Using High Spatial Resolution Imagery to Assess the Relationship between Spatial Features and Census Data: A Case Study of Accra, Ghana

by Avery Sandborn

B.S. in Geography, May 2013, University of Maryland-College Park
B.A. in Music, May 2013, University of Maryland-College Park

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Thesis directed by

Ryan Engstrom
Associate Professor of Geography

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Abstract of Thesis

Using High Spatial Resolution Imagery to Assess the Relationship between Spatial Features and Census Data: A Case Study of Accra, Ghana

As developing countries experience substantial urban growth and expansion, remotely sensed based estimates of population and demographic characteristics can provide researchers and humanitarian aid workers timely and spatially explicit information for planning and development. In this exploratory analysis, high spatial resolution satellite imagery, in combination with fine resolution census data, is used to determine the degree to which spatial features are able to identify spatial patterns of demographic variables in Accra, Ghana. Traditionally when using satellite imagery, spectral characteristics are used on a per-pixel basis to produce land cover classifications; however, in this study, a new methodology is presented that quantifies spatial characteristics of built-up areas, and directly relates them to census-derived variables. Spatial features are image metrics that analyze groups of pixels in order to describe the geometry, orientation, and patterns of objects in an image. By using spatial features, city infrastructure variations, such as roads and buildings, can be quantified and related to census-derived variables, such as living standards, housing conditions, employment and education. To test the associations between spatial patterns and demographic variables, five spatial features (line support regions, PanTex, histograms of oriented gradients, local binary patterns, and Fourier transform) were quantified and extracted from the imagery, and then correlated to census-derived variables. Findings demonstrate that, while spectral information (such as the normalized difference vegetation index) reveals many strong correlations with population density, housing density, and living standards, spatial features provide comparable correlation coefficients with density and housing characteristics. The results from this study suggest that there are relationships between spatial features derived from satellite imagery and socioeconomic characteristics of the people of Accra, Ghana.

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Chapter 1: Introduction

In an age of rapid urbanization and densification, the ability to identify demographic characteristics and vulnerable communities is an imperative part of addressing the population's changing needs. Census and household surveys are important tools for harnessing this information; however, the administration and analysis of this data is expensive and is often only completed every ten years. These issues are further magnified in developing cities, as these areas often need demographic information in timely and spatially explicit manners in order to make informed planning and policy decisions.

To solve this challenge, other techniques that can be used to complement and improve census surveys should be examined. One solution to compensate for a lack of complete census data is estimating population parameters from remotely sensed imagery. This technique is highly desirable due to the consistency of satellites passing over an area, the quick turnaround time from collection to analysis, and the locational preciseness of the data derived from the image. Being able to correlate population characteristics with remotely sensed features affords a prompt and efficient way to monitor communities' characteristics and vulnerabilities. Remotely sensed estimates allow population information to be examined in between census collections, and afford regions that are unable to implement census surveys with the ability to collect and analyze demographic data.

Using remotely sensed products can help to identify, map, and monitor the drivers, impacts, and patterns of built-up surface change and urban morphology (Herold et al. 2002). A sensor's ability to measure surface properties of tone, color, and texture may potentially enable greater standardization and efficiency of observing land cover and population on an intra-urban scale. Commercial high spatial resolution satellite (CHSRS) imagery allows for the most complete depiction of these surface properties, as its spatial resolution typically measures less than four meters, compared to medium resolution imagery which ranges from four to thirty meters (Satellite Imaging Corporation 2013). Historically, however, high spatial resolution imagery was sparsely used for urban research due to its monetary restraints, as well as its limited availability, which started to be widely used only after 1999 (Herold et al. 2002, Gamba et al. 2007). As higher resolution imagery becomes increasingly available and accessible, remotely sensed data allows for a very detailed analysis of the land cover and population, and can provide useful information for urban planners and developers (Sawaya et al. 2013), as well as humanitarian assistance organizations in times of disaster response (Cutter 2003).

Many studies have employed the use of satellite imagery for land cover and land use change (LCLUC) classifications (Chen & Stow 2003, Lu & Weng 2006). Conventional LCLUC classification studies primarily aim to categorize land covers in discrete classes. To achieve this, many studies utilize spectral information, which categorize land cover classes on a per-pixel basis by spectral signatures. Spectral signatures represent the reflectance values in each wavelength of the electromagnetic spectrum (Xu 2007). This common technique is suitable for classifying water and vegetation, as they have unique spectral signatures that are very distinctive.

