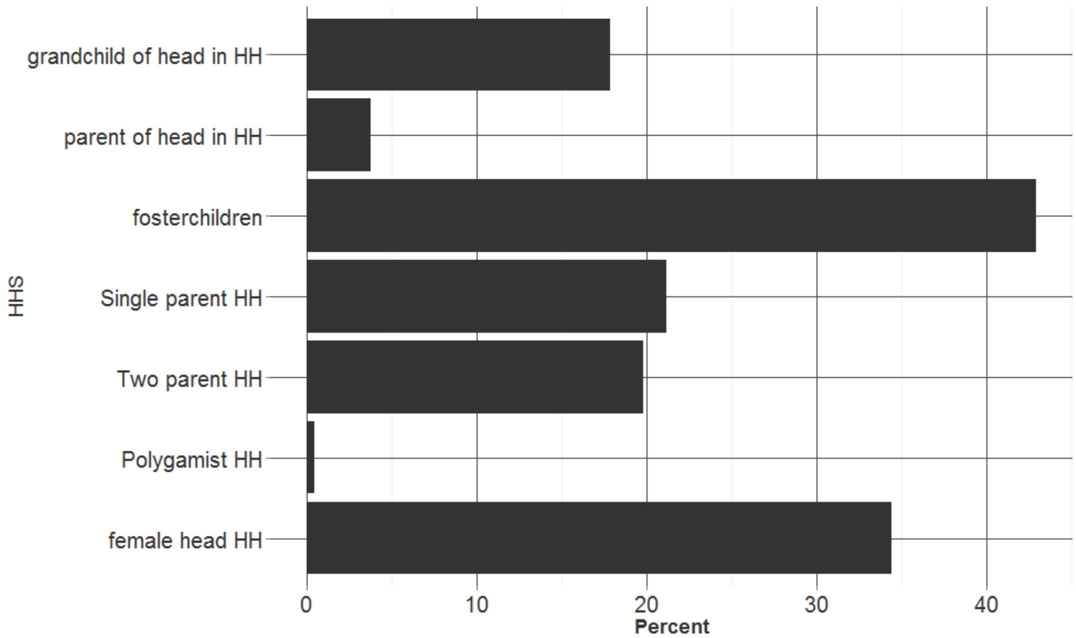


Figure 27: Distribution of household structure variables for 450 m cells

The distribution of living arrangements throughout the range of urban contexts shows that within the most common living arrangements there is a higher concentration of households hosting foster children in the most urban end of the urban context spectrum. On the other hand, single parent households and female headed households are more common in areas located on the least urbanized end of the urban spectrum (Figure 28)

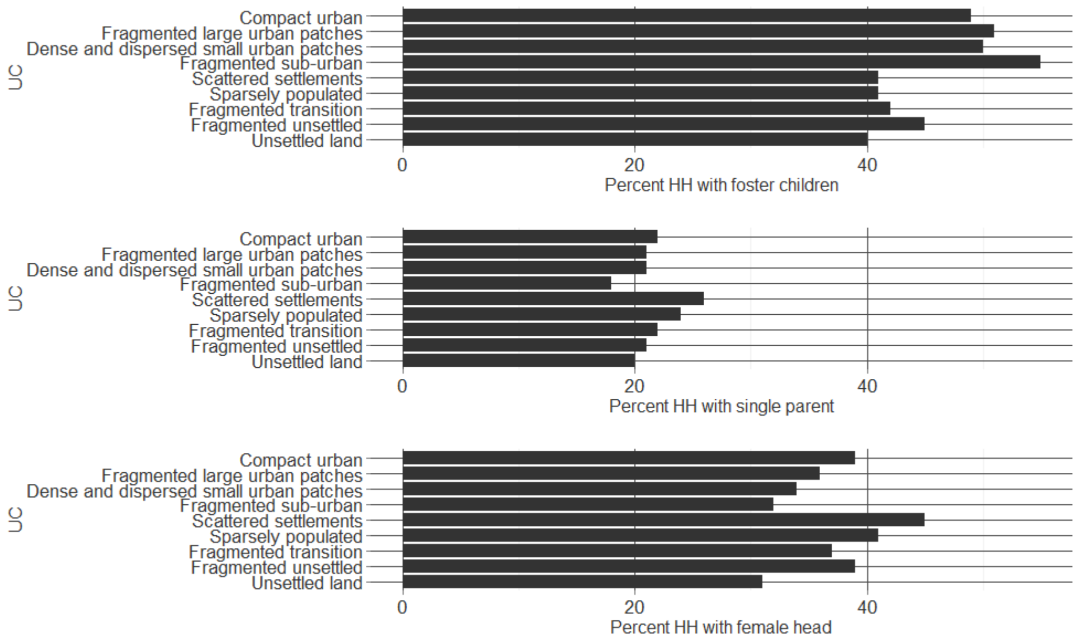


Figure 28: Distribution of selected living arrangements per urban context class

As with living arrangements, fertility levels vary substantially throughout the urban context. Examining the average age standardized children ever born for each urban context class it is evident that the lowest fertility is found in the class dense and dispersed small urban patches, followed by the fragmented sub urban class and the fragmented large urban patches (Figure 29). The highest fertility is seen in the unsettled land and fragmented transition classes while intermediate fertility levels are found both in the compact urban core and the scattered settlements that stretch throughout the countryside.

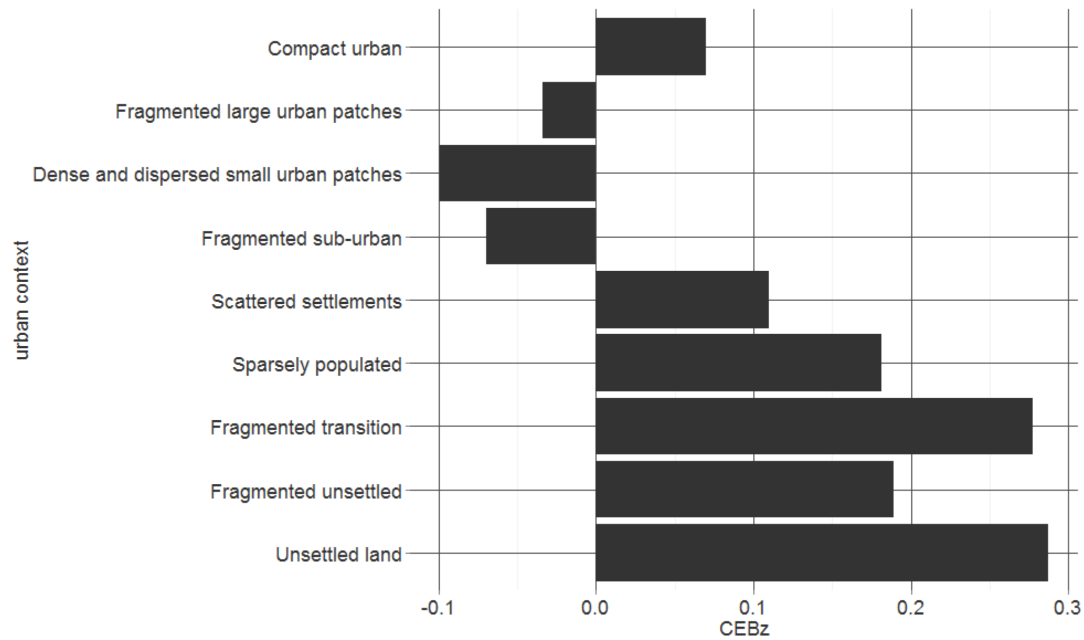


Figure 29: Average age standardized Children ever born (CEBz), $CEBz = \frac{CEB_{individual} - avgCEB_{agegroup}}{standard\ deviationCEB_{agegroup}}$ per urban context class

The number of cells with population data varies widely from one unit of analysis to the next. For example, in the case of the 450 m cells we have over 58 000 cells with land cover data but only 4014 of those cells coincide with towns. On the other hand, for 14400 m cells we have 90 cells with land cover data and 87 of those coincide with towns. Given this variability, and given the fact that there was no *a priori* theory about which spatial scale is “best,” it was decided to assess the effects of scale on the relationship between fertility and urban context by running a set of ordinary least square regressions for the six different scales of analysis.

B. Ordinary least squares (OLS) regression

Fertility levels were modeled through ordinary least squares regression using household structure and urban context as explanatory variables of interest controlling for characteristics of the household head, the housing and women. Variables with Variance Inflation Factors (VIF) over 6 were removed from the model in order to reduce multicollinearity. The explanatory variables were added in five blocks, the first block corresponds to a set of dummy variables describing urban context (as described in the previous section). For the smaller units of analysis (450 to 3600 m cells) one dummy variable was created for each one of the eight urban classes leaving the unsettled land class as the reference class. For the larger units of analysis (7200 to 14400 m) one dummy variable was created for each one of the five urban classes, leaving the unsettled land class as the reference class. The second block included variables of interest describing living arrangements. The third to fifth blocks correspond to the control variables, in which the third block describes characteristics of the head of household, the fourth block describes housing characteristics and the fifth block summarizes women's characteristics.

1. OLS for 450 m cell unit of analysis

Results from the OLS regression with variables aggregated at 450 m cells indicate that the urban context alone accounts for 16% of the variance from cell to cell in the level of fertility (the average CEBz). This increases slightly to 18% when we add the household structure variables, then jumps to 29% when head of household characteristics are introduced, slight increase to 31% with the addition of housing characteristics, and finally to 36% when we add in the variables related to the characteristics of adults females in the household (Table 5). Results show that urban context at this scale of analysis plays an important role in shaping fertility levels with five urban classes resulting in p-values below 0.1 when all the controls are included. Compact urban, fragmented large urban patches, dense and dispersed small urban patches, fragmented suburban all show significant negative associations with fertility levels with the highest coefficient corresponding to the fragmented large urban patches class. Among the urban classes with significant negative associations with fertility, the most consolidated compact urban class is the one with the weakest of the coefficients. On the other hand the variable fragmented transition shows a significant positive correlation with fertility, meaning that above average fertility levels are found in the least urbanized areas where landscape fragmentation is an indicator of early rural settlements. It is interesting to note that the fragmented transition variable only becomes significant after all controls are added. Results from the first block indicate that all urban context variables but the fragmented transition were significant. This result indicates that while some of the differences between urban classes are explained by the characteristics of the household head, housing and women in the case of the fragmented transition class, these differences aren't captured by the control variables.

The standardized coefficients observed for the household structure variables indicate that few living arrangements have significant impacts on fertility levels in the study area. Lower fertility levels are observed for households with single parents and female heads, where p values under 0.001 indicate a strong association between fertility and these specific living arrangements. In terms of religion and ethnicity, results from OLS show that non-traditional religions tend to have a significant positive correlation with fertility while the only ethnic group that shows higher than average fertility corresponds to those with a household head belonging to the Ga ethnic group. Households that have a head of household who moved from a different district within the last five years tend to have significantly lower fertility levels than average. This result points to the importance of the connection between migration and fertility onsets. Finally it is worth mentioning that the percentage of women aged 15 to 20 that remain single is significantly associated with lower fertility levels, a result that indicates that delaying marriage is an important driver of fertility decline in the region.

Table 5: 450 m cell OLS regression coefficients (y:cebz, n: 4015)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.187***	-0.14***	-0.107***	-0.059***	-0.047**
Fragmented large urban patches	-0.31***	-0.249***	-0.186***	-0.122***	-0.098***
Dense and dispersed small urban patches	-0.198***	-0.165***	-0.11***	-0.067***	-0.056***
Fragmented sub-urban	-0.176***	-0.147***	-0.103***	-0.064***	-0.055***
Scattered settlements	-0.093***	-0.065***	-0.031*	-0.018	-0.015
Sparsely populated	-0.081***	-0.059***	-0.028*	-0.016	-0.012
Fragmented transition	-0.009	0	0.014	0.018	0.024.
Fragmented unsettled	-0.086***	-0.062***	-0.02	-0.014	-0.014
R2 :0.1647					
Household structure					
Number of extended family members		-0.04.	-0.042*	-0.029	-0.031.
Grand children of the head in HH		0.071**	-0.019	-0.031	-0.032
Parents of the head in HH		0.031*	0.003	0	0.004
Foster children in HH		0.04	-0.057.	-0.053	-0.04
Single parent in HH		-0.03	-0.102***	-0.111***	-0.115***
Two parent HH		0.056.	-0.016	-0.029	-0.033
Polygamist HH		0.009	-0.011	-0.017	-0.019
Female head in HH		-0.085***	-0.083***	-0.085***	-0.089***
R2 :0.1798					
Characteristics of the head of HH					
Catholic			-0.216***	-0.182***	-0.15***
Protestant			-0.278***	-0.221***	-0.169***
Christian			-0.16***	-0.142***	-0.103***
Muslim head of HH			-0.096***	-0.082***	-0.064***
Akan			-0.073**	-0.079***	-0.077***
Ga			0.134***	0.121***	0.097***
Ewe			-0.17***	-0.163***	-0.156***
Moved from district in last 5 years			-0.065***	-0.037*	-0.032*
Different usual residence			0.039*	0.031*	0.022
R2 :02916					
Housing characteristics					
Permanent walls				-0.197***	-0.164***
Permanent roof				0.102***	0.126***
Piped water				-0.08***	-0.044*
Own toilet				-0.123***	-0.109***
R2 :0.3166					
Women's characteristics					
With primary education					0.158***
With no schooling					0.147***
Employed in informal sector					-0.026
Women 15-20 single					-0.161***
R2 :0.3619					

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

2. OLS for 900 m cell unit of analysis

Results from OLS regression with variables aggregated to a 900 m cell indicate that urban context and household structure explain 32% of the variance in fertility with all the control variables included, a slightly lower R^2 than for the 450 m cell unit of analysis (Table 6). The association between urban context and fertility is comparable to one seen for the 450 m cell of analysis with five out of the eight urban classes showing significant coefficients. The highest negative coefficient corresponds to the fragmented large urban patches class while the lowest one is found again in the compact urban area. It is interesting to note that at this scale of analysis the class scattered settlements shows a significant negative correlation to fertility with a standardized coefficient that is comparable to the one for the compact urban areas. This result shows that at this scale of analysis fertility levels in the consolidated compact urban neighborhoods are comparable to the ones seen in scattered settlements found outside of the city.

Living arrangements at the 900 m scale of analysis seem to have similar impacts on fertility levels, with both female headed households and single parent households showing the most significant negative associations with fertility. Additionally the variable average number of extended family members in the household shows a slightly lower negative correlation with fertility at this scale of analysis. Positive significant coefficients are seen at this scale of analysis for households where the head has a different usual residence and belongs to the Ga ethnic group. Negative significant coefficients on the other hand remain unchanged for households where the household head belongs to a non-traditional religion and has moved from a different district within the last five years. The percentage of women age 15 to 20 never married remains significantly associated with lower fertility levels as it was the case for the previous scale of analysis.

Table 6: 900 m cell OLS regression coefficients (y:cebz, n: 3382)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.046**	-0.032*	-0.047**	-0.04*	-0.033*
Fragmented large urban patches	-0.22***	-0.194***	-0.153***	-0.13***	-0.103***
Dense and dispersed small urban patches	-0.2***	-0.191***	-0.114***	-0.084***	-0.066***
Fragmented sub-urban	-0.092***	-0.088***	-0.056***	-0.045**	-0.036*
Scattered settlements	-0.127***	-0.102***	-0.067***	-0.044**	-0.035*
Sparsely populated	-0.121***	-0.094***	-0.045**	-0.026.	-0.022
Fragmented transition	-0.019	-0.006	0.004	0.007	0.006
Fragmented unsettled	-0.062***	-0.04*	0.011	0.016	0.006
R^2 :0.1054					
Household structure					
Number of extended family members		-0.053.	-0.101***	-0.088***	-0.093***
Grand children of the head in HH		0.063*	-0.01	-0.005	0.002
Parents of the head in HH		0.036*	0.009	0.01	0.016
Foster children in HH		0.05	-0.023	-0.03	-0.014
Single parent in HH		-0.048	-0.112***	-0.118***	-0.12***
Two parent HH		0.027	-0.037	-0.049	-0.05
Polygamist HH		0.015	0.002	0	-0.003
Female head in HH		-0.108***	-0.087***	-0.094***	-0.098***
R^2 :0.1247					
Characteristics of the head of HH					
Catholic			-0.229***	-0.199***	-0.168***
Protestant			-0.266***	-0.216***	-0.17***
Christian			-0.167***	-0.144***	-0.104***
Muslim head of HH			-0.099***	-0.092***	-0.071***
Akan			-0.075**	-0.086***	-0.087***
Ga			0.167***	0.146***	0.121***
Ewe			-0.183***	-0.177***	-0.165***
Moved from district in last 5 years			-0.086***	-0.062**	-0.053**
Different usual residence			0.064***	0.054**	0.041*
R^2 :02549					
Housing characteristics					
Permanent walls				-0.177***	-0.152***
Permanent roof				0.147***	0.155***
Piped water				-0.06**	-0.036.
Own toilet				-0.127***	-0.117***

R^2:0.2794	
Women's characteristics	
With primary education	0.156***
With no schooling	0.126***
Employed in informal sector	-0.032.
Women 15-20 single	-0.16***
R^2:0.3232	

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

3. OLS for 1800 m cell unit of analysis

Results from OLS regression with variables aggregated to 1800 m cell remain very close to the 900 m cell unit with an R^2 of 0.32 (Table 7). Urban context explains less of the variability in fertility at this spatial scale since the number of significant classes dropped to four with the fragmented sub-urban class showing no significance at all in explaining fertility. The highest negative coefficient for this scale of analysis remains in the fragmented large urban patches; followed closely by the dense and dispersed small urban patches class. Compact urban and scattered settlements have comparable significant negative coefficients, with the compact urban showing a slightly lower fertility than the scattered settlements.