However, the use of spectral values often encounters difficulties in integrating varied spectral signatures of built-up materials into a single land cover type of urban area. The built-up class is composed of many different materials that make up buildings, roads, and open spaces, as well as many different land use categories, including formal and informal residential, commercial, and industrial zones. In addition to the broad range of materials and land uses in built-up areas, soil and urban spectral signatures are very similar, and prove difficult for automated methods to differentiate between (Herold et al. 2002, Lu & Weng 2006). This problem is exaggerated in sub-Saharan countries for multiple reasons. When rooftops rust or soils are blown onto roads, the spectral signature of the actual built-up feature can be obscured (Roth 2007). Other times, building rooftops are made out of wood, bamboo, or other natural materials, just as many streets are dirt roads. This can also cause confusion for the classification algorithm, resulting in a built-up feature being inaccurately classified as a natural land cover class (Stoler et al, 2012).

Spatial feature extraction offers a new and innovative approach to identifying built-up areas and, more specifically, correlations with population characteristic estimates. Spatial features are image metrics that examine multiple groups of pixels at once to quantify the geometry, orientation, patterns, and spatial variability of objects within an image (Herold et al. 2003). In an urban context, spatial features focus on extracting geometric, structural, and textural patterns of external building features, and can counteract the confusion observed between the broad variations in spectral signatures of built-up areas. Since built-up areas share a unique set of spatial and textural characteristics, such as straight lines, rectangular features, and building layout and distribution, spatial feature extraction can help to supplement spectral identification techniques, for instance by helping to differentiate between a built-up area and barren soil or clouds, which have similar spectral characteristics.

In addition to studying LCLUC, applying these spectral and spatial extraction techniques directly to demographic characteristics can help to gain specific and quick information about the housing type and properties which may relate to population characteristics. By moving away from the discrete land cover classes that generalize the population within them, spatial metrics can show within-city variations in living conditions and other socioeconomic characteristics. Being able to quantify these spatial features at a local level can help to measure the variations of population characteristics within the built-up area. In 2008, a group of twenty-one remote sensing and slum monitoring experts met with the aim of identifying contemporary techniques to map slums with high resolution imagery (Sliuzas et al. 2008). One of the main outcomes from this meeting was a motivation for designing and implementing automated quantitative approaches to studying slum mapping. These approaches included measures of land cover, textural contrast, building size, orientation, and location. Quantifying spatial features may provide one such avenue of studying slums via remote sensing.

While some studies have attempted to relate impervious land cover layers to population and housing density (Azar et al. 2010, Azar et al. 2013), none have fully explored or tested the possibility of directly relating remotely sensed image metrics to informal settlement mapping, or more broadly, demographic characteristics. This undertaking has the potential to uncover relationships between the physical properties of building shape, size, and layout and the characteristics of the people who live within them. These relationships between spatial features and population characteristics undoubtedly has numerous applications to assist LCLUC identification methods, expand demographic profiling of cities, and guide city administrators, urban planners, and humanitarian aid workers in making more informed analyses and decisions regarding the population.

It is important to note the wide variety of terminology used to describe built-up land cover in the literature. Weeks (2010) describes “urban” as “a place-based characteristic that incorporates elements of population density, social and economic organization, and the transformation of the natural environment into a built environment.” Additionally, there has been substantial confusion between the terms “impervious” and “built-up”. Impervious surfaces refer to any area which is made out of materials in which water cannot infiltrate and materials that are primarily associated with human activities through transportation and buildings (Lu & Weng 2009). Because impervious surfaces include naturally occurring materials, such as bare rock and packed soil, and the fact that not all rooftops in developing countries are impermeable to water, this surface type is not the best descriptor to measure urban areas. Built-up areas indicate the presence of humans, and have long been recognized as important aspects in many urban-environmental studies (Li et al. 2011, Zhang et al. 2014). While some literature may use the terms “urban” or “impervious” in their research, for the purposes of this study, the term “built-up” will be used to represent urban areas in which humans have altered the landscape for habitation.

The remainder of this paper is organized as follows. Chapter 2 is an extensive review of previous literature related to studying built-up areas with remotely sensed imagery, spatial feature extraction and interpretation, spectral and spatial feature comparison, and relating remotely sensed features to census variables and socio-economic indicators. Chapter 3 describes the research question, hypothesis, and scope of work. Chapter 4 is a detailed methodology, including study area, data requirements, and data processing. Results, analysis, and discussion are presented in Chapter 5, while conclusions and future work are detailed in Chapter 6.

Chapter 2: Literature Review

2.1 Studying Built-Up Areas via Remote Sensing

Studying urban areas via remotely sensed technologies has become an important and widely used application of digital image processing. At the conception of urban ecosystem modeling via remote sensing, was the V-I-S (vegetation-impervious surface-soil) model (Ridd 1995), which remains a commonly applied method in contemporary works (Van de Voorde et al. 2011, Schneider 2012, Weng 2012). Within the model, a combination of green vegetation, impervious surface material, and exposed soil land covers are considered the basis of any urban environment. The V-I-S model uses proportions of these land cover classes to identify various urban land uses, such as grassy yards, central business districts, and bare soil, respectively.