The association between living arrangements and fertility remains unchanged from the 900 m cell to the 1800 m cell with female headed households, single parent households and average number of extended family household members showing significantly lower fertility levels than average. At the 1800 m scale the variable household head residing in a different residence still has a positive effect on fertility, however its significance dropped from a p value below 0.5 to one below 0.1. Fertility levels are still evidently lower for households where the household head belongs to a non-traditional religion and significantly higher for households where the household head belongs to the Ga ethnic group. At this scale the variable household head moved within the last five years has no longer a significant negative effect on fertility. It seems that with the larger unit of analysis the urban context class is unable to detect neighborhoods with predominant migrant populations. As we increase the unit of analysis it is clear that the urban context definition loses the ability to identify diverse neighborhoods within the city.

Table 7: 1800 m cell OLS regression coefficients (y:cebz, n: 2270)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.059**	-0.05*	-0.061**	-0.064**	-0.058**
Fragmented large urban patches	-0.16***	-0.152***	-0.115***	-0.112***	-0.087***
Dense and dispersed small urban patches	-0.206***	-0.208***	-0.127***	-0.112***	-0.086***
Fragmented sub-urban	-0.047*	-0.049*	-0.03.	-0.022	-0.014
Scattered settlements	-0.126***	-0.117***	-0.078***	-0.057**	-0.043*
Sparsely populated	-0.13***	-0.106***	-0.048*	-0.029	-0.022
Fragmented transition	-0.013	-0.01	0.002	0.003	0.009
Fragmented unsettled	-0.1***	-0.087***	-0.024	-0.018	-0.02
R^2:0.09482					
Household structure					
Number of extended family members		-0.01	-0.094**	-0.08*	-0.075*
Grand children of the head in HH		0.044	-0.016	-0.015	-0.008
Parents of the head in HH		0.039.	0.015	0.021	0.025
Foster children in HH		0.061	-0.007	-0.023	-0.007
Single parent in HH		-0.036	-0.105**	-0.109**	-0.108**
Two parent HH		0.023	-0.03	-0.042	-0.031
Polygamist HH		0.001	-0.012	-0.013	-0.011
Female head in HH		-0.114***	-0.085**	-0.087**	-0.085**
R^2:0.1162					
Characteristics of the head of HH					
Catholic			-0.246***	-0.206***	-0.176***
Protestant			-0.263***	-0.204***	-0.165***
Christian			-0.183***	-0.158***	-0.126***
Muslim head of HH			-0.089***	-0.084***	-0.07***
Akan			-0.064*	-0.081**	-0.083**
Ga			0.22***	0.189***	0.158***
Ewe			-0.159***	-0.16***	-0.161***
Moved from district in last 5 years			-0.063**	-0.035	-0.025

Different usual residence	0.063**	0.047*	0.037.
R^2 :0.2534			
Housing characteristics			
Permanent walls		-0.185***	-0.138***
Permanent roof		0.183***	0.168***
Piped water		-0.071**	-0.052*
Own toilet		-0.132***	-0.126***
R^2 :0.2846			
Women's characteristics			
With primary education			0.148***
With no schooling			0.118***
Employed in informal sector			-0.01
Women 15-20 single			-0.145***
R^2 :0.3242			

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

4. OLS for 3600 m cell unit of analysis

Results from the OLS regression with variables aggregated to 3600 m cells yielded a higher R^2 of 0.38 (Table 8), meaning that at this larger scale urban context and household structure explain more of the variability in fertility levels. The association between urban context and fertility dropped considerably at this scale of analysis with only three urban classes showing significant coefficients. At this scale fragmented large urban patches, dense and dispersed small urban patches and fragmented sub-urban areas have significant negative coefficients with the highest one corresponding to the fragmented large urban patches class and the lowest one the fragmented sub-urban class. With greater cell size, some of the differences that were observed between neighborhoods disappear. For example the compact urban core doesn’t seem to have a significantly different fertility level than any of the other urban neighborhoods.

At this scale of analysis household structure variables with significant correlation to fertility are limited to polygamist households and female headed households, both with negative standardized coefficients. On the other hand households where the head of household has a different place of residence tend to have higher fertility as was the case with smaller cells of analysis. However, the effect seems to get stronger at this scale with a much higher standardized coefficient. In terms of religion we can see that at this scale household heads belonging to non-traditional religions preserve their negative association with fertility with the exception of Muslim heads which is not significant. As for ethnicity households where the head belongs to the Ga ethnic group continue to show higher than average fertility levels.

Table 8: 3600 m cell OLS regression coefficients (y:cebz, n: 925)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.005	-0.011	-0.026	-0.033	-0.025
Fragmented large urban patches	-0.197***	-0.18***	-0.142***	-0.127***	-0.107***
Dense and dispersed small urban patches	-0.123***	-0.118***	-0.083**	-0.079**	-0.065*
Fragmented sub-urban	-0.167***	-0.166***	-0.097***	-0.08**	-0.067*
Scattered settlements	-0.124***	-0.113***	-0.075**	-0.047	-0.036
Sparsely populated	-0.176***	-0.146***	-0.074*	-0.042	-0.038
Fragmented transition	-0.011	-0.016	0.013	0.015	0.023
Fragmented unsettled	-0.106***	-0.104***	-0.019	-0.005	-0.003
R^2:0.1095					
Household structure					
Number of extended family members		0.089.	-0.044	-0.031	-0.033
Grand children of the head in HH		0.125*	0.027	0.011	0.023
Parents of the head in HH		0.047	0.018	0.02	0.017
Foster children in HH		0.092	0.023	-0.007	0.014
Single parent in HH		0.082	0.008	-0.005	-0.012
Two parent HH		0.109	0.04	0.016	0.026
Polygamist HH		-0.056.	-0.071*	-0.077**	-0.056.
Female head in HH		-0.187***	-0.152***	-0.15***	-0.135**
R^2:0.1505					
Characteristics of the head of HH					

Catholic	-0.219***	-0.18***	-0.161***
Protestant	-0.282***	-0.226***	-0.205***
Christian	-0.242***	-0.221***	-0.195***
Muslim head of HH	-0.046	-0.036	-0.02
Akan	-0.066	-0.085.	-0.079
Ga	0.288***	0.263***	0.24***
Ewe	-0.21***	-0.221***	-0.223***
Moved from district in last 5 years	-0.085*	-0.058.	-0.046
Different usual residence	0.104***	0.089**	0.085**
R^2:0.3445			
Housing characteristics			
Permanent walls		-0.155**	-0.097.
Permanent roof		0.154***	0.12**
Piped water		-0.089*	-0.08*
Own toilet		-0.113***	-0.111***
R^2:0.3667			
Women's characteristics			
With primary education			0.096**
With no schooling			0.047
Employed in informal sector			0.017
Women 15-2 single			-0.118***
R^2:0.3867			

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

5. OLS for 7200 m cell unit of analysis

Results from OLS regression with variables aggregated for 7200 m cell yielded a higher R^2 of 0.43 (Table 9); however most of the variables of interest seem to have lost their power to explain fertility levels at this scale. None of the six urban classes from the urban context show significant associations with fertility, a result that confirms that with the larger cell size greater variance blurs the correlation between the characteristics of the urban context and demographic variables. The association between living arrangements and fertility is significantly lower for this cell size with only two variables showing significant coefficients. Polygamist household show a significant positive coefficient same as households where the head of household has a different residence an effect that is maximized for this variable at this scale of analysis. The connection between religion, ethnicity and fertility remains mostly unchanged with household heads belonging to non-traditional religions showing significantly lower fertility and households where the household head belongs to the Ga ethnic group showing significantly higher fertility.

Table 9: 7200 m cell OLS regression coefficients (y:cebz, n:291)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.168**	-0.157**	-0.13**	-0.077	-0.063
Fragmented sub-urban	-0.228***	-0.219***	-0.153**	-0.09	-0.07
Scattered settlements	-0.034	-0.012	-0.012	0.015	0.034
Sparsely populated	-0.179**	-0.15*	-0.059	-0.049	-0.043
Fragmented transition	-0.072	-0.101.	0.017	0.018	0.038
R^2 :0.0793					
Household structure					
Number of extended family members		0.171.	-0.081	-0.023	-0.008
Grand children of the head in HH		0.179.	0.032	-0.014	-0.008
Parents of the head in HH		0.082	0.065	0.068	0.057
Foster children in HH		0.3.	0.146	0.111	0.155
Single parent in HH		0.286*	0.132	0.124	0.113
Two parent HH		0.233.	0.164	0.138	0.18
Polygamist HH		0.171**	0.077	0.124*	0.119*
Female head in HH		-0.193*	-0.113	-0.141	-0.084
R^2 :0.1667					
Characteristics of the head of HH					
Catholic			-0.252***	-0.194***	-0.179***
Protestant			-0.236***	-0.179**	-0.182**
Christian			-0.24***	-0.229***	-0.195**
Muslim head of HH			-0.093.	-0.134*	-0.111.
Akan			0.092	0.055	0.042
Ga			0.492***	0.45***	0.403***
Ewe			-0.127	-0.212.	-0.236*
Moved from district in last 5 years			-0.071	-0.031	-0.041
Different usual residence			0.126*	0.123*	0.129*
R^2 :0.3926					
Housing characteristics					
Permanent walls				-0.052	-0.018
Permanent roof				-0.055	-0.101
Piped water				-0.078	-0.071
Own toilet				-0.229***	-0.214***
R^2 :0.4204					
Women's characteristics					
With primary education					0.133*
With no schooling					0.014
Employed in informal sector					-0.028

Women 15-20 single	-0.131*
R^2:0.4388	

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

6. OLS for 14400 m cell unit of analysis

Finally results from the OLS regression with variables aggregated to 14400 m cell produced an R^2 of 0.63 but again most of the variables of interest were not significant (Table 10). In terms of the urban context compact urban and fragmented sub urban classes show a barely significant negative association with fertility. With the large unit of analysis most of the detail about the urban context is lost and there is limited differentiation between urban from non-urban effects. The magnitudes of the association that we see for the two classes are almost identical, which does not really allow to differentiate fertility levels between urban classes. At this scale the only living arrangement that shows a significant association with fertility levels corresponds to polygamist households, where the positive coefficient indicates an above average fertility level.

Defining urban context with the largest of the cell sizes provides essentially no explanatory value for fertility since none of the urban classes have significant coefficients. Upon comparing results from OLS regression at different levels of aggregation we conclude that smaller units of analysis seem to capture homogeneous areas characterizing the urban context, which have the strongest associations with demographic characteristics. The connection between fertility, household structure and urban context is further examined for the smallest (450 m) unit of analysis.

Table 10: 14400 m cell OLS regression coefficients (y:cebz, n: 88)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.311**	-0.339**	-0.251*	-0.197	-0.241.
Fragmented sub-urban	-0.188.	-0.187	-0.221	-0.147	-0.254.
Scattered settlements	-0.008	-0.097	-0.011	0.015	0.008
Sparsely populated	-0.181	-0.189	-0.102	-0.06	-0.048
Fragmented transition	-0.056	-0.161	0.041	0.07	0.117
R^2 :0.07908					
Household structure					
Number of extended family members		0.124	0.068	0.089	-0.141
Grand children of the head in HH		0.393	0.207	0.062	0.105
Parents of the head in HH		-0.081	-0.072	0.015	0.066
Foster children in HH		0.724	0.102	-0.209	0.427
Single parent in HH		0.704	0.101	-0.157	0.086
Two parent HH		0.14	0.094	-0.13	0.091
Polygamist HH		0.313*	0.203.	0.308**	0.393***
Female head in HH		-0.384*	-0.195	-0.427*	-0.298
R^2 :0.2407					
Characteristics of the head of HH					
Catholic			-0.268*	-0.241*	-0.169.
Protestant			-0.07	0.042	-0.123
Christian			-0.295.	-0.307.	-0.366*
Muslim head of HH			0.031	-0.069	-0.101
Akan			-0.158	-0.131	-0.163
Ga			0.281	0.239	0.083
Ewe			-0.409.	-0.561*	-0.723**
Moved from district in last 5 years			0.225	0.154	0.2
Different usual residence			0.013	0.03	0.2
R^2 :0.4287					
Housing characteristics					
Permanent walls				0.204	0.499*
Permanent roof				-0.08	-0.138
Piped water				-0.158	0.036
Own toilet				-0.4**	-0.389**
R^2 :0.4736					
Women's characteristics					
With primary education					0.003
With no schooling					-0.542*
Employed in informal sector					0.933***
Women 15-20 single					-0.207
R2 :0.6324					

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

7. OLS for 450 m cell unit of analysis and spatially filtered variables

The strength of the association between fertility, household structure and urban context was further examined by controlling for spatial autocorrelation in the OLS model. The residuals from the 450 m cell OLS regression were tested for spatial autocorrelation, producing a highly significant Moran's I with z score of 34.74 ($p < .000$), that indicated the incidence of spatial autocorrelation in the OLS regression model (Figure 30).

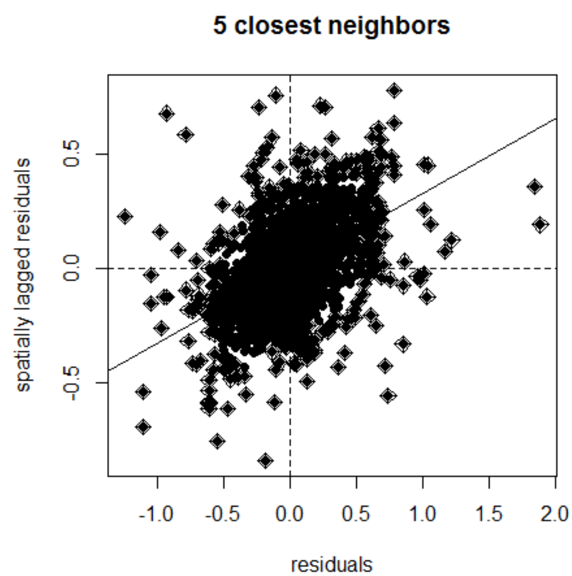


Figure 30: Moran's I scatter plot for 450 m OLS residuals

Each independent variable was analyzed for spatial autocorrelation with Moran's I, and all household structure, household head, housing and women characteristics variables produced significant levels of spatial autocorrelation. Once the incidence of spatial autocorrelation was established the G_i^* statistic was estimated for a series of increasing distances for each one of the sets of independent variables until maximum spatial autocorrelation was reached and critical distances were defined (Figure 31)

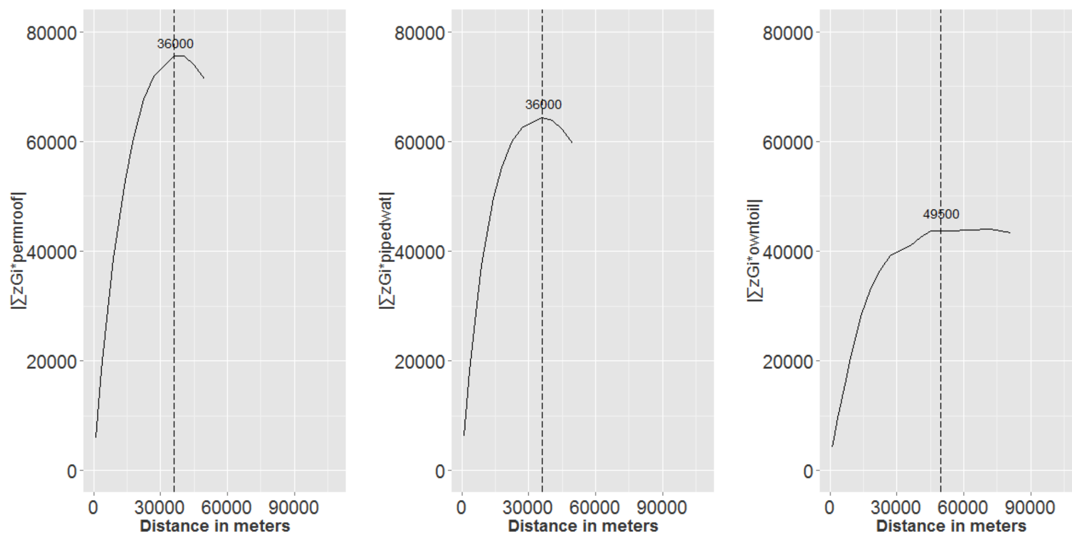


Figure 31: Critical distances for GI* for selected housing characteristic variables

Having defined the critical distance for each of the independent variables, the distances were used to generate spatially filtered variables. The Getis spatial filter technique was used to decompose each individual variable into its spatial and non-spatial components. Filtered spatial and non-spatial components were then used as explanatory variables for an OLS regression with fertility defined as the dependent variable.