Since the V-I-S model was created, many researchers have agreed that urban areas are complex landscapes and have taken on the challenge of identifying and mapping urban area variation (Small 2004). A common method to analyzing land cover is through using spectral reflectance values. Simply using spectral signatures to identify land cover classes works well for discriminating between vegetation and water surfaces, however discrimination between impervious and soil classes is more difficult. To overcome this challenge, many studies have tested the use of vegetation differencing techniques (Masek et al. 2000) and built-up, water, and soil-adjusted vegetation indices derived from multispectral bands (Zha et al. 2003, Xu 2007).

With increased availability of high spatial resolution imagery, a second approach to urban land cover analysis has emerged focusing on spatial features within landscapes.

While spectral signatures identify land cover classes on a per-pixel bases, spatial feature analysis examines multiple groups of pixels at once to determine if distinct shapes, orientations, patterns, and the spatial variability of objects can be extracted from the image and used to identify variations within the city. Spatial features are identified by the occurrence and distribution of linear features and defined shapes with an image. For example, measures of spatial features often pull out road networks and individual buildings within built-up areas (Huang et al. 2007).

Spatial feature extraction from remotely sensed imagery is fairly new, stemming from various other disciplines and venues such as photograph enhancement (Burns et al. 1986), facial detection (Ahonen et al. 2004), motion detection (Palaniappan et al. 2010), and radio wave noise removal (Benesty et al. 2009). By applying these techniques to satellite imagery in built-up areas, spatial patterns of the built-up landscape can be detected and analyzed. The specific spatial features used in this study are described thoroughly in section 2.3 and include the following: line support regions (LSR) which characterize line attributes (Yu et al. 1999), PanTex which is a rotation invariant grey-level co-occurrence matrix (GLCM) texture measure (Pesaresi et al. 2008), histogram of oriented gradients (HoG) which captures structure orientations (Dalal & Triggs 2005), local binary patterns (LBP) which define contiguous regions (Wang & He 1990), and Fourier transform (FT) which examines pattern frequency (Smith 1997).

2.2 Combining Spectral Information and Spatial Features

Recent literature has used feature comparison as a vehicle for determining how effective specific features can classify or unveil spatial patterns of land cover. Generally, GLCM, a simple matrix that determines how often adjacent pixels have the same gray-level value, has been a popular technique for spatial feature analysis (Pesaresi et al. 2008). However, many newer spatial features, including those presented in this research, have been increasingly examined.

Examination of spatial feature classification performance was conducted by Bayram et al. (2011) on QuickBird-2 imagery of Fethiye, Turkey. Their results showed that LBP and the Gabor spatial feature, a linear Gaussian filter used for edge detection, were the most effective in classifying traditional land cover (water, forest, urban, and crop), and HoG and GLCM did not perform as well as expected. Overall, Bayram et al. (2011) concluded that edge orientation based features are not suitable for identifying water or forest classes and should be avoided in these areas.

Within the built-up landscape, Ella et al. (2008) analyzed settlement classification in Soweto, South Africa using a variety of spatial features, including GLCM, LBP, and Lacunarity, a distribution measure of gaps. Their research showed that LBP produced the most accurate classification results, followed closely by GLCM. Lacunarity paled in comparison to LBP and GLCM, however, produced better results than other one-dimensional feature vectors such as Moran's I, Geary's C index, and G index.

Because built-up areas exhibit many textural and structural characteristics, it is also desirable to examine various combinations of these spatial features together as classification schemes. By combining features together, improvements can be made to the identification process of built-up areas. Additionally, spatial feature outputs can differ greatly based on the study area context and image resolution, making it imperative to understand the differences between feature performances.

Graesser et al. (2012) used various spatial features, including PanTex, HoG, and LSR, to map formal and informal neighborhoods in four semi-arid developing cities: Caracas, Venezuela, La Paz, Bolivia, Kabul Afghanistan, and Kandahar, Afghanistan. They found that combinations of spatial features were more powerful in accurately classifying neighborhoods than single features, indicating that multiple spatial features make up built-up areas. Specifically, results found that PanTex, HoG, and LSR were consistent in predicting formal and informal neighborhoods, as well as indicated that vegetation indices consistently had low accuracies in differentiating between urban areas. Discussion also noted that LSR was less accurate in Kabul, where building size does not vary as much as the other three cities.

Similar to Graesser et al. (2012), Zhang et al. (2003) found that single texture features performed poorly in classification algorithms, while accuracy increased with the addition of three or four texture measures. In this study in Beijing, China, GLCM texture features were studied in combination with computationally simple texture measures that calculate the number of different grey levels occurring in a cell window and filter edges using high-pass kernels. Results from the Zhang et al. (2003) study also showed that homogenous areas required less texture features to produce accurate classifications than did heterogeneous areas.