Table 11: Regression coefficients from OLS with spatially filtered variables (y:cebz, n: 4015)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	0	0	0	0	0
Compact urban	-0.187***	-0.164***	-0.129***	-0.066***	-0.049**
Fragmented large urban patches	-0.31***	-0.292***	-0.228***	-0.135***	-0.091***

Dense and dispersed small urban patches	-0.198***	-0.186***	-0.126***	-0.075***	-0.052***
Fragmented sub-urban	-0.176***	-0.173***	-0.123***	-0.071***	-0.048**
Scattered settlements	-0.093***	-0.069***	-0.039**	-0.016	-0.006
Sparsely populated	-0.08***	-0.062***	-0.024.	-0.008	-0.004
Fragmented transition	-0.01	0.003	0.031*	0.035*	0.042**
Fragmented unsettled	-0.087***	-0.073***	-0.021	-0.014	0.005
R2 :0.1647 AIC: 979					
Household structure					
Number of extended family memb. filtered		-0.039	0.61***	0.591***	0.369**
Number of extended family memb. Spatial		-0.013	-0.717***	-0.697***	-0.463***
Grand children of the head in HH filtered		0.089***	0.026	0.02	0.023
Grand children of the head in HH spatial		0.077*	0.109***	0.112***	0.104***
Parents of the head in HH filtered		0.115***	0.057*	0.064*	0.063*
Parents of the head in HH spatial		-0.097**	-0.04	-0.056.	-0.046
Foster children in HH filtered		0.042	-0.019	-0.01	-0.012
Foster children in HH spatial		0.109***	0.084**	0.165***	0.069*
Single parent in HH filtered		-0.033	-0.081**	-0.088***	-0.083***
Single parent in HH spatial		0.047*	0.005	0.023	-0.016
Two parent HH filtered		0.086**	0.024	0.011	-0.004
Two parent HH spatial		-0.045.	-0.044.	-0.044.	-0.029
Polygamist HH filtered		-0.184***	-0.111*	-0.03	-0.02
Polygamist HH spatial		0.193***	0.092*	0.001	-0.005
Female head in HH filtered		-0.074***	-0.075***	-0.071***	-0.059***
Female head in HH spatial		-0.106***	-0.132***	-0.063.	-0.101**
R2 :0.19 AIC:871					
Characteristics of the head of HH					
Catholic filtered			-0.14***	-0.117***	-0.084***
Catholic spatial			-0.101***	-0.074***	-0.017
Protestant filtered			-0.25***	-0.193***	-0.122***
Protestant spatial			-0.201***	-0.143***	-0.085***
Christian filtered			-0.123***	-0.097***	-0.027
Christian spatial			-0.152***	-0.128***	-0.16***
Muslim filtered			-0.024	0.007	0.026
Muslim spatial			-0.148***	-0.161***	-0.127***
Akan filtered			-0.093***	-0.089***	-0.062***
Akan spatial			0.064**	0.084***	0.09***
Ga filtered			0.193***	0.173***	0.154***
Ga spatial			-0.061**	-0.085***	-0.123***
Ewe filtered			-0.119***	-0.13***	-0.098***
Ewe spatial			-0.087**	-0.108***	-0.073*
Moved from district in last 5 years filtered			-0.058**	-0.046*	-0.022
Moved from district in last 5 years spatial			-0.018	0.01	-0.028
Different usual residence filtered			0.015	0.012	-0.023
Different usual residence spatial			0.021	0.014	0.046.
R2 :0.342 AIC: 55					
Housing characteristics					
Permanent walls filtered				-0.198***	-0.161***
Permanent walls spatial				-0.182***	-0.152***
Permanent roof filtered				-0.005	0.035
Permanent roof spatial				-0.043	0.02
Piped water filtered				-0.081***	-0.032
Piped water spatial				-0.017	0.021
Own toilet filtered				-0.07***	-0.06***

Own toilet spatial	-0.026	-0.031.
R2 :0.3652 AIC: -80		
Women's characteristics		
With primary education filtered		0.093***
With primary education spatial		0.115***
With no schooling filtered		0.182***
With no schooling spatial		-0.093***
Employed in informal sector filtered		-0.006
Employed in informal sector spatial		0.009
Women 15-20 single filtered		-0.159***
Women 15-20 single spatial		-0.047.
R2 :0.4206 AIC:-440		

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

Results from the OLS regression using spatially filtered variables yielded a higher R^2 of 0.42 than from simple regression results (0.36). Results from spatially filtered OLS show that the urban context variables are significantly associated to fertility levels, with five out of the eight classes showing significant coefficients (Table 11). Lower fertility levels are seen in the more urbanized areas characterized as compact urban, fragmented large urban patches, dense and dispersed small urban patches and fragmented suburban, with the highest of the negative coefficients found in the fragmented large urban patches class and the lowest in the fragmented suburban class followed closely by the consolidated compact urban core. On the other hand higher fertility than average is seen only for the fragmented transition class which is one of the least urbanized areas in the urban context scheme. Comparing results from the OLS with filtered variables and unfiltered ones we can see that the standardized coefficient for the fragmented transition class increased in significance. This result indicates that when controlling for spatial autocorrelation in several of the independent variables we are controlling for some of the spatial dependence found in the more urban portion of the urban gradient, improving our ability to capture associations taking place on the less urban portion of the gradient.

Some interesting differences are apparent in the associations between living arrangements and fertility levels for spatially filtered OLS and unfiltered OLS. Results from OLS with unfiltered variables showed that female headed households and single parent households had the lowest fertility. Results from the OLS with spatially filtered variables indicate that the negative coefficient seen for the variable female headed household can be decomposed into significant negative coefficients from both the filtered and spatial components of the variable. In the case of the single parent variable the negative coefficient comes entirely from the filtered component of the variable itself, with no spatial component. Results from the spatially filtered OLS show that the spatial components of households with grandchildren of the head, foster children and two parents present in the household have significantly lower fertility levels than average. In the case of the variable average number of extended family members in the households we see that both the spatial and filtered components exhibit significant associations with fertility. While this last variable was not significant in the OLS with unfiltered variables, it is worth noting that the effects of the filtered and spatial components in the OLS with filtered variables are opposite. While the spatial component has a strong negative effect the filtered component has a strong positive effect on fertility. Finally in the spatially filtered OLS a significant positive spatial effect on fertility is observed for households where the household head has a different place of residence.

The lower fertility levels observed for households with heads belonging to non-traditional religions can in most cases be decomposed into significant filtered and spatial effects with the exception of Catholic heads which only have significant non-spatial effects and Muslim heads which only have significant spatial effects. The higher fertility levels that we have consistently seen for households with heads belonging to the Ga ethnic group can be decomposed in two opposite effects in the OLS with filtered variables. While the filtered component shows a strong significant positive association with fertility, the spatial component of the variable has a significant negative correlation with fertility. The consistently lower fertility that we have seen for women 15 to 20 never married can be attributed to the filtered component of the variable in the spatially filtered OLS.

The residuals from the new OLS regression were tested again for spatial autocorrelation, resulting in a highly significant Z score of 30.60 ($p < .000$) that indicates remaining spatial autocorrelation in the association between fertility, household structure and urban context (Figure 32).

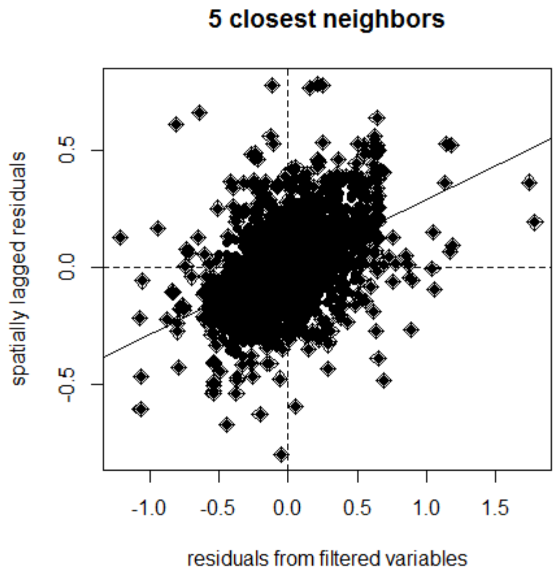


Figure 32: Moran scatter plot for residuals of filtered variables OLS

C. Spatial error model

Given that spatial autocorrelation persists in the OLS regression with the spatially filtered variables a spatial error model was used to improve the model and specify the spatial component in the error term. Comparing the results from the OLS regression with the spatial error model we can see that the inclusion of the spatial error term improved the model fit. The OLS regression with filtered variables generated a log likelihood of 280, which was increased to 632 upon running the spatial error model. The Akaike info Criterion (AIC) estimates indicate a clearly higher model fit, going from -440 for the OLS to -1143 in the spatial error model (Table 12). The spatial autoregressive coefficient, λ of 0.528 is highly significant ($p < .000$) indicating high levels of autocorrelation in the variables unaccounted for by the model.

The urban context variables are significant in explaining fertility in the spatial error model with five out of the eight variables showing p values below 0.01. The highest negative coefficients are found in the fragmented large urban patches while the lowest ones are found in the fragmented suburban areas. The fragmented transition class, on the opposite end of the urban spectrum scheme, shows a significant positive association with fertility pointing to higher fertility levels in the least urbanized areas of the study area. A close look at the variables of interest reveals that the magnitudes of most coefficients remain unchanged in the spatial error model. The spatial component of the variable grandchildren of the head has a significant positive impact on fertility, the same as for the spatial component of the variable foster children in the household, while the spatial component of the variable polygamist households has a significant negative effect on fertility. The negative association between single parent households and fertility is exclusively a filtered effect in the spatial error model with no significant spatial component. Female headed households on the other hand have both significant negative effects on fertility for the filtered and spatial component. The average number of members of extended family in the household keeps opposite effects on fertility in the spatial error model with the filtered component showing a strong positive effect while the spatial component has a strong negative effect.

The significantly lower fertility levels seen in households with heads of household belonging to non-traditional religions is exclusively a non-spatial effect in the spatial error model, with the exception of Christian and Muslim heads where the effects are only spatial. As it was the case for the OLS with spatially filtered variables results from the spatial error model show that the lower fertility levels seen in households where the head belongs to the Ga ethnic group can be decomposed into two opposite effects. While the filtered variable has a strong significant positive effect on fertility the spatial component of the variable has a strong significant negative effect on fertility.

Table 12: Spatial error model coefficient estimates (y:cebz, n: 4015)

	Block1 β	Block2 β	Block3 β	Block4 β	Block5 β
Urban context					
(Intercept)	-0.008	-0.009	-0.005	-0.006	-0.006
Compact urban	-0.147***	-0.133***	-0.119***	-0.07***	-0.054***
Fragmented large urban patches	-0.22***	-0.203***	-0.19***	-0.116***	-0.085***
Dense and dispersed small urban patches	-0.126***	-0.117***	-0.101***	-0.064***	-0.048***
Fragmented sub-urban	-0.12***	-0.114***	-0.104***	-0.061***	-0.047***
Scattered settlements	-0.054***	-0.042***	-0.025*	-0.008	0
Sparsely populated	-0.045***	-0.034**	-0.024*	-0.014	-0.005
Fragmented transition	0.016	0.023.	0.034*	0.039**	0.039**
Fragmented unsettled	-0.03*	-0.021	-0.009	-0.006	0.007
Lambda	0.613***				
Pseudo R^2 :0.381 AIC: -213 Log like:118					
Household structure					
Number of extended family memb. filtered		0.069	0.482***	0.487***	0.338*
Number of extended family memb. Spatial		-0.14	-0.585***	-0.593***	-0.437**
Grand children of the head in HH filtered		0.034	0.016	0.007	0.02
Grand children of the head in HH spatial		0.079*	0.103***	0.108***	0.105***
Parents of the head in HH filtered		0.048.	0.022	0.019	0.031
Parents of the head in HH spatial		-0.053	-0.025	-0.028	-0.027
Foster children in HH filtered		0.028	0.015	0.015	0.019
Foster children in HH spatial		0.033	0.08**	0.165***	0.122***
Single parent in HH filtered		-0.053*	-0.067**	-0.078**	-0.066**
Single parent in HH spatial		-0.003	-0.026	-0.017	-0.039.
Two parent HH filtered		0.055*	0.017	0.003	-0.008
Two parent HH spatial		-0.043.	-0.006	-0.011	-0.002
Polygamist HH filtered		0.012	0.02	0.086.	0.096*
Polygamist HH spatial		-0.04	-0.058	-0.135**	-0.136**
Female head in HH filtered		-0.072***	-0.06***	-0.056**	-0.053**
Female head in HH spatial		-0.103**	-0.152***	-0.092*	-0.103**
Lambda		0.618***			
Pseudo R^2 :0.398 AIC: -296 Log like:175					
Characteristics of the head of HH					
Catholic filtered			-0.123***	-0.097***	-0.057***
Catholic spatial			-0.066***	-0.037.	0.001

Protestant filtered	-0.207***	-0.147***	-0.072***
Protestant spatial	-0.183***	-0.119***	-0.041.
Christian filtered	-0.044*	-0.017	0.044*
Christian spatial	-0.171***	-0.142***	-0.157***
Muslim filtered	-0.012	0.017	0.027
Muslim spatial	-0.136***	-0.146***	-0.119***
Akan filtered	-0.063**	-0.058**	-0.035.
Akan spatial	0.079***	0.102***	0.095***
Ga filtered	0.131***	0.114***	0.087***
Ga spatial	-0.084***	-0.114***	-0.147***
Ewe filtered	-0.104***	-0.124***	-0.11***
Ewe spatial	-0.051	-0.078*	-0.073*
Moved from district in last 5 years filtered	-0.039*	-0.028	-0.018
Moved from district in last 5 years spatial	-0.053*	-0.03	-0.03
Different usual residence filtered	0.032	0.028	0.009
Different usual residence spatial	-0.009	-0.014	-0.007
Lambda	0.537***		
Pseudo R^2 :0.456 AIC: -659 Log like:374			
Housing characteristics			
Permanent walls filtered		-0.206***	-0.146***
Permanent walls spatial		-0.164***	-0.108**
Permanent roof filtered		-0.033	-0.012
Permanent roof spatial		-0.068.	-0.034
Piped water filtered		-0.085***	-0.023
Piped water spatial		-0.021	0.031
Own toilet filtered		-0.085***	-0.08***
Own toilet spatial		-0.048*	-0.051**
Lambda		0.535***	
Pseudo R^2 :0.478 AIC: -810 Log like:458			
Women's characteristics			
With primary education filtered			0.079***
With primary education spatial			0.135***
With no schooling filtered			0.216
With no schooling spatial			-0.047.
Employed in informal sector filtered			0
Employed in informal sector spatial			0.029
Women 15-20 single filtered			-0.151
Women 15-20 single spatial			-0.048.
Lambda			0.528***
Pseudo R^2 :0.52 AIC: -1143 Log like:632			

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

D. Geographically weighted regression

Results from OLS and spatial error models show that there is a strong association between fertility, household structure and urban context. However, the variance in the strength of the association between dependent and independent variables points to the possibility that there is non-stationarity in the models. Running the same OLS regression for each one of the urban context classes separately it becomes evident that there is a fair amount of spatial variability in the association between living arrangements and fertility within the study area. The variable female headed household showed a consistent significant negative association with fertility throughout all the models (unfiltered OLS, filtered OLS and spatial error model), yet results from OLS run on one urban context class at a time show that there are significant differences in the strength of that association from place to place. While the highest negative coefficients are concentrated in the outskirts of the urban areas of Greater Accra and Tema, positive coefficients can be seen in the less urbanized area defined as fragmented transition (Figure 33).

The strength of the association between the average number of extended family members in the household and fertility levels shows similar spatial variability patterns. While higher fertility levels are seen in households with numerous extended family members within the city of Accra lower fertility levels are seen in households with numerous extended family members found in the least urban areas of the study area (Figure 34).