It is important that researchers also note the limitations of using only spatial features in their analyses, as similar geometric shapes can represent many different objects (Puissant et al. 2006). Therefore, optimal analysis may consist of combining spatial features with spectral information. This type of analysis improves land cover and use discrimination, and is shown to effectively characterize highly complex urban areas

(Plaza et al. 2007). While spatial features are often indicative of urban areas, spectral reflectance is still an important influence in classification accuracy (Small 2005). In one study in Sudan, researchers warn that presences of scattered vegetation in bright soil areas can overestimate built-up areas. This is due to the fact that this landscape could produce the same spatial pattern as scattered buildings. To compensate, they added a vegetation index to the PanTex operator, and found that accuracy moderately improved and reduced the commission error of PanTex classification (Pesaresi & Gerhardinger 2011).

While not associated with urban land cover, a separate study focuses on mixing textural features together with spectral information to differentiate nut orchards from woody vegetation (Reis & Taşdemir 2011). Because the specific orchards had similar spectral signatures to woodlands, this research focused on extracting Gabor features from panchromatic QuickBird-2 imagery and merging spectral values with them. The use of Gabor, which uses combinations of Gaussian filters with sinusoids to detect edges (Daugman 1985), resulted in overall producer accuracy increasing by ten percent from the accuracy of spatial features and spectral information used separately (Reis & Taşdemir 2011).

2.3 Description of Spatial Features

2.3.1 Line Support Regions (LSR)

LSR represent lines and their attributes extracted from a set of pixels (Yu et al. 1999). LSR was first introduced as a low-level representation of straight lines in natural images and photographs (Burns et al. 1986), but has since been applied to studies aimed at representing settlement structures from remotely sensed imagery (Kim & Muller 1999, Unsalan & Boyer 2004, Unsalan 2006, Graesser et al. 2012).

The concept behind the LSR algorithm is relatively simple, and is clearly outlined in Wang et al. 2012 (Figure 1). To compute, LSR, gradient orientations are first calculated by measuring gray-level change over a small area of pixels, and discerning the local direction of the steepest intensity change (Burns et al 1986). Pixels are then grouped and binned into histograms based on their gradient orientations. Pixels in the same histogram bins are taken as support regions. Each support region represents a candidate area for a straight line since all local gradients share a common orientation. It is important to note that while all grouped gradient orientations are extracted as weak line segments, low gradient orientation groups are filtered out, and only areas with high gradient direction variation are extracted as line segments. Once the line segment is extracted, many attributes can be calculated, such as location, orientation, length, and width (Wang et al. 2012).

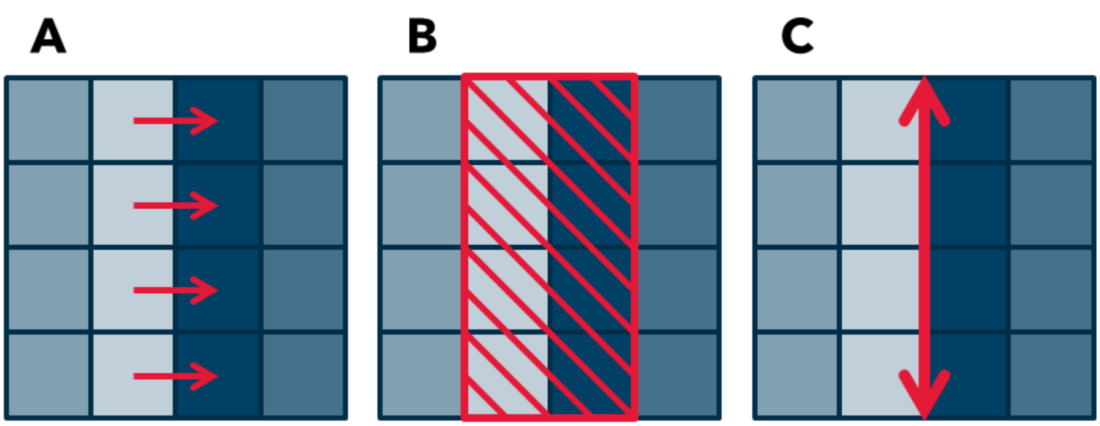

Figure 1: Line Support Region (LSR) Calculation: The LSR algorithm involves A) calculating gradient orientation, B) determining the line support region, and C) extracting the line and its attributes.

Generally, built-up areas contain more frequent and longer line segments (due to the presence of buildings and roads), while rural areas contain shorter and more randomly distributed lines (Unsalan 2006). More specifically, LSR may help to differentiate between formal and informal housing areas, as formal neighborhoods tend to have more uniform buildings and established roads, while informal neighborhoods tend to have more inconsistent and impromptu housing patterns and less distinct roadways (Graesser et al. 2012).