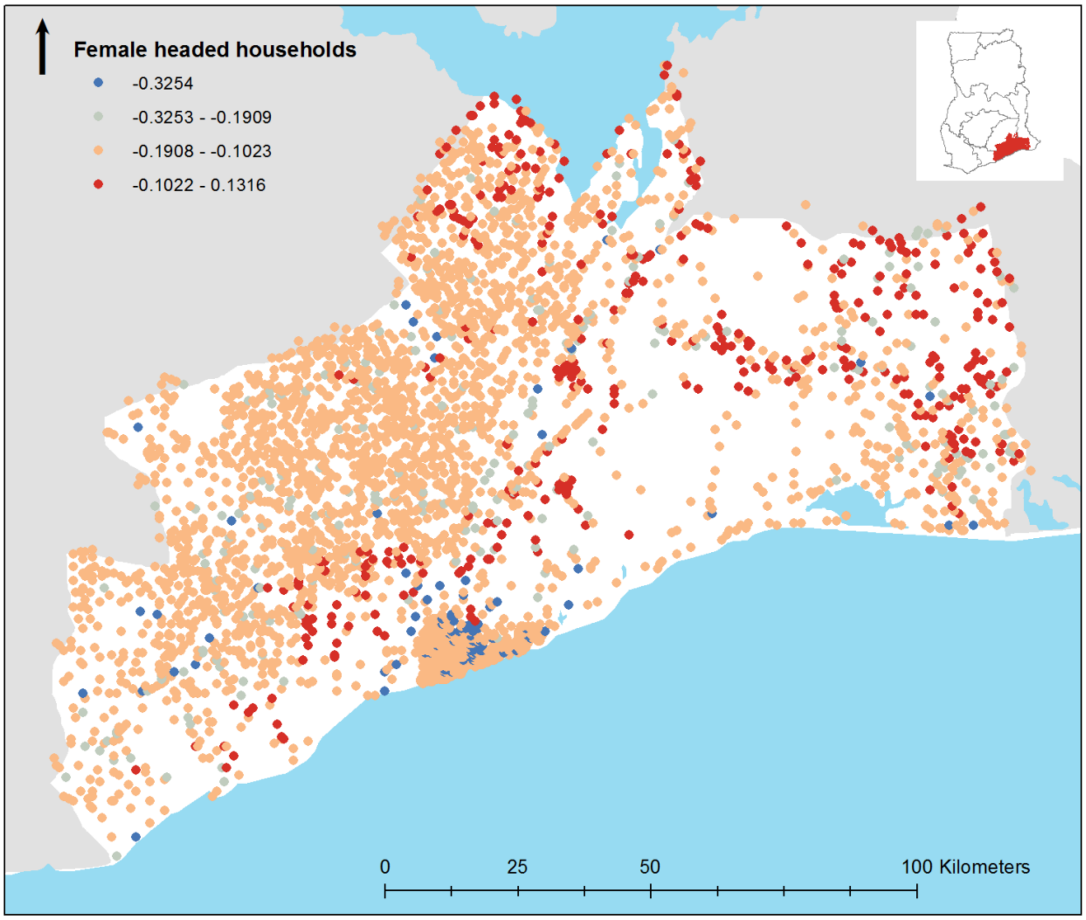


Figure 33: Female headed household coefficient estimates for OLS with one urban class at a time

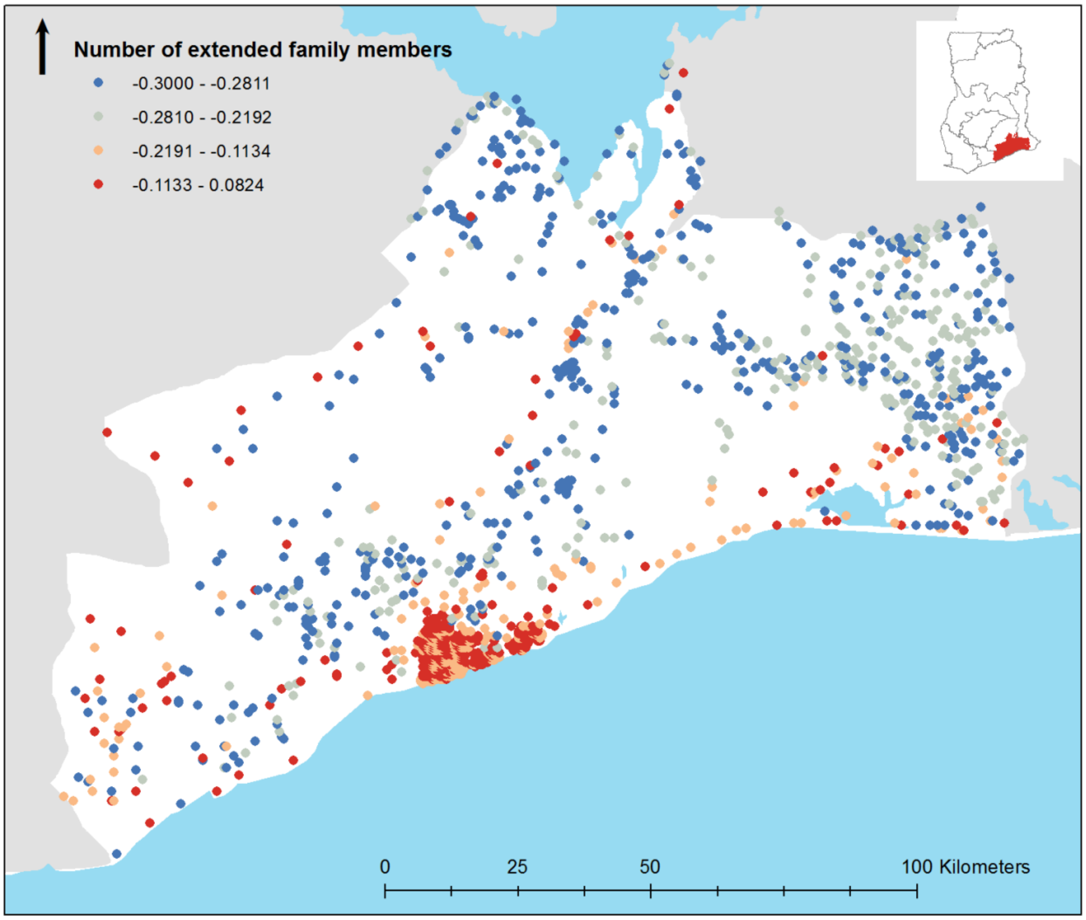


Figure 34: Average number of extended family members in household coefficient estimates for OLS with one urban class at a time

The main hypothesis in this study is that fertility is associated with living arrangements and that those in turn are associated with different urban contexts. As the complexity of urban contexts varies spatially it is expected that the strength of the association between those urban contexts, living arrangements and fertility levels will also vary through space. In order to capture the spatial heterogeneity of the association between dependent and independent variables the strength of the correlation between urban context, living arrangements and fertility levels was tested through geographically weighted regression (GWR) and the spatial distribution of coefficients was estimated.

In order to assess the effects of the urban context on fertility levels through GWR the urban classification was rescaled into a continuous variable. The rescaled urban context ranges from 0 to 100, where 100 correspond to the compact urban class and 0 to the unsettled land class (Table 13).

Table 13: Urban context class rescaled

	Rescaled Urban context class
Compact urban	100
Fragmented large urban patches	88
Dense and dispersed small urban patches	75
Fragmented sub-urban	62
Scattered settlements	50
Sparsely populated	38
Fragmented transition	25
Fragmented unsettled	12
Unsettled land	0

Before estimating spatial heterogeneity in the model an OLS regression was run replacing the urban context dummy variables by the rescaled continuous urban context one. Results from the OLS showed that the rescaled urban context variable has a significant negative relationship with fertility levels, where areas belonging to the more urban side of the spectrum have significantly lower fertility levels than those found on the least urbanized side of the spectrum (Table 14).

Table 14: Spatial error model coefficient estimates (y:cebz, n: 4015)

	Estimate β
Urban context	
(Intercept)	0
Compact urban	-0.073***
Household structure	
Number of extended family members	-0.034.
Grand children of the head in HH	-0.025
Parents of the head in HH	0.005
Foster children in HH	-0.031
Single parent in HH	-0.106***
Two parent HH	-0.025
Polygamist HH	-0.019
Female head in HH	-0.088***
Characteristics of the head of HH	
Catholic	-0.15***
Protestant	-0.166***
Christian	-0.103***
Muslim head of HH	-0.061***
Akan	-0.086***
Ga	0.099***
Ewe	-0.151***
Moved from district in last 5 years	-0.031*
Different usual residence	0.022
Housing characteristics	
Permanent walls	-0.17***
Permanent roof	0.101***
Piped water	-0.048*
Own toilet	-0.115***
Women's characteristics	
With primary education	0.163***
With no schooling	0.157***
Employed in informal sector	-0.025
Women 15-20 single	-0.166***
R^2:0.36 AIC: -77	

.p<0.1, *p<0.05, **p<0.01, ***p<0.001

Results from the OLS regression show that single parent households and female headed households have significantly lower fertility levels than average whereas households where the household head has a different place of residence have significantly higher fertility levels. These results are consistent with the findings in the previous sections.

GWR was used to model fertility over space using household structure and urban context as the independent variables of interest while controlling for the characteristics of the head of household, housing and women. The same variables used in section 5.2.1 were used for the GWR with the exception that the urban context dummies where replaced by a rescaled continuous version of the same variable. The average local R^2 generated by the GWR reaches 0.82 and spreads from the lower end of 0.57 to a high 0.95 (Figure 35). The variance in fertility level that is explained by the independent variables is lowest in the rural areas located the farthest from Greater Accra in the far east, west and north edges of the study site and also for a cluster within the city of Greater Accra. This result indicates that the model performance is lower for the two opposite extremes of the urban context and is the highest for the intermediate urban classes where the R^2 is the highest.

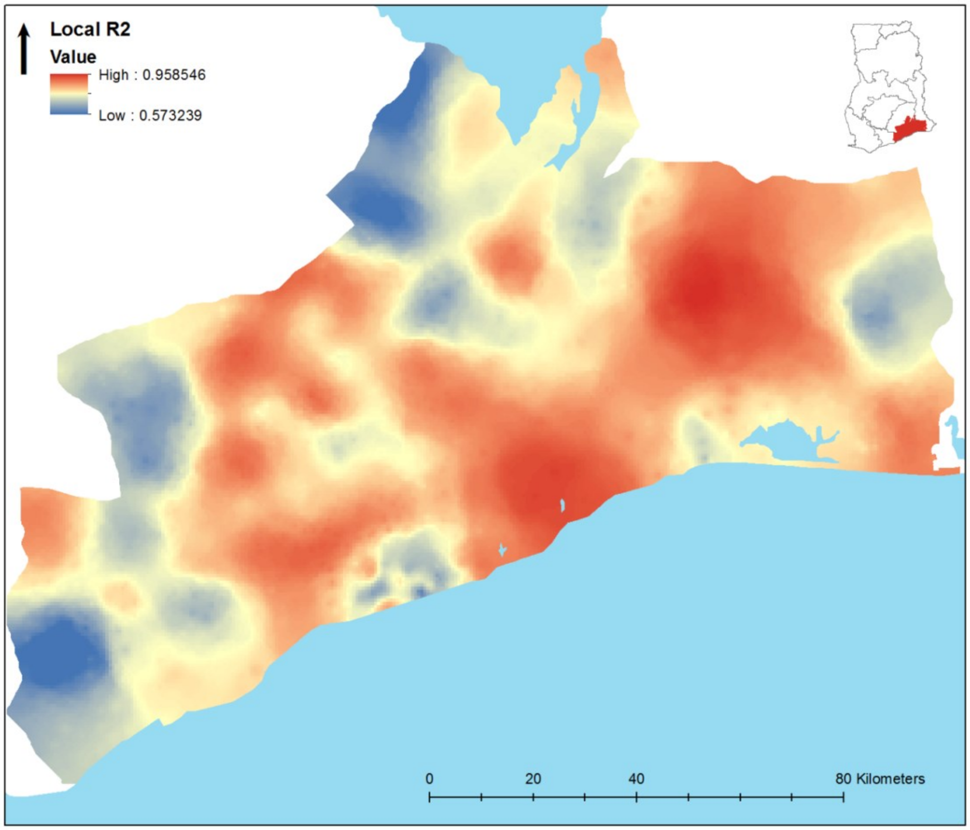


Figure 35: Local R^2 from GWR for model: $CEBz_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)urban\ context_i + \beta_2(u_i, v_i)HH\ structure_i + \beta_3(u_i, v_i)HH\ head_i + \beta_4(u_i, v_i)housing_i + \beta_5(u_i, v_i)women_i + \varepsilon$

Results from the OLS using the rescaled urban context variable as one of the independent variables show that degree of urbanization is overall negatively associated with fertility levels. However as it was shown in previous sections, there are specific instances where urbaneness is associated with higher fertility. Fertility levels were consistently higher throughout the study in the fragmented transition--a result that indicates that towards the lower end of the urban spectrum the effects on fertility are reversed. Results from GWR show the detail of the spatial distribution of the urban context effect on fertility. Coefficients for the rescaled urban context variable indicate that strong positive relationships with fertility are restricted to four hot spots, two of them coinciding with areas that are not very densely populated and the remaining two corresponding to the city centers of Greater Accra and Tema (Figure 36).

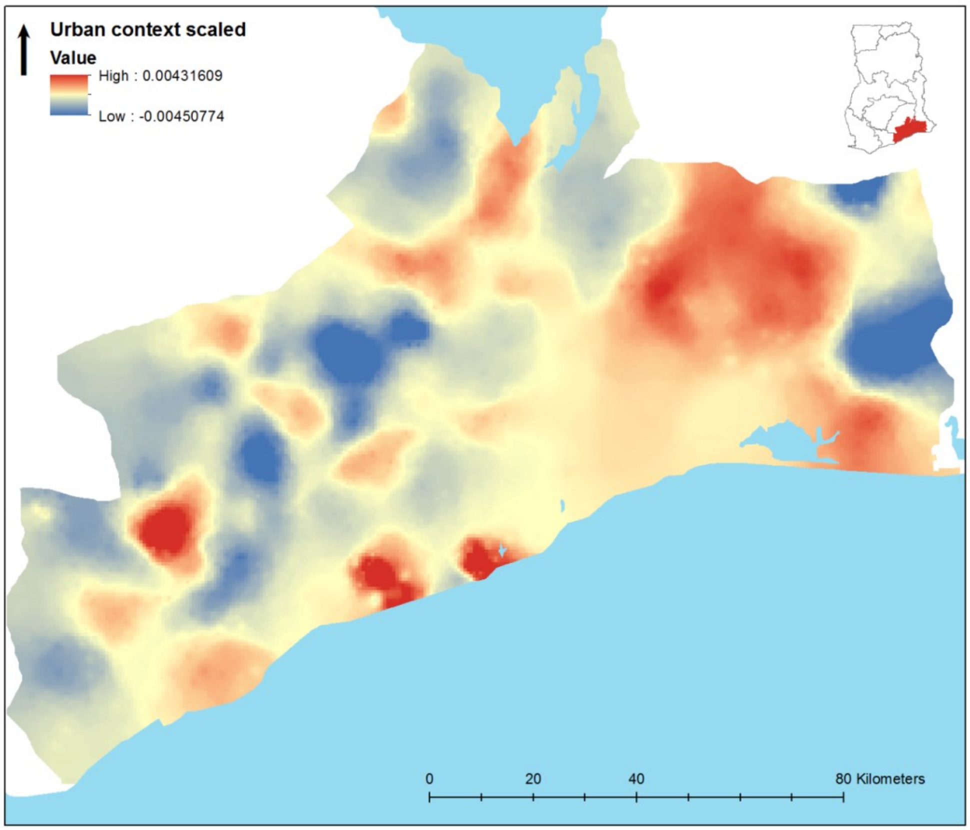


Figure 36: Urban context coefficient estimates from GWR

Results from OLS and spatial error model showed that the most consistently significant living arrangement variables predicting fertility are female headed households, single parent households and household head with a different place of residence. Throughout this study single parent and female headed households have exhibited significantly lower fertility levels; whereas households where the head resides in a different residence have shown significantly higher fertility levels. Results from the GWR analysis show that those positive and negative effects on fertility are more complex when examined spatially.

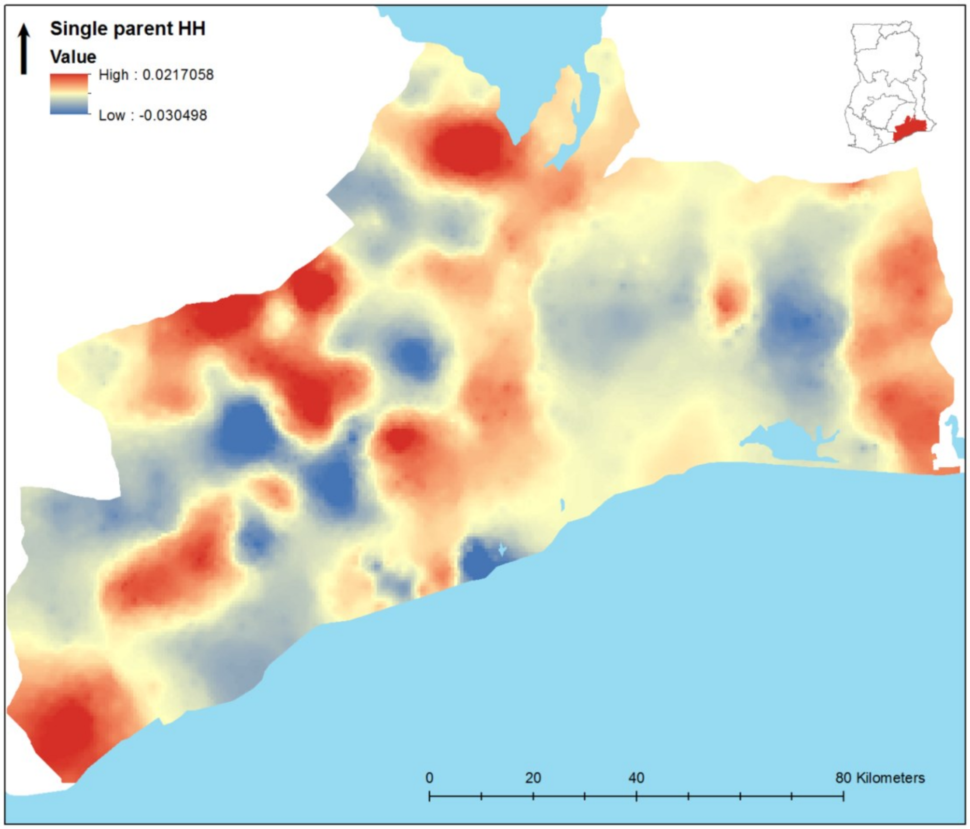


Figure 37: Single parent household coefficient estimates from GWR

Even though single parent households tend to have lower fertility levels globally, at local scales results from GWR show that there are particular areas where single parent households have higher fertility levels than average. Higher fertility is seen for single parent households in areas that are vastly rural on the western, eastern and northern edges of the study area but also in the rural areas immediately adjacent to the city of Accra (Figure 37). It is worth noting that fertility is relatively low for single parent households located on the banks of the Volta River.