2.3.2 PanTex

PanTex is a texture measure which extracts built-up areas from panchromatic imagery. The feature is derived from the GLCM, and was specifically designed for use in the urban context as a built-up index (Pesaresi et al. 2008). PanTex is a new technique that has been used in only a few studies focused on urban land cover identification and classification (Pesaresi et al. 2011, Pesaresi & Gerhardinger 2011, Graesser et al. 2012).

To calculate PanTex, GLCM contrast is computed in multiple directions around a block of pixels (Figure 2). Once the contrast is calculated, the minimum of all directional contrast is taken as the value for PanTex. Contrary to using the local average of spectral information, using the average operator of the directional contrast in the PanTex calculation produces an undesirable edge effect that captures elongated features in addition to objects. Instead, by using the minimum operator, PanTex allows for a much more clear discrimination between edges of an elongated feature and the edges representing a rectangular object. In summary, PanTex values are high when all surrounding pixels have high contrast compared to the center block of pixels, and PanTex values are low when at least one surrounding pixel has low contrast compared to the center block of pixels.

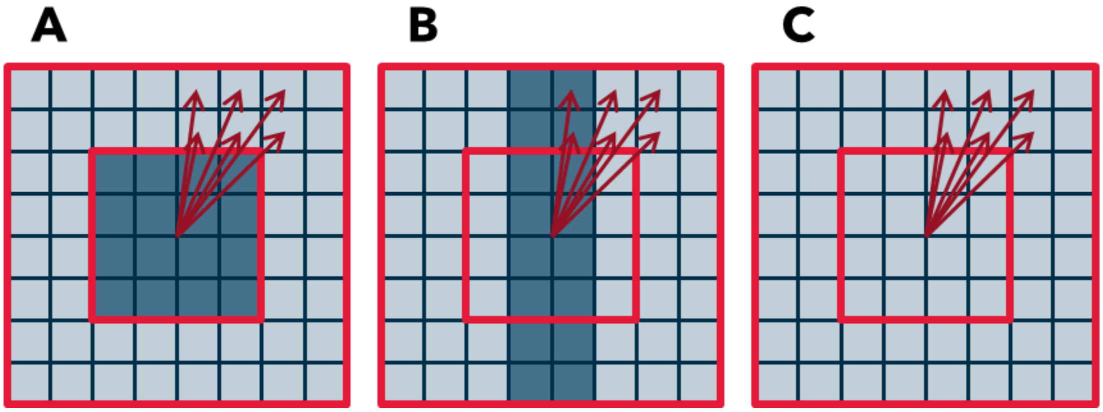

Figure 2: PanTex Calculation: A) PanTex calculation for an object the size and shape of the block of pixels (e.g. building), B) PanTex calculation for an elongated feature (e.g. road), and C) PanTex calculation for a surface (e.g. field).

Although the elongated features that PanTex excludes are part of the built-up environment, eliminating them helps to narrow areas in the urban landscape in which people actually reside in (Pesaresi et al. 2008). In the urban landscape, elongated features represent roads, sidewalks, or fences, while rectangular or square shape features represent buildings. A low PanTex value indicates that the surface beneath the pixel block does not represent a single object the size and shape of the pixel block. In this case, the surface beneath the pixel block could have an elongated feature (e.g. road) or could be somewhat homogenous and represent a surface (e.g. field). High values of PanTex indicate that the underlying surface is heterogeneous and contains an object (e.g. building) that is the size and shape of the pixel block.

2.3.3 Histogram of Oriented Gradients (HoG)

HoG is an object and edge detection method derived from capturing the distribution of structure orientation and is relatively invariant to local geometric transformations and image rotation (Dalal & Triggs 2005). While widely used for human and pedestrian detection in photographs (Dalal & Triggs 2005, Suard et al. 2006, Zhu et al. 2006), HoG has been used in aerial photography for vehicle tracking (Palaniappan et al. 2010, Liang et al. 2013) and sparsely used in land cover classification (Graesser et al. 2012).

Generally, the HoG methodology is based on evaluating local histograms of pixel gradient orientations throughout the imagery. The first step toward calculating HoG is to compute gradient vectors for each set of pixels, shown in Equations 1 and 2:

Equation 1: GVM $GVM = \frac{\Delta x}{\Delta y}$

Equation 2: GVA $GVA = arctan(GVM)$

where GVM represents the gradient vector magnitude, x represents the change in the adjacent pixels in the x direction, y represents the change in the adjacent pixels in the y direction, and GVA represents the gradient vector angle (Dalal & Triggs 2005). Once all gradient vectors are calculated, each pixel in the block contributes a weighted vote for one of eight orientation bins stored in a histogram.

Once the histogram is computed, the HoG output can be interpreted. By calculating the variance, skew, and kurtosis of the eight-binned histogram, a HoG analysis may reveal information about residential land use classes. If the histogram is skewed, the majority of orientations fell into one or two bins, and a less skewed histogram indicates that orientations were evenly spread throughout the bins. For a negative kurtosis, low peakedness shows a flat and wide peak, indicating a similar number of edge orientations in all bins, and vice versa. These HoG outputs can be applied to built-up landscape analysis, for example, as informal neighborhoods, due to their irregular orientations, may show low peakedness because they have a similar amount of edges in each bin.

2.3.4 Local Binary Patterns (LBP)

LBP is a simple texture measure that that determines the relationships of a center pixel to its surrounding pixels. The LBP operator was originally developed as a three-level operator, in which each neighboring pixel could have one of three possible values: 0 for a lower intensity, 1 for an equal intensity, and 2 for a higher intensity than the center pixel) (Wang & He 1990). This operator was later transformed to a two-level operator (0 for a lower intensity and 1 for an equal or higher intensity than the center pixel), which reduces the calculation time and eliminates variations in brightness (Ojala et al. 1996). It has been widely used in studies that focus on detection facial and motion analysis (Ahonen et al. 2004, Hadid et al. 2004, Hablani et al. 2013).

The general idea of computing LBP is simply to compare each center pixel to its neighbor pixels (Ella et al. 2008). Each neighbor is given a binary value of 0 or 1, where 0 represents a neighbor with a lesser value than the center pixel, and 1 represents a neighbor with a value higher than or equal to the center pixel (Figure 3). In creating a binary representation of the block, the data can be interpreted spatially to determine what local texture pattern the LBP pixel set has detected (Hadid et al. 2004). Uniform local patterns indicate regions with, at most, two contiguous regions, and include flat areas, edges, corners, and line ends, while non-uniform local patterns have more than two contiguous regions, and do not appear to represent a texture feature (Figure 4). Finally, histograms can be built that show the frequency of each local pattern occurring.

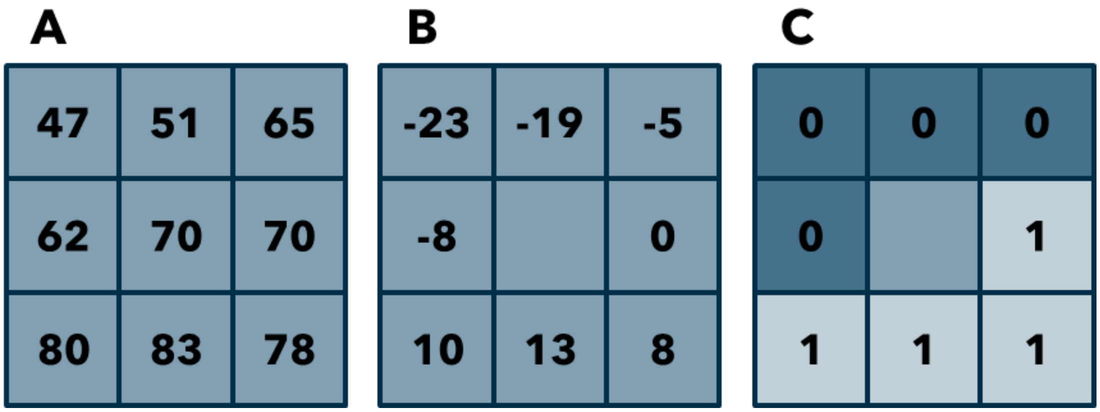

Figure 3: Local Binary Pattern (LBP) Calculation: A) Sample values of pixels, B) differences from center pixel, and C) binary value assigned to surrounding pixels.