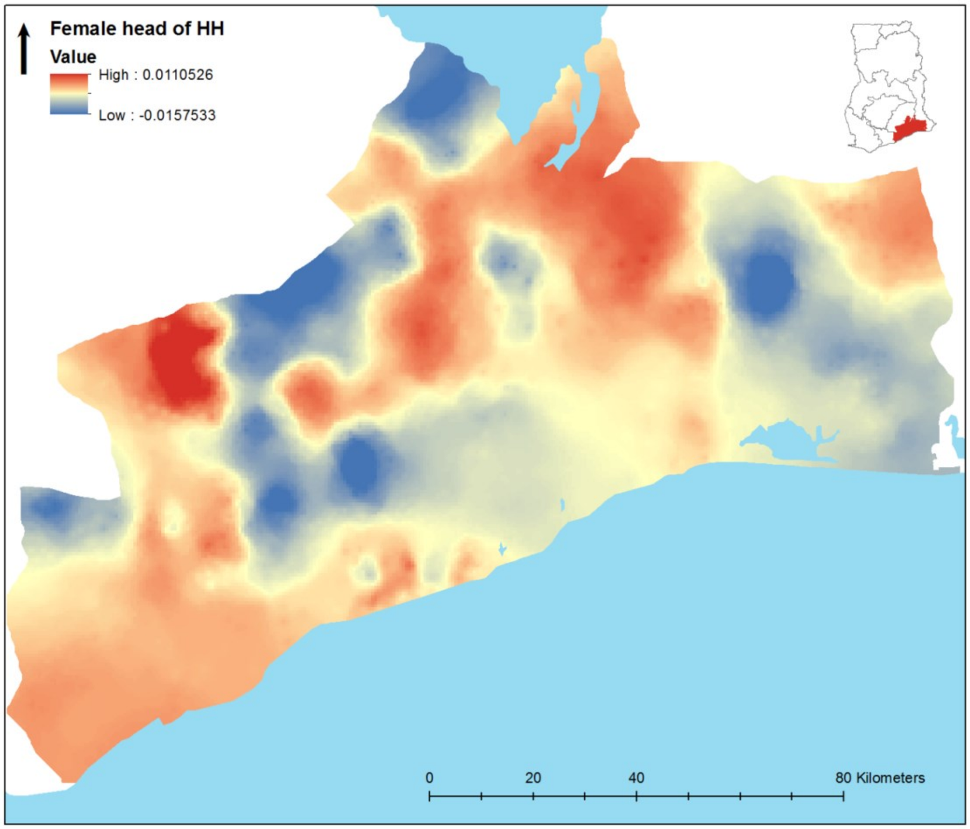


Figure 38: Female headed household coefficient estimates from GWR

The consistently significantly lower fertility levels that were observed throughout the study for female headed households can be split into below average and above average fertility levels by GWR (Figure 38). The spatial distribution of the coefficients for the female headed household show a clear network pattern, where lower fertility connects areas that coincide with major settlements and cities. An interesting example is the town of Koforidua, northeast of Accra, where we see an isolated island of lower fertility.

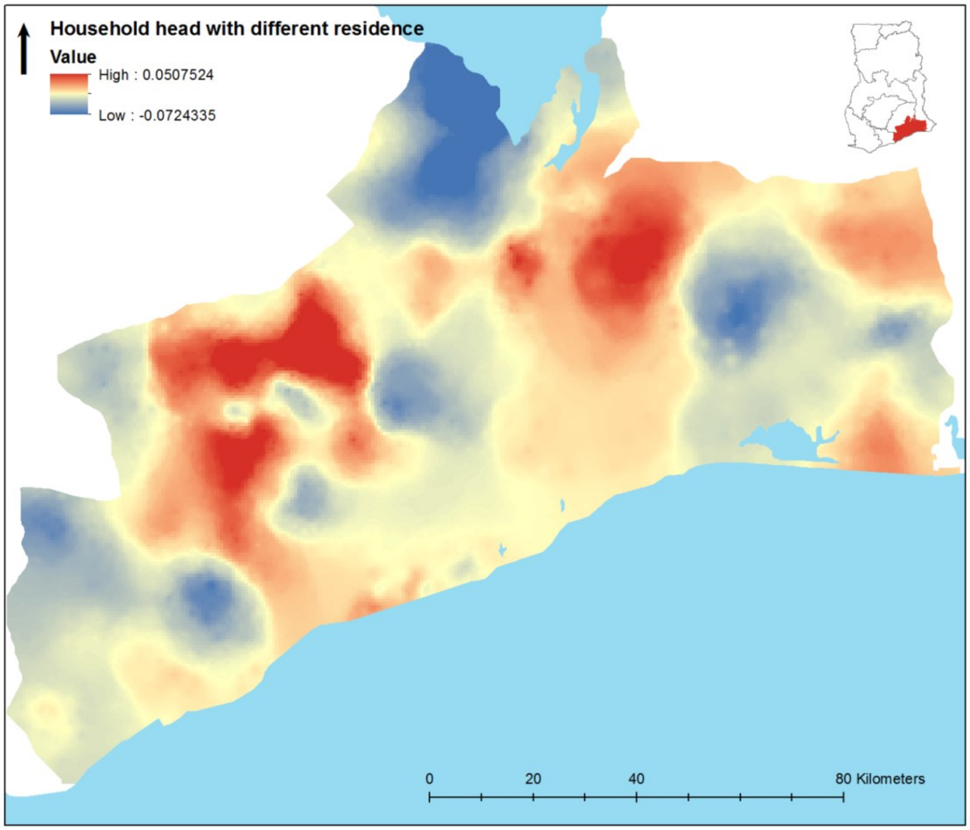


Figure 39: Household head with different residence coefficient estimates from GWR

The significantly higher fertility in households where the household head has a different usual residence is also split by GWR into lower than average and higher than average fertility. Lower fertility is seen in households where the household head is away mostly in rural areas while fertility tends to be higher in smaller inland settlements (Figure 39), a result that indicates that temporary outmigration might be connected to increased reproduction levels in rural areas of the region.

VI. Discussion

A. Defining the urban context

Results showed that spectral mixture analysis applied to Landsat ETM+ using a VIS model is a valuable approach for mapping built and vegetation land covers using moderate resolution imagery. Error assessment of the SMA-based built and vegetation land cover maps are very encouraging with fairly low commission and omission errors. However, it is important to recognize that SMA had difficulties detecting impervious surfaces in urban areas where soil and built land covers are highly mixed, as it is the case in most cities of developing countries. The lack of paved areas and the prevalence of soil and mixed pixels in populated areas in our study area make it challenging to distinguish settlements from undeveloped spaces. In testing different combinations of end-members for SMA it became clear that there is a fair amount of confusion between impervious surfaces and bright soils. Even though misclassification errors were reduced by excluding bright undeveloped land from the analysis, the final SMA output still tends to under-estimate the extent of the built environment. This finding illustrates the need to improve sub-pixel classifications for urban mapping in developing countries and suggests that a multiple end-member approach to SMA might generate an improved land cover classification.

In this study the problem associated with confusion between impervious and soil cover was addressed by using satellite SAR data as an additional source of imagery. The moderate resolution optical imagery used for SMA was thus complemented with moderate resolution ERS-2 radar imagery used to extract measures of texture. Combining both sources of imagery provides a useful approach to urban/built mapping that takes advantage of the distinct sensitivities that radar and optical sensors have for distinguishing land surface materials and features. Research in diverse environments has consistently found that radar imagery is particularly useful for urban mapping when combined with optical imagery (Haack and Bechdol 2000; Haack et al. 2002).

The capacity of SAR sensors to detect differential backscatter associated with surface roughness and micro-topography makes SAR imagery suitable for detection of artificial structures given their propensity to generate mixed returns. Radar texture, in particular, provides important information about the heterogeneity of the land surface, a feature that is very sensitive to man-made features found in built environments. The most important limitation of radar imagery is the effect of topography on the magnitude of radar backscatter. Hill and mountain sides interact with the radar beam generating ranging anomalies that can be confused with the presence of artificial features and distort the image geometry. Some of the terrain generated backscatter can be normalized through terrain correction and severe layover effects should be masked out. However, areas where a single pixel captures the entire extent of a slope are affected by foreshortening distortions that are harder to remove. Given these issues, the utility of radar imagery for settlement mapping is mostly restricted to areas with minimal topographic variation. In this study area terrain distortions were located in a few isolated ridges at higher elevations in areas that were not significantly populated. Terrain distortions were removed from the study area through the use of masks, although such an approach wouldn't be appropriate for areas with major settlements located at higher elevations.

Results from error assessment of the radar-based classification of built vs. non-built cover show that there is a fair amount of commission error where built and non-built classes tend to be confused. This finding confirms that radar texture is not efficient for urban mapping as a single data source. Still, our results show low levels of omission error indicating that radar texture is an effective way of detecting some of the built land cover that was missed by the optical imagery. Close inspection of the image classification results shows that radar texture is particularly effective in detecting small settlements. This is likely due to the 12.5 m spatial resolution of the ERS-2 radar imagery, relative to the 30 m Landsat ETM image data.

Comparing the SMA-based land cover classification and the radar-based built/non-built classification with the CERSGIS land cover land use map showed that both optical and radar imagery have limitations in detecting accurately all built features independently. While there was a fair amount of omission in the SMA-based classification, the radar-based classification had a higher incidence of commission inaccuracies. By combining the SMA- and radar-based land cover classes the attempt was made to overcome the limitations of each independent classification and generate a more accurate depiction of the urban environment in the study area.

This study proposed a novel characterization of the urban context based exclusively on pattern characteristics of the landscape. A series of landscape metrics were estimated for built and vegetation land cover maps with the goal of differentiating areas based on the degree of landscape fragmentation. The assumption is that as city or settlement centers become more densely urbanized the built environment becomes more compact, whereas towards the outskirts of the city the land cover conversion brought by urban expansion means higher fragmentation and dispersion. The pattern-based urban context definition is based on relative fragmentation of both the built environment and vegetation land cover. A compact urban core is found at the most urbanized end of the spectrum, with a predominant built land cover class and very low levels of landscape fragmentation. As distance from the compact urban core increases, the built environment becomes increasingly fragmented giving way to urban dispersion and interspersion (Figure 40).

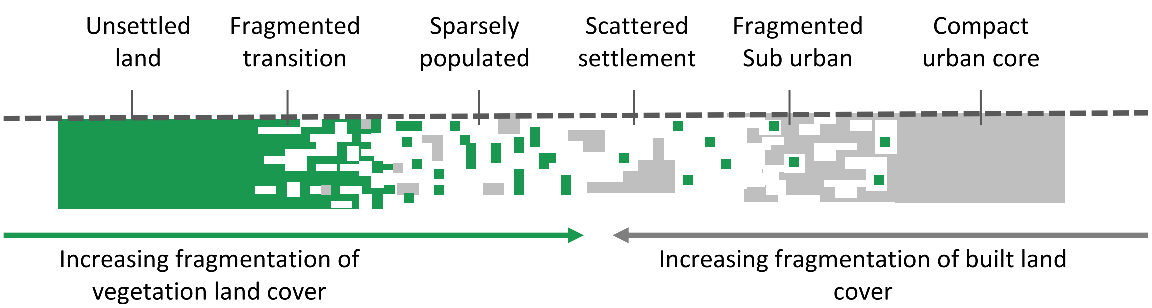


Figure 40: Pattern-based urban context gradient

With distances from the city center reaching beyond the city limits, landscapes change to scattered settlements and sparsely populated areas where fragmentation of the built environment peaks, and that is gradually replaced by areas transitioning from their natural state into cleared spaces suggestive of potential settlement. In the least urbanized end of the spectrum unsettled lands are identified by lower levels of fragmentation in the vegetation land cover, while in transitioning spaces we start to see clearings linked to a growing fragmentation of the vegetation cover.

The pattern-based definition of the urban context used in this study captures a wider range of urban environments than traditional rural/urban classifications. By differentiating the compact urban city center from highly fragmented suburban areas and scattered settlements, the urban context definition identifies important pattern differences among inhabited spaces.

Landscape metrics were used to estimate relative levels of landscape fragmentation using different levels of aggregation that allowed comparing the definition of urban subzones at different scales. The smallest unit of analysis, a 450 m grid cell, detected small compact neighborhoods, while the largest unit (14400 m) identified very diverse sub-metropolitan areas. Comparing results from estimated levels of fragmentation at different scales showed convincingly that greater detail of landscape pattern was detected with smaller units of analysis. Larger cells captured a wider range of morphological features which tended to blur differences between urban subzones and homogenizing areas that smaller cells showed were rather heterogeneous.

Results from the error assessment of the 450 m urban context classification suggest that the top five most urban classes in the urban context classification match a significant share of the areas manually labeled as built by CERSGIS. With a producer's accuracy reaching 94.4%, the pattern-based urban context map seems to identify as urban most of the areas classified as built by the CERSGIS map. This agreement-disagreement table, however, doesn't provide any detail about the accuracy of the transitional classes detailed in the urban context map, since the aggregated class only differentiates built from non-built. The lower 67.8% user's accuracy indicates problems of confusion between built and non-built classes, an issue that is somewhat expected given the discrepancies in scale and classification schemes between the two land cover maps. By aggregating the land cover classes into a uniform grid cell unit of analysis, important information about individual urban features was lost, but this was a trade-off in order to be able to incorporate contextual measures of fragmentation and measures of texture into a more complex urban class that would be compatible with demographic analysis.

B. Scale, fertility, urban context and living arrangements

Results from section 5.2 indicate that the association between fertility, urban context and living arrangements varies with different levels of aggregation. The R^2 obtained in the OLS regressions indicate that the variance in fertility explained by the selected independent variables of interest and controls fluctuates between different scales of analysis. An R^2 of 0.36 was obtained for the smallest unit of analysis. As cell size increased to 1800 m the R^2 dropped to its lowest value of 0.32 and then increased to a maximum of 0.63 for the largest cell of 14400 m. Even though we see a highly improved R^2 for the larger cell sizes it is important to note that very few of the independent variables of interest and controls are significant predictors of fertility at this scale. This result indicates that even though the independent variables explain a fair amount of the variance in the dependent variable they fail as individual predictors of fertility levels. At this coarsest spatial scale the independent variables seem to be capturing compounded effects that are a product of contextual interactions and also aggregation effects that are a manifestation of the ecological fallacy. This result is not surprising given that there are significant differences between associations estimated at the individual level and those estimated for aggregated units. Ecological correlations in effect vary dramatically based on the heterogeneity of the data between subareas as well as on the homogeneity of the data within subareas (Robinson 1950). By increasing the cell sizes the variance of both independent and dependent variables are averaged, creating areas that are very homogeneous between them. On the other hand, with smaller cell sizes the variance of independent and dependent variables increases, generating areas that are very homogeneous within them and heterogeneous between them.

1. Scale and the association between urban context and fertility

Defining urban context with different size units of analysis provided an important first view of the effect that scale has on the strength of the association between household structure, urban context and fertility levels in the study area. Comparing the results from OLS for each cell size we can conclude that when assessing the connection between urban context and fertility levels, the relative size of the urban unit of analysis plays an important role. As was discussed in the previous section, while larger units of analysis tend to explain more of the variance in fertility levels the urban context classes are more significant in explaining fertility for smaller cells. The two smallest units of analysis (450 and 900 m) have the highest number of significant urban classes explaining fertility levels. In the case of the 450 m cells, the four most urban classes have significantly lower fertility levels than the average for the study area, whereas the less urban class, fragmented transition, has significantly higher fertility than the average for the study area. When doubling the cell size to 900 m, results show that the five most urban classes within the urban context have significantly lower fertility levels than average, including the scattered settlement class. The lowest fertility level is found in the fragmented large patches urban class within the group of five most urban contexts. At this scale the compact urban class has fertility levels comparable to those found in scattered settlements in the countryside. With the increase in cell size we see that areas identified as fragmented transition lose their significant positive association with fertility levels. The demographic characteristics of these transitional areas found in the least urbanized end of the urban spectrum seem to be small enough to be absorbed by other urban classes. When doubling the cell size to 1800 m the number of significant urban classes explaining fertility levels drops to three, with the least urbanized class, fragmented sub-urban, losing its significance. This result shows that by defining an even larger urban subzone the demographic differences that were evident within the city at smaller scales tend to disappear. We can infer that the demographic characteristics of the fragmented transition class are better captured by the smallest unit of analysis (450 m) whereas the ones of the fragmented suburban class are better captured by the slightly larger 900 m one.

With a cell size of 3600 m the urban context classes that are significantly associated with lower fertility levels slide down from the most urban end of the urban context spectrum into transitional classes. At this scale, lower fertility levels are seen for three intermediate urban context classes: fragmented large urban patches, dense and dispersed small urban patches and fragmented suburban. With the larger cell size, the compact urban area lost its significance in explaining lower fertility levels in the study area. This result indicates that the larger urban contexts defined by the 3600 m cell fail to capture some of the demographic characteristics found in the most consolidated parts of urban areas. The 3600 m cell absorbs the city center and the demographic characteristics that were evident in smaller cell sizes are averaged out.