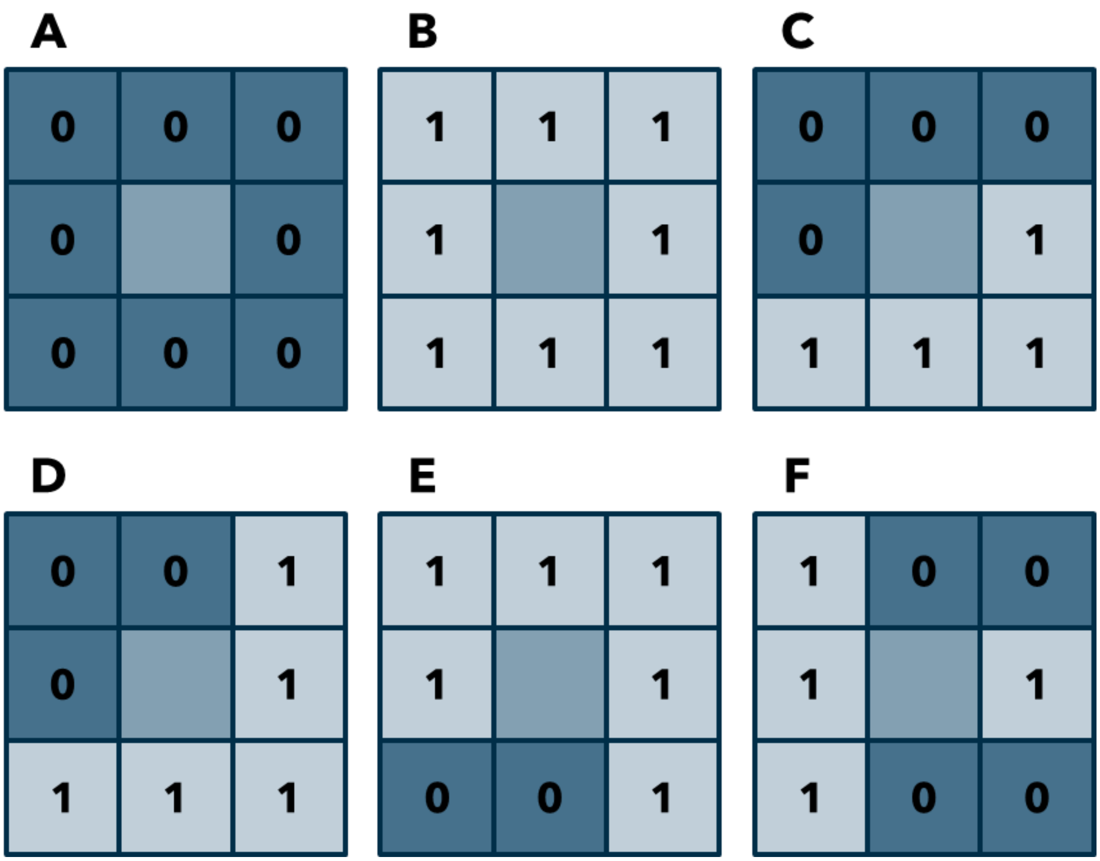

Figure 4: Local Binary Pattern (LBP) Examples: A) flat surface, B) flat surface, C) edge, D) corner, E) line end, and F) non-uniform pattern.

Similar to HoG, the distribution variables of the resulting histogram reveal powerful information about patterns occurring in the image. These variables, mean, variance, skew, and kurtosis, are known as the local binary pattern moments (LBPM). In interpreting LBPM, a positive kurtosis, for example, exhibits high peakedness and indicates there are both elongated edges and smooth, flat objects, which are abundant in settlement classes and could represent building rooftops.

2.3.5 Fourier Transform (FT)

FT decomposes images into different spatial frequencies (Smith 1997). Named after Joseph Fourier, Fourier Theory states that any signal can be expressed as a sum of a series of sinusoids (Bracewell 1978). Although FT use was intended in the time domain as sinusoids, images have their information encoded in the spatial domain as edges (Smith 1997). FT has most often been used in noise removal in both sound processing (Benesty et al. 2009) and image processing (Xie et al. 2012).

The first step towards using FT as a spatial feature is to compute the power spectrum. FT attempts to represent the input image a power spectrum, or a summation of sinusoidal variation. The Cartesian plane shows how the frequencies are distributed throughout the image. Higher frequencies are pixel values that change rapidly across the image and are located at the edges of the plane. Lower frequencies correspond to larger scale features in the image, and are located at the center of the plane.

Once the FT is computed at a given scale, a radial profile is extracted. The radial profile is similar to a circle drawn around the Cartesian plane of the power spectrum. By computing the variance of the radial profile, information about how the frequencies vary throughout the image can be examined. A uniform neighborhood might give a very smooth power spectrum in the radial profile, whereas a neighborhood with many land cover variations might give a noisier power spectrum within the radial profile, as the difference between low and high variances would be greater.

Additionally, FT often employs the use of filters on images to highlight certain features of the image (Costen et al. 1996). Applying a low-pass filter over the power spectrum, the image becomes blurred due to the loss of high frequencies. Conversely, applying a high-pass filter will result in an image that consists of mostly sharper and crisper edges, and loses larger regions of dark and bright.

2.3.6 Normalized Difference Vegetation Index (NDVI)

Although classified as a spectral feature, the normalized difference vegetation index (NDVI) is used in this research as a comparative study to spatial features. NDVI is one of the best known and most widely used vegetation indices (Jensen 2007). It is a simple spectral indicator that assesses whether a pixel has green vegetation by using Equation 3:

Equation 3: NDVI

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

where NIR represents the spectral reflectance captured in the near-infrared region and Red represents the spectral reflectance captured in the visible (red) region (Rouse et al. 1974). High values of NDVI indicate the highest possible density of green vegetation and low values indicate less dense vegetation cover, and NDVI is considered to be negatively correlated with built-up land cover. While the use of NDVI is extremely common in land cover classification (Lunetta et al. 2006), it has also been used in conjunction with other spatial features to see if a combination of spatial and spectral information can improve classification methods in built-up areas (Pesaresi & Gerhardinger 2011, Graesser et al. 2012).