With a cell size of 7200 m none of the urban context classes are significant explanatory variables for fertility levels in the study area. This means that at this scale the larger subzones fail to capture any significant association between urban context and fertility levels once all the control variables are added. The increased variance in demographic characteristics captured by the 7200 m cell blurs any possibility of distinguishing significant fertility patterns within the urban context. However for the largest unit of analysis, 14400 m, two of the six urban context classes appear to have significant effects on fertility levels. The compact urban area and fragmented suburban classes show comparable lower than average fertility levels. This large cell identifies demographic differences that are very similar to the classic distinction between urban and non/urban areas.

Comparing results from OLS for different cell sizes we can conclude that the smallest unit of analysis (450 m cell) captures the wider diversity of demographic characteristics throughout the urban context. The smallest cell not only identifies differences within the city by pinpointing specific neighborhoods where fertility levels are the lowest and the highest, it also allows identifying areas in the countryside where fertility levels are higher than average. This smallest unit of analysis provides a fairly complete picture of the urban gradient that detects both ends of the urban context spectrum.

2. Scale and the association between household structure and fertility

Results from OLS for different units of analysis show that the association between fertility and family structure is fairly stable throughout scale for small cell sizes (450 to 1800 m). While female headed households, single parent households and larger extended family households are consistently associated with lower fertility levels, households with a head residing away or a head belonging to the Ga ethnic group tend to be associated with above average fertility. The correlation that was identified between extended family residence and lower fertility levels is a rather unexpected result given that previous research in developing countries linked household size to higher reproductive levels (Bongaarts 2001). This finding indicates that the small units of analysis used in this study are effective in detecting demographic patterns that are characteristic of urban environments where fertility levels tend to be below average but at the same time high costs of living combined with shortage of housing encourage sharing of quarters. In effect, extended family living arrangements are fairly prevalent in West African cities where migrants rely heavily on family networks.

On the other hand, as was the case for the urban context variables, the significance of the living arrangement variables seems to decrease substantially with larger units of analysis. Results for larger cell sizes (3600 to 14400 m) indicate that very few of the independent variables pertaining to living arrangements are significantly associated with fertility levels. For cell sizes between 3600 m and 14400 m, OLS regressions identified a significant association between polygamist households and fertility levels. However, it has to be noted that those effects are inverted with differing cell sizes. For the smaller 3600 m cell size, polygamist households are associated with significantly lower fertility levels than average, a result that is consistent with previous research in the region. For larger cell sizes (7200 and 14400 m) the effects of polygamist households on fertility are reversed showing higher levels of fertility than average. This result is unexpected since research has shown that women sharing a husband tend to have less access to their partners and less exposure to intercourse (Bongaarts, Frank and Lesthaeghe 1984; Dodoo 1998). Examining closely the distribution of polygamist households in the study area, it is evident that they tend to be localized, with very few rural areas showing high prevalence of polygamy. With larger cell sizes, the share of subzones where polygamy is practiced increases, eliminating any of the local differences that were detected by small cell sizes. It is apparent that polygamy is generally practiced in our study area in few small rural areas which are not captured by the large cell size unit of analysis.

Consistently higher fertility levels are seen throughout most of the scales of analysis for households where the head of household has a different usual residence and households where the household head belongs to the Ga ethnic group. These results are significant regardless of the size of cell used for the analysis showing that they are not localized effects but rather a widespread association between a type of household and higher fertility. The positive association of the Ga head of household, a patrilineal ethnic group, with fertility levels confirms findings in the region that identified significant differences in fertility outcomes between matrilineal and patrilineal lines of descent. Takyi and Dodoo (2005) found that women in matrilineal ethnic groups tend to be more successful in achieving their reproductive preferences than those belonging to patrilineal ones. The positive association found between household heads residing away and higher fertility levels on the other hand is a result that is somewhat surprising, since one would expect that women residing in households where the head is not regularly present would have fewer opportunities to get pregnant. However, this result indicates that even when the head resides away the structure of the household is preserved, a trend that suggests the prevalence of patterns of temporary or circular migration that seem to be associated with higher fertility levels.

Lower fertility levels are seen throughout the study for areas where a significant share of women aged 15 to 20 remain single, a result that indicates the importance of delaying marriage as an significant driver of fertility decline in the region (Weeks et al. 2010).

C. Urban context, fertility and living arrangement spatial components

Results from the OLS regression with the 450 m unit of analysis indicate that there is a significant association between urban context, living arrangements and fertility. As expected, significantly lower fertility levels are seen in areas that are on the more urbanized end of the urban spectrum and higher fertility levels are seen on the least urbanized end of the spectrum. At the same time, significantly lower fertility levels are observed in single parent households and female headed households, while significantly higher fertility levels are found in households where the head has a different usual residence and the head belongs to the Ga ethnic group. The OLS regression produced nine variables of interested with significant association to fertility with an R^2 of 0.36. The model fit was higher upon correcting for spatial autocorrelation in the independent variables through the use of spatial filters. Results from the OLS using spatially filtered variables show a higher R^2 of 0.42 and some subtle changes in the significance of the independent variables of interest. The strength of the effects of the urban context variables changed slightly when including controls for spatial components for all the other independent variables. While in the original OLS the dense and dispersed small urban patches class had the exact same effect on fertility as the fragmented suburban class, when controlling for spatial components in the OLS the dense and dispersed small urban patches class exhibits a slightly higher coefficient. The same is observed for the less urban fragmented transition class where adding the spatial component controls increases the positive coefficient from the original OLS. Even though none of the urban context variables were spatially filtered themselves it is evident that by controlling for spatial components in the different independent variables some of the spatial components of the urban context variables are captured. The spatially filtered OLS shows a strengthening in the association between fertility levels and urban context. By filtering the independent variables the model is able to isolate spatial dependence in the model and capture the effects of urban context on fertility without any of the bias of the neighbor effects.

When controlling for spatial components in the independent variables we can identify significant changes in the association between living arrangements and fertility levels. While only two living arrangement variables had significant effects on fertility for the original OLS the spatially filtered OLS identifies five living arrangements with significant association to fertility levels. Single parent and female headed households are negatively associated with fertility, although for single parent households lower fertility is solely explained by the filtered component of the variable. This result indicates that lower fertility levels found within single parent households do not follow any significant spatial distribution pattern but are rather found in random places through the study area. On the other hand, the lower fertility levels detected in households with female heads are the product of both filtered and spatial component of the variable. This means that there is a significant spatial pattern in the location of the female headed households with lower fertility where neighboring female headed households are influenced by the lower fertility levels. This result confirms previous findings in the region that associate female headed households with fewer children than male headed households (Lloyd and Gage-Brandon 1993).

Larger households with numerous extended family members are significantly associated with fertility in the spatially filtered OLS, although that association can be decomposed into opposite effects. While the filtered variable has a significant positive correlation to fertility, the spatial component has a significant negative correlation to fertility. This result indicates that even though overall larger households can be associated with women having larger families, in localized areas such as cities the preference for fewer offspring may be associated with the forced sharing of residences due to urban housing constraints.

A finding that is worth mentioning is the significance of the spatial component for two variables that were not significant in any of the original OLS regressions. The spatial component of the variable grandchildren of the head residing in the household has a significant positive association with fertility while the spatial component of the variable two parent households has a significant negative association with fertility. This result indicates that higher fertility levels are found in households with grandchildren of the head but only when those are clustered together, a common occurrence in smaller settlements in the more rural areas. On the other hand lower fertility levels are found in households with children that have two parents residing in the household but only when those households are clustered together, particularly in more urbanized areas where the nuclear family model is spreading.

The use of a spatial error model that controlled for spatial autocorrelation in the error produced satisfactory results based on the comparison of measures of goodness of fit. This last model included a spatial autoregressive error term in the regression that controls for the spatial autocorrelation that wasn't captured by the spatial filter. Results from the spatial error model show an improved peudo-R^2 of 0.53 with the Akaike Information Criterion (AIC) decreasing from -440 to -1143.

The effects of the urban context on fertility levels are slightly modified by the spatial error model in comparison to the spatially filtered OLS regression. Even though the same urban classes remain significant, the strength of the association between urban class and fertility level changed slightly. In the spatially filtered OLS significant negative effects on fertility were the highest for the fragmented large urban patch class, followed by dense and disperse small urban patches, fragmented suburban and were the lowest for the compact urban class. In the case of the spatial error model the strongest significant negative effect on fertility remains in the fragmented large urban patches class, but is then followed by the compact urban and then the dense and dispersed small urban patches classes with the lowest effects found in the fragmented suburban class. All coefficients for fragmented large urban patches, dense and dispersed urban patches and fragmented suburban classes decreased in the spatial error model compared to the filtered OLS, while the coefficient for the city centric compact urban class increased from 0.049 to 0.054. Results from the spatial error model for the urban context show that when controlling for unaccounted spatial autocorrelation in the error term, the strength of the association between fertility and urban context increases significantly for the more consolidated compact urban parts of the city. Additionally it is evident that by controlling for the unaccounted spatial autocorrelation, urban classes with intermediate effects on fertility levels shift towards the city center and the lowest effects move towards the city's periphery. The highest negative effects on fertility remain on the fragmented large urban patches found within the city, an effect that is consistent with our findings in the filtered OLS and the standard OLS. This result indicates that by controlling for spatial autocorrelation in the model the gradient effect that identified stronger negative impacts on fertility towards the outskirts of the city shift towards the city center. This finding indicates that there are important spatial effects in the association between fertility levels and urban context, with attitudes towards lower reproductive levels initiating within the most urban areas of cities and slowly spreading into contiguous areas.

The association between living arrangements and fertility remains very similar for the spatial error model when compared with the spatially filtered OLS. Significantly lower fertility levels are seen in single parent, female headed and larger extended family households. The spatial distribution of households with grandchildren of the head appears to be an important driver of higher fertility levels, as was also observed for the spatially filtered OLS model. This is particularly evident in small settlements in rural areas where compound living is common and higher fertility prevails in households with different generations.

Two variables that are significant in the spatial error model that were not significant in any of the previous OLS models are households with foster children and polygamist households. For both of these variables the spatial distribution of the households plays an important role in shaping fertility levels. Households with foster children that have an above average fertility level tend to be clustered together just as households that practice polygamy that have a below average fertility level are likely to be located in close proximity of each other. These two results point to an association between living arrangements and fertility that is representative of rural households where the practice of fosterage is accompanied by higher reproductive levels and where polygamy is more prevalent.

D. Urban context, fertility and living arrangements: spatial heterogeneity

Spatial variance in the association between household structure, urban context and fertility is a sign of the incidence of spatial heterogeneity when modeling fertility with the selection of independent variables. GWR was used to examine the spatial patterns of the variance in the association between dependent and independent variables. GWR is particularly useful to visualize the spatial patterns of the effects of each independent variable on the dependent variable. Examining the results from the GWR revealed interesting patterns in the way that the independent variables are associated with fertility levels. The urban context, for example, shows both positive and negative association with fertility, a result that is consistent with findings in previous sections. Higher fertility levels are consistently seen in the more rural areas that coincide with the fragmented transition class as it was defined in the urban context map. Two hot spots of higher fertility are also evident within the urban areas of Accra and Tema, indicating very specific areas within the most consolidated urban areas where reproductive levels are comparable to those found in rural areas. These areas with higher fertility levels found within the city tend to correspond to very centric neighborhoods where it is very likely that slum-like living conditions tend to replicate living environments found in the countryside. This result confirms the trend identified in the OLS and spatial error models where within urban areas the more consolidated and poor compact city centers tend to have higher fertility in some cases at levels comparable to those seen in rural areas.

In terms of living arrangements, results showed consistently that single parent households have significantly lower fertility levels regardless of where those households are located. Examining the coefficients produced by the GWR, it can be seen that there are spatial patterns in the distribution of the effects of single parent households on fertility. It is clear that single parent households tend to have higher fertility levels in rural areas, where it's possible that a parent being away is the product of temporary out-migration. Higher fertility levels are also evident in households with single parent households found in the rural areas immediately adjacent to Accra and Tema. These areas are rapidly changing with the expansion of the city, but despite their proximity to the city they are not yet fully urbanized and seem to mirror some of the rural demographic characteristics.

In the case of female headed households, the pattern identified for single parent households and urban context is replicated but more pronounced than for the latter two variables. Lower fertility levels in female headed households seem to spread following a network of settlements with a noticeable spike in fertility within the city of Accra. This localized hot spot of higher fertility relates again to the most consolidated and poor city center, an area that regardless of being found within the heart of the city shows demographic characteristics comparable to those found in rural areas. It is worth noting that this hot spot found within the city of Accra is immediately surrounded by a lower fertility buffer that matches the location of wealthier fragmented suburban as were described by Yeboah (2003).

Finally, results from GWR show that the strongest association between fertility and households where the head has a different usual residence is mostly found in inland rural areas. This is a result that is not surprising given that these are the areas that are likely to see the highest rates of temporary/circular out-migration.

Results from this study indicate that there is a significant connection between fertility and urban transitions in this region of West Africa. Through the use of a pattern-based definition of urban context this study was able to identify a more detailed connection between degree of urbanization and fertility levels. The urban gradient approach identified how diverse urban contexts have diverse reproductive preferences in our study area. Research in the region has shown that overall fertility levels tend to be lower in the city in comparison to the countryside (Caldwell 1967; Casterline 2001), yet clear differences in fertility levels taking place within the city were identified in this study. The more consolidated urban city center shows fertility levels comparable to rural areas, thus differing from those seen in the rest of the city. At the same time, the lowest fertility levels are clearly seen towards the edges of the city where suburbanization is spreading and accommodating the wealthiest more westernized population. These more westernized populations are leaving behind traditional living arrangements which are being replaced by a surge in single parent households and especially in female headed households.

VII. Conclusions

This study examined the diversity of demographic characteristics that define urban contexts in a region of West Africa. The main goal was to evaluate if there is a connection between the degree of urbanization of an area, patterns of living arrangements and women's reproductive levels. An alternative definition of urban/rural spaces is proposed using an urban gradient approach that is solely based on the pattern characteristics of the landscape. Through the use of remote sensing and GIS, an urban context definition is created mapping urban spaces in a manner that is independent of demographic and socio-economic indicators, thus allowing to gauge how closely tied together urban and fertility transitions are.

Results from this research indicate that there is a strong connection between fertility levels and urban context in the coastal areas of Ghana. The more urbanized classes of the urban context show significantly lower than average fertility levels while the least urbanized classes show significantly higher than average fertility levels. These results not only allow us to differentiate rural from urban fertility levels, they also identify differences in fertility levels within the city. While the poorer, densely populated city centers tend to have higher fertility levels than the rest of the city, lower fertility levels are identified in wealthier consolidated neighborhoods. Reproductive levels in the wealthier parts of the city seem to be leading the trend towards fertility decline, whereas the limited access to resources of poor neighborhoods seems to be replicating rural living conditions within the city and show reproductive levels comparable to those found in the countryside.

It is important to note that even though there are significant differences in fertility levels within the city, those differences are considerably influenced by spatial effects. By examining the spatial components of the association between fertility levels and urban context it became evident that a significant share of the correlation between the two variables is the product of neighborhood effects. Wealthier neighborhoods with below average fertility levels have significant impacts on the reproductive levels of adjacent neighborhoods. This result indicates that fertility and urban transitions are very closely tied together with fertility levels being the lowest for the city center and gradually growing as distance from the city center increases. Even though this study only provides a cross-sectional approximation to the association between fertility and urban contexts, it is reasonable to assume that the significance of the spatial effects is an indicator of the importance of spatial diffusion in the spread of family planning within the urban environment. The importance of the spatial components points to the significance of geographic diffusion patterns in the spread of family planning such as those identified through the history of the demographic transition in western Europe in the late XIX century (Watkins 1991). In this Ghanaian urban context the high density of highly urbanized environments promotes the accumulation of resources, the spread of education and the expansion of social networks that facilitate the diffusion of innovations such as delaying marriage and the use of contraception. As Lesthaeghe and Surkyn (1988) pointed out, cultural innovations tend to spread from higher to lower socio-economic strata through imitation. However, this diffusion process is highly constrained by traditional cultural and social structures.

In West Africa, cultural context has traditionally played an important role in shaping reproduction decisions, where numerous offspring ensure the care of the elderly and the survival of the lines of descent (Caldwell and Caldwell 1987). This research explored the connection between social structures found within the household and fertility levels by examining how different living arrangements correlate to fertility levels. The findings indicate that there are clear patterns that connect household structure, fertility, and urbanization. Female headed and single parent households are consistently linked to lower than average fertility levels, a result that associates decreasing fertility levels with the spread of smaller nuclear households that is taking place in the developing world (Bongaarts 2001). At the same time, larger extended family households are paradoxically associated with below average fertility levels because of important spatial effects. Even though previous research in the region linked large households with above average fertility levels, findings from this research indicate that there is a significant transformation in the spatial distribution of living arrangements and how they connect to fertility. While larger than average households used to be representative of rural areas, where fertility tends to be higher, the scale and pace of urbanization in the region has made access to housing in cities very scarce and turned extended family housing into a city phenomenon. Given the lack of resources sharing quarters has become a predominant feature of the West African city, where larger households are significantly associated with lower than average fertility levels.

On the other hand, households where the head has a different residence are associated with above average fertility levels, a result that indicates that short term or temporary migration is associated with higher fertility. This is in contrast to the negative association found with households where the head moved from a different region in the last five years. Even though migration and especially migration to the city has been linked to declining fertility levels (White et al. 2005), this research indicates that for the specific case of short term migration that relationship is reversed. The high mobility of the household head is characteristic of poor rural areas where traditional household structure and reproductive behaviors aren't significantly disrupted by temporary migration.

This research compared different scales of analysis to assess the association between land cover and demographic patterns finding that smaller units of analysis captured the widest range of demographic characteristics. However it is important to recognize that these results are still limited by the level of aggregation. Using an even smaller cell size may allow smaller neighborhoods and rural enclaves to be identified that are missed by the 450 m cell. Although using a uniform grid cell unit of analysis is not necessarily the optimum way to characterize the urban environment, in this study the uniform unit allowed merging land cover and demographic data originally collected at different scales.

Even though the results confirm that diverse urban contexts are associated with diverse demographic patterns, it is important to recognize that the pattern-based definition of the urban context is still an arbitrary definition of space. There is no consensus on what constitutes an urban place and that means that there will be many different ways of characterizing urban spaces. This study proposes defining urban context based on characteristics of landscape fragmentation, an approach that is easily replicable in other data poor environments. At the same time, it is important to recognize that the urban context classification derived in this study is a relative measure of degree of urbanization that is based on the fragmentation characteristics of this particular landscape. Other research will have to test its replicability in different geographic settings.

These results show that urban contexts are much more diverse than portrayed by traditional rural/urban classifications, both from a demographic perspective and an urban pattern perspective. This research is a novel attempt at explaining the differences that exist between rural and urban fertility levels in developing countries where the fast pace of urbanization is creating very diverse urban environments. Further research is necessary to expand the understanding of how the urban context is linked to demographic patterns and more specifically to elucidate how emerging urban environments in the developing world are shaping fertility levels. Future research includes refining the pattern-based definition of the urban context by incorporating a multiple end-member component to the spectral mixture analysis and by decreasing the cell size unit of analysis. Improvements in the modeling of the association between urban context and demographic characteristics could be attained through structural equation and multi-level approaches. Finally, given the global urbanization trends, it would be interesting to compare patterns of land use land cover change with changes in demographic patterns.

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Appendices

A. Landscape metrics for all cell sizes

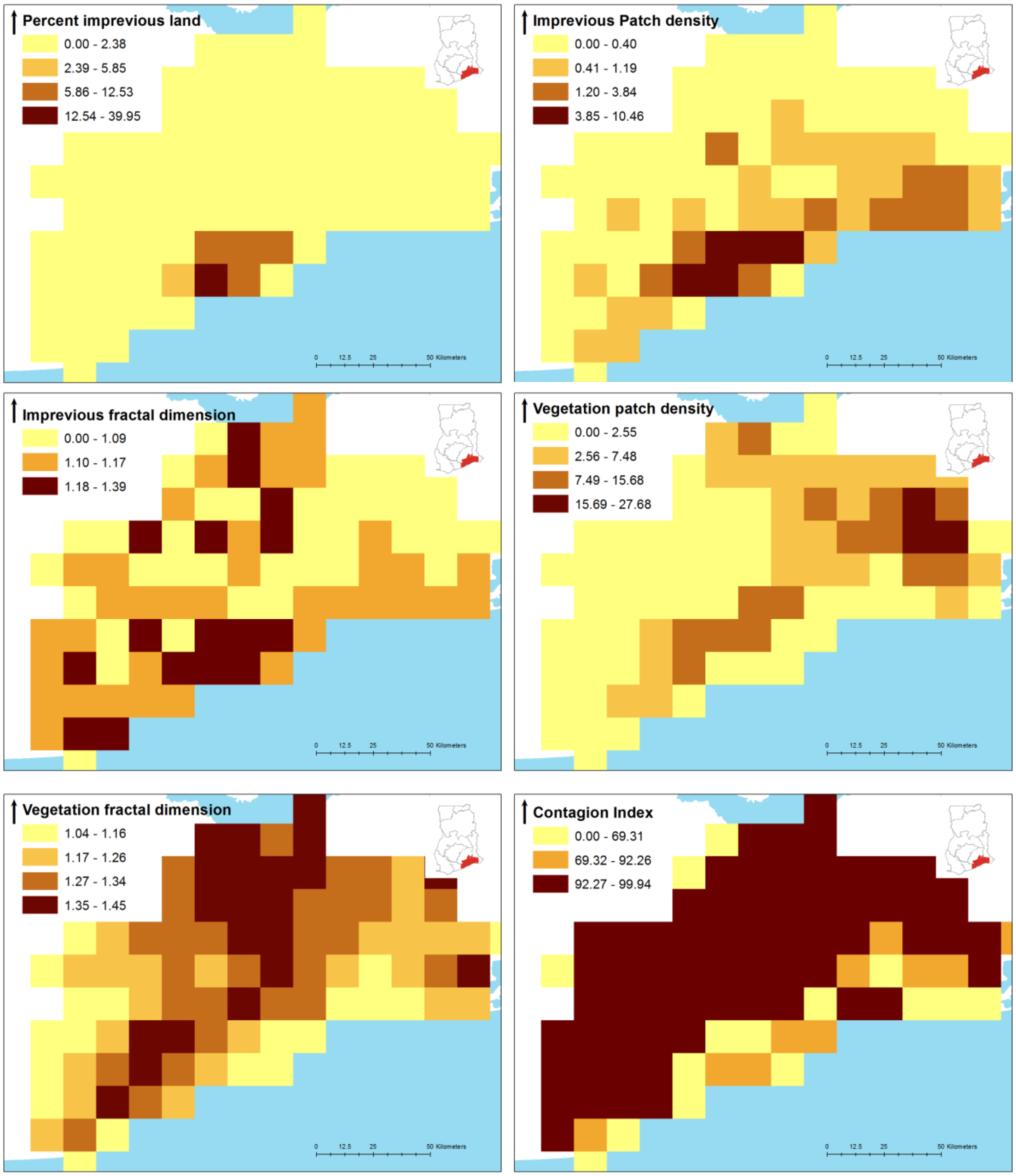

Figure 41: Landscape and class metrics for 14400 meters cell unit of analysis

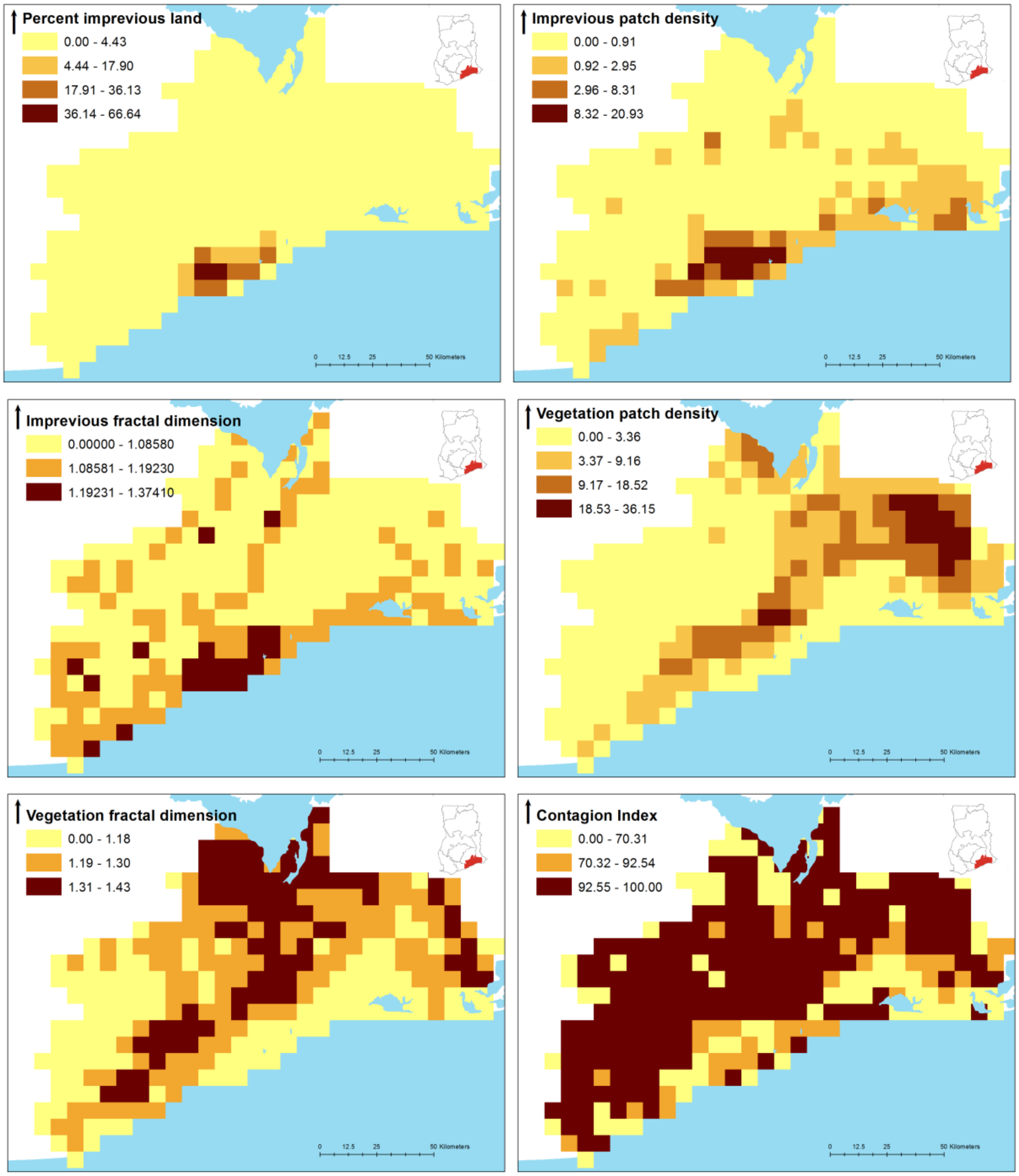

Figure 42: Landscape and class metrics for 7200 meters cell unit of analysis

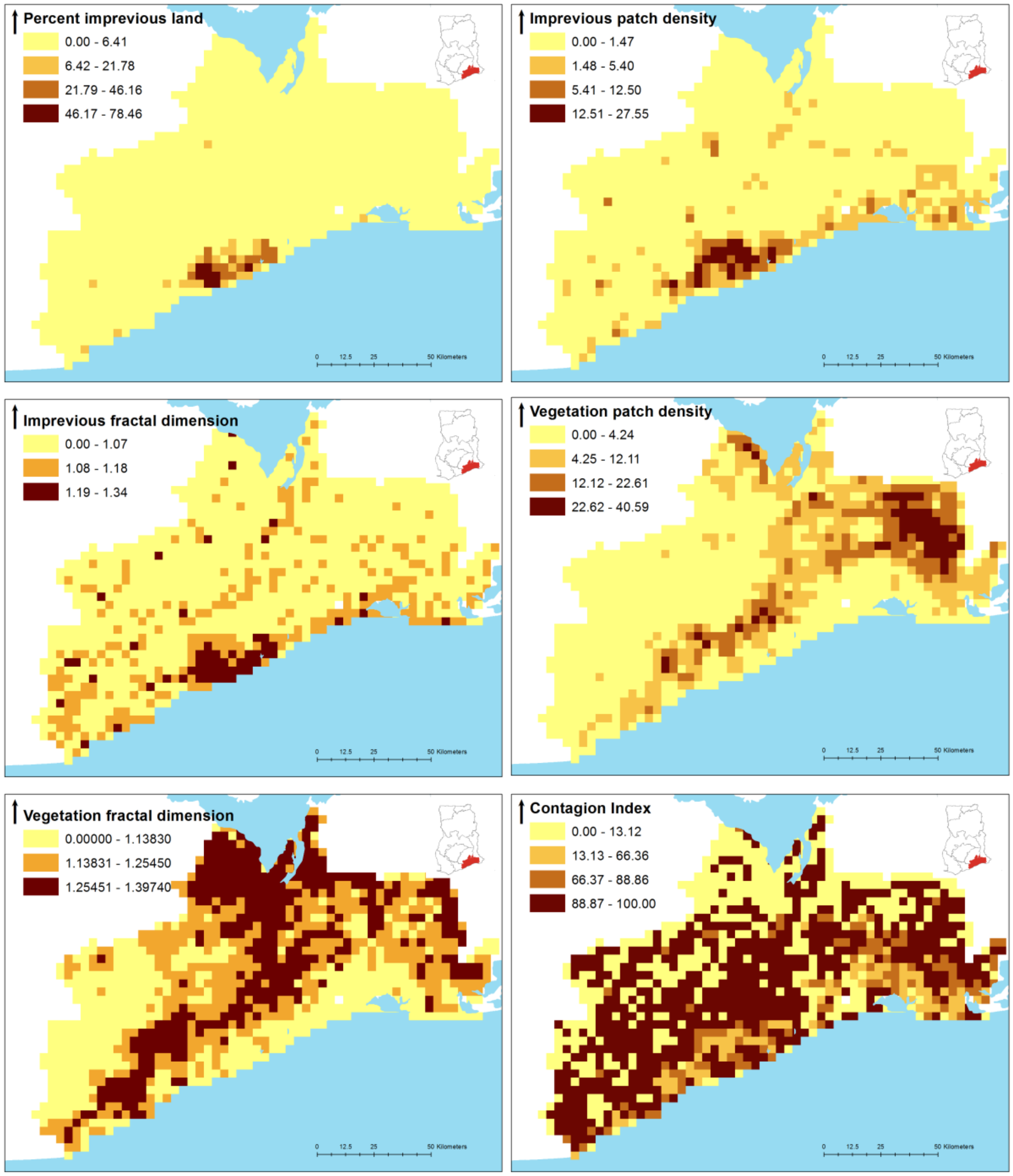

Figure 43: Landscape and class metrics for 3600 meters cell unit of analysis

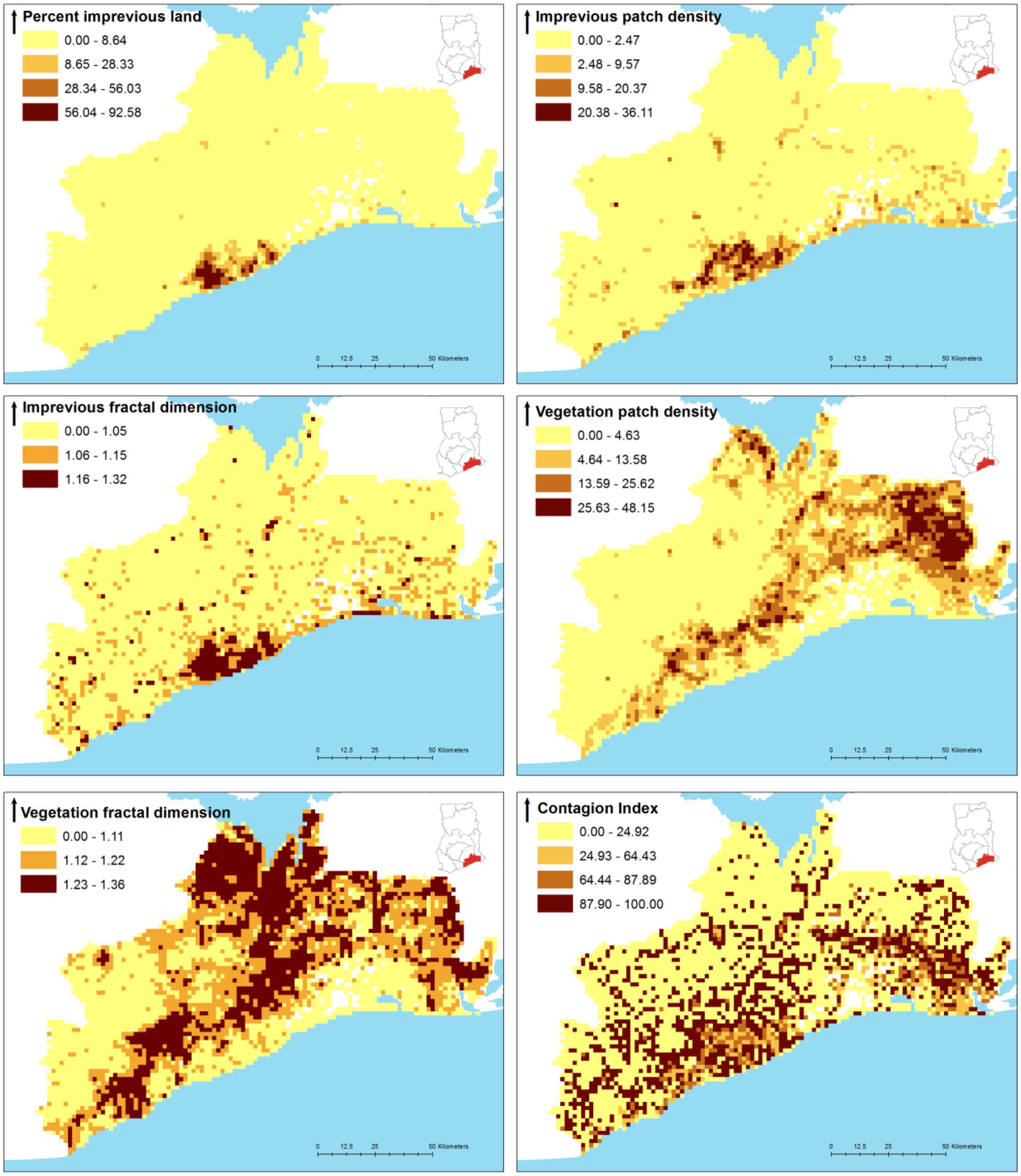

Figure 44: Landscape and class metrics for 1800 meters cell unit of analysis

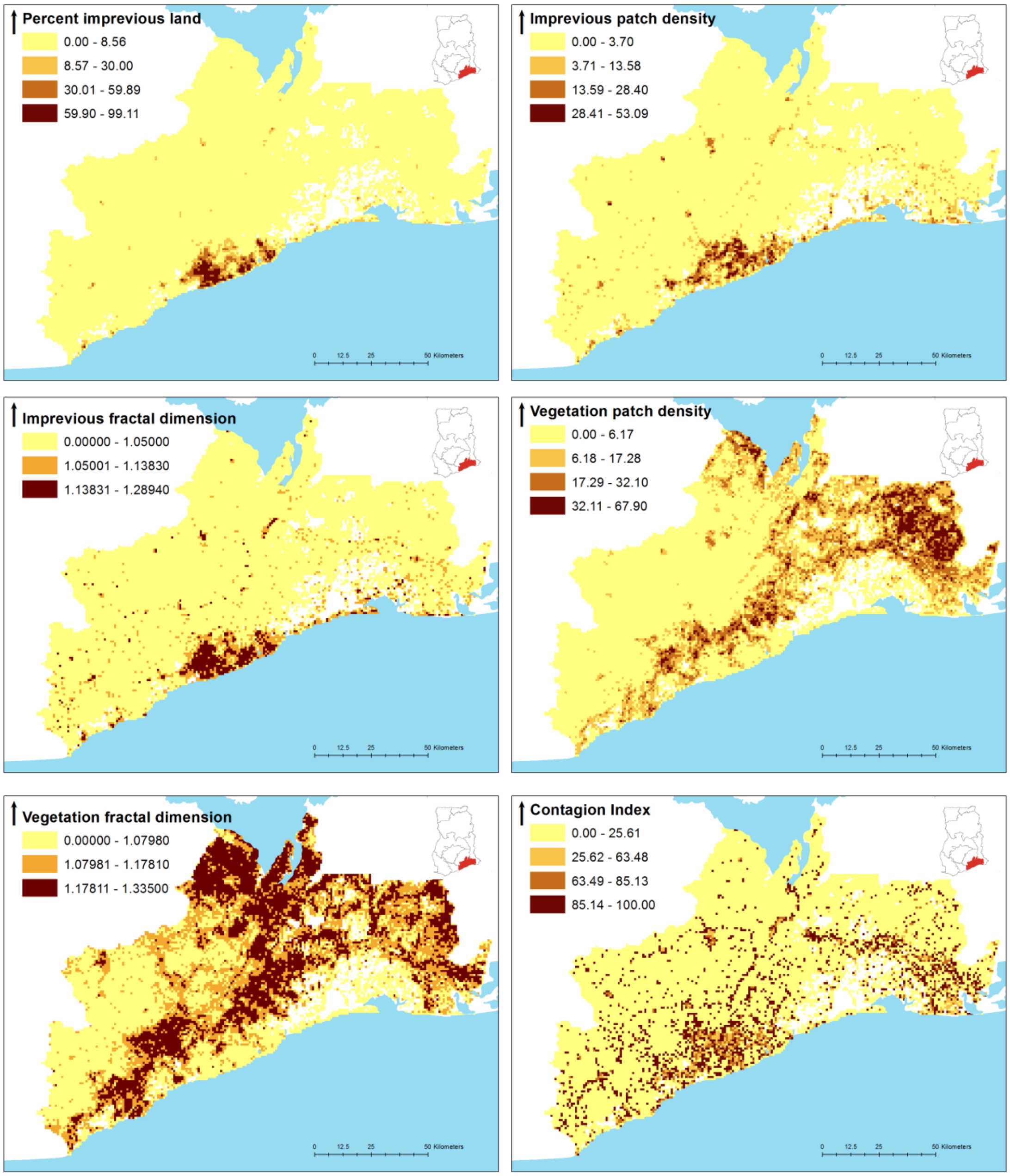

Figure 45: Landscape and class metrics for 900 cell unit of analysis

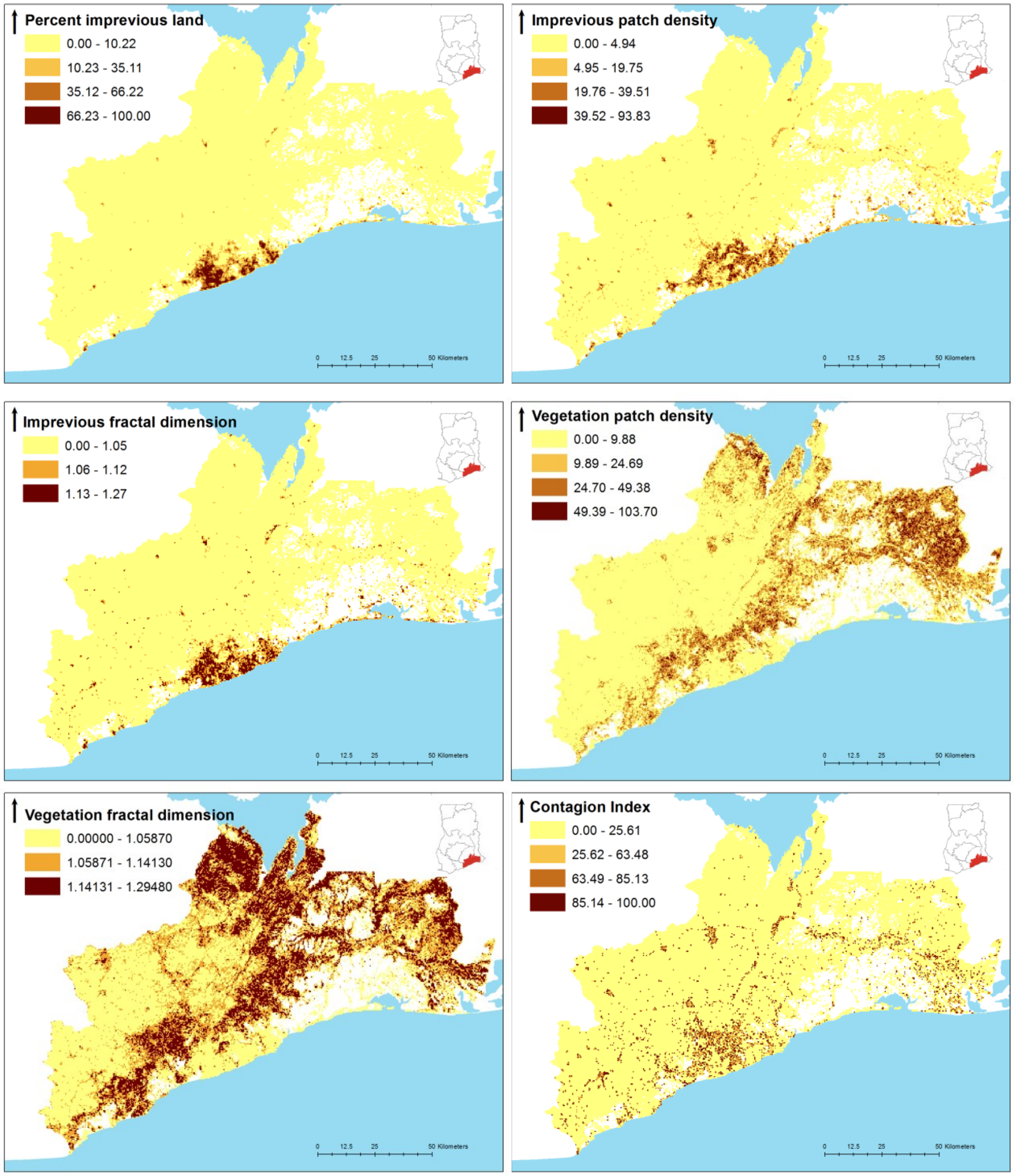

Figure 46: Landscape and class metrics for 450 cell unit of analysis

B. Urban context definitions for all scales of analysis

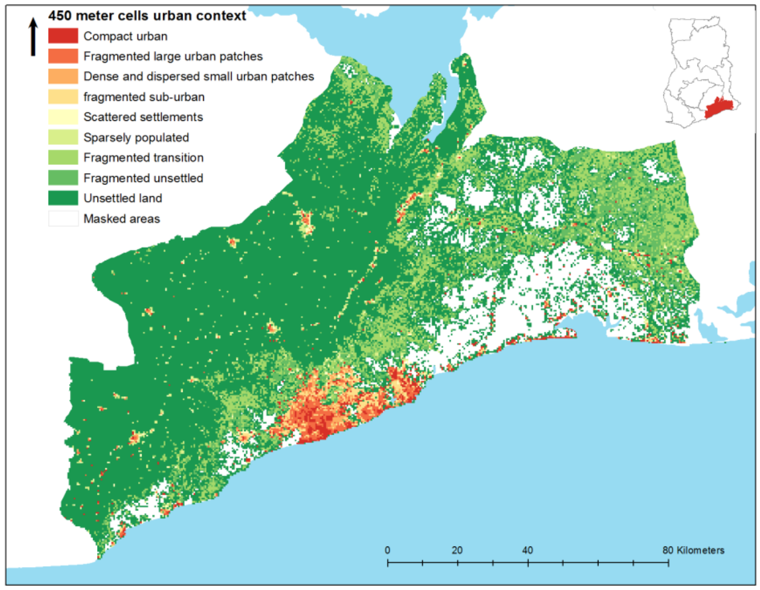

Figure 47: 450 meter urban context classification

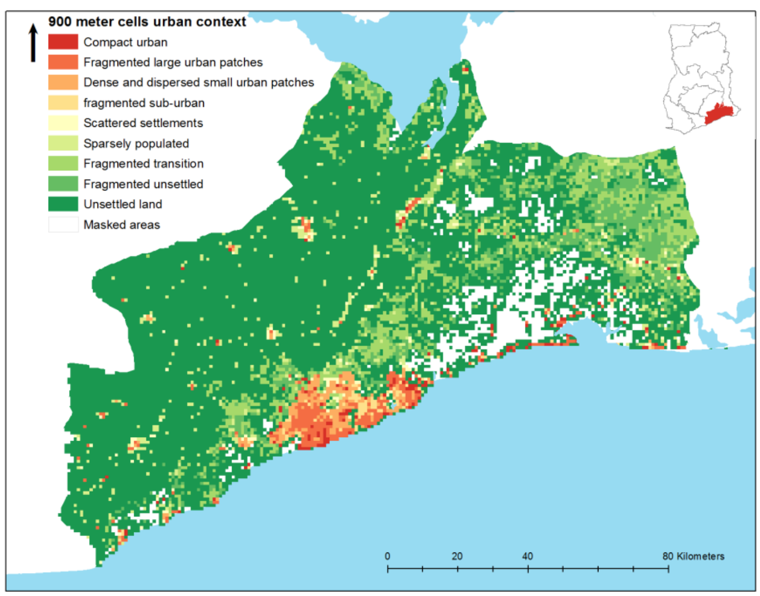

Figure 48: 900 meter urban context classification

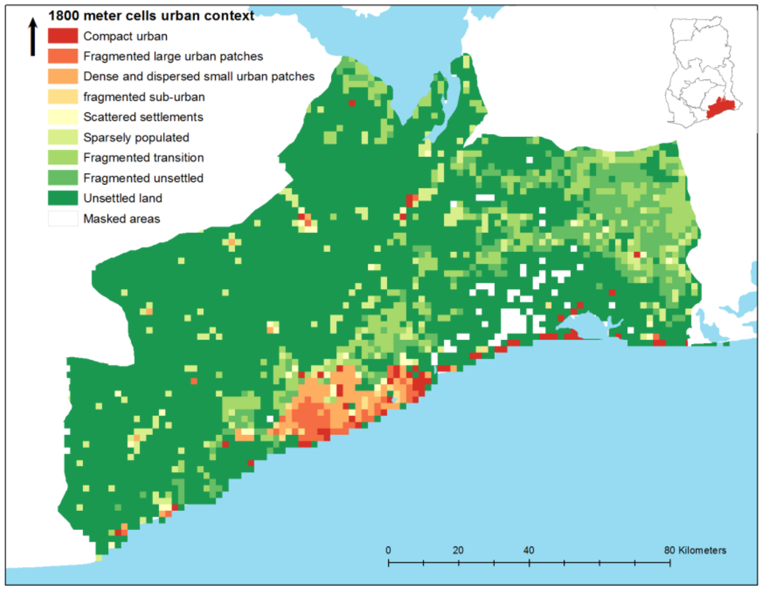

Figure 49: 1800 meter urban context classification

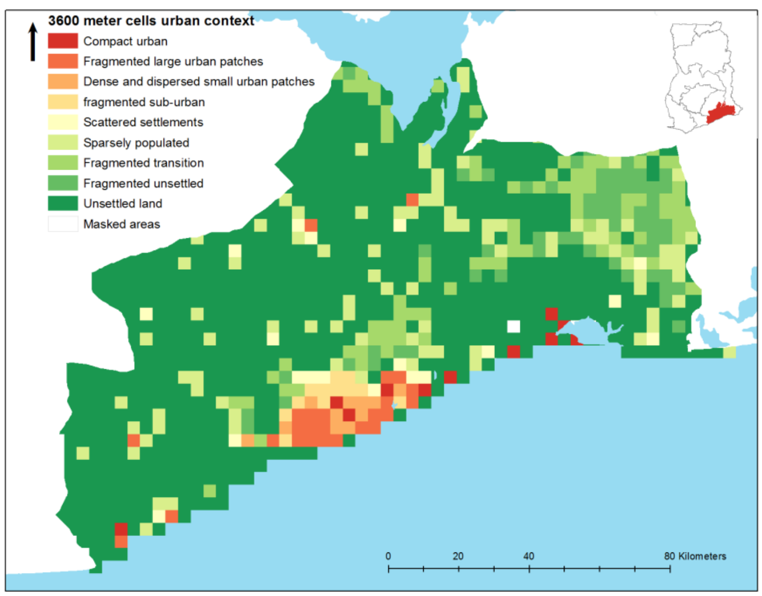

Figure 50: 3600 meter urban context classification

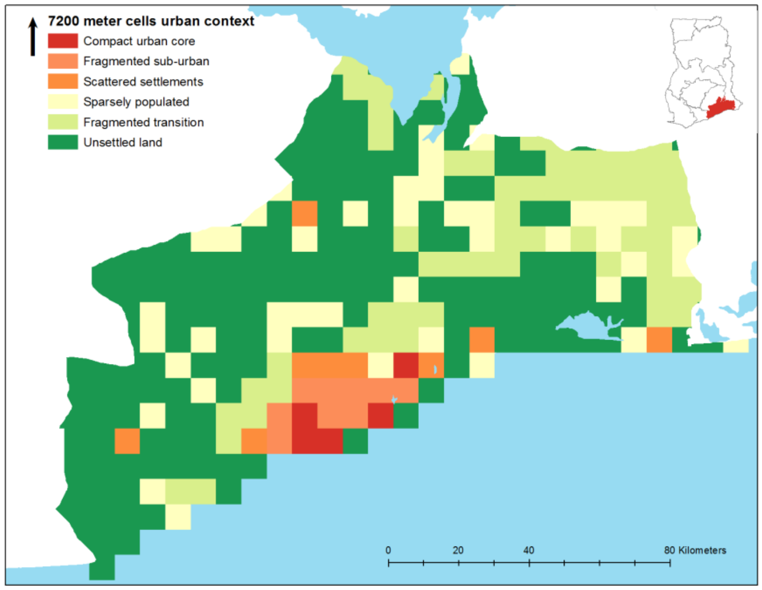

Figure 51:7200 meter urban context classification

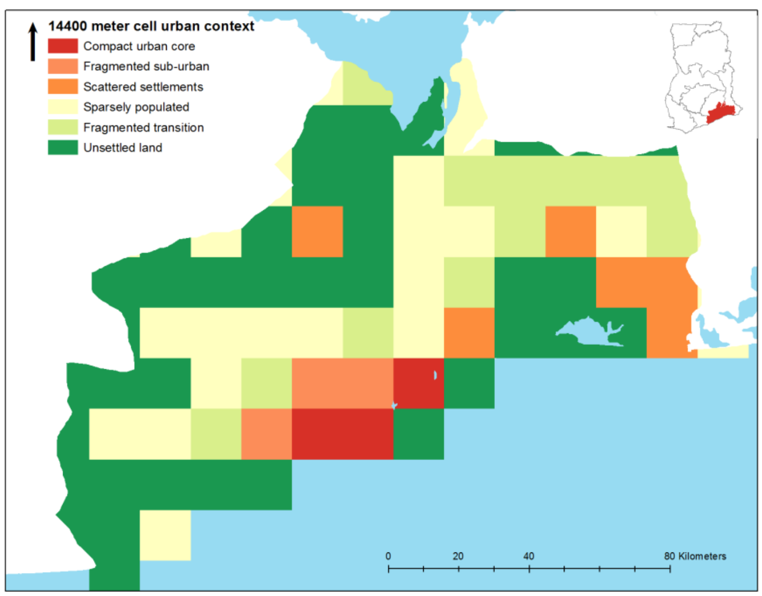

Figure 52: 14400 meter urban context classification