2.4 Relating Remotely Sensed Features to Demographic Information

Relating remotely sensed data to demographic information is an increasingly popular trend, as it proves to be a useful tool to estimate population and their characteristics (National Research Council 2007). There are many examples in the literature of relating satellite imagery directly to population estimates. A traditional global population estimation technique is nighttime light satellite imagery (Elvidge et al. 2007a, Elvidge et al. 2007b), however is limited by coarse spatial resolution and lacks the ability to identify populated areas without electricity.

More recent research focused on population estimation techniques have been conducted in developed regions, and with readily available census data. An Australian study classified Landsat TM imagery as residential land cover, and then uniformly distributed population data of each zone. This research, however, expressed the need for refinement in in areas of extreme over prediction and under prediction of population in less dense and denser areas respectively (Harvey 2002). Lu et al. explored extraction of impervious surface in Indiana from Landsat ETM+ imagery and relating it to population density estimation models, achieving an overall high degree of accuracy (Lu et al. 2006).

A few studies have explored the usage of classification and regression tree (CART) methodologies to distribute population at national levels. A combination of remotely sensed percent-impervious layer and ancillary data was used to distribute population in Haiti (Azar et al. 2010), and a combination of remotely sensed per-pixel built-up area layer and a population likelihood layer was used to create a gridded population dataset in Pakistan (Azar et al. 2013).

Remotely sensed population estimates have become increasingly desired, especially in areas that are prone to natural disasters and regions that lack complete census data. In times of emergency, remotely sensed data can produce timely and spatially explicit population estimates. However, much of this research is limited to regions with readily available census data and very high resolution imagery.

Beyond population estimates, socio-economic characteristics can also be estimated from remotely sensed data (Lo & Faber 1997), yet appear less frequently in the literature than pure population number and density estimates. Jensen & Cowan (1999) suggest "quality-of-life" indicators can be estimated by extracting urban and suburban site and situation attributes. Site attributes include information about buildings (size, height, etc.) and lots (size, density, vegetation health, paved roads, etc.). Situation attributes include information about the adjacency to community amenities (schools, hospitals, open space, etc.) and adjacency to nuisances and hazards (traffic, floodplains, steep terrain, etc.). By measuring the ease of access to these societal opportunities, "quality-of-life" indicators may be used to assess the human well-being for groups of people (Li & Weng 2007, Rahman et al. 2011).

Of the studies that have integrated remotely sensed information and demographic data, many have been focused in developed areas, data-rich countries, and more localized areas (Patino & Duque 2013). Lo & Faber (1997) assessed census data in Athens-Clarke County, Georgia using land cover classification, NDVI, and surface temperature data derived from Landsat imagery. Their results found that NDVI showed strong positive correlations with per capita income, population density, and median home value. This research demonstrated that NDVI, along with other remotely sensed features can complement census data in socio-economic status assessment. Additional research revealed positive correlations between impervious surface and minority and poverty populations in Massachusetts (Ogneva-Himmelberger et al. 2009). Similar research in Indianapolis, Indiana showed positive correlations between vegetation and income, house value, and education levels (Li & Weng 2007). Also in Indiana, Lu & Weng (2005) found that incorporating textural variances derived from higher resolution imagery significantly improved classification accuracy, while lower resolution texture features did not improve the accuracy.

The strong correlations observed between land cover and socio-economic status have also been occasionally studied in the developing world to map poverty and housing quality. In Accra, Ghana, previous literature employed Ridd's V-I-S model for comparison with slums defined by the United Nations Habitat (Weeks et al. 2007) and examined the relationship with vegetation cover and housing quality (Stow et al. 2013). Results showed that the best predictor of slums was a lack of vegetation; however, having a high proportion of impervious surface did not necessarily define all slums (Weeks et al. 2007). Researchers also showed that low housing quality areas had less than five percent vegetation cover, and despite already having extremely low vegetation cover, slums experienced densification and decreased vegetation cover over the eight-year time range (Stow et al. 2013).

2.5 Summary

The aforementioned literature illustrates the serious knowledge gaps pertaining to the following two themes: spatial feature extraction and the integration of remotely sensed features with census-derived demographic indicators. Spatial features present additional geometric information that can be combined with spectral information to aid land cover classification schemes. Remotely sensed data, and spatial features in particular, offers a timely and spatially explicit way of identifying vulnerable populations during emergencies and natural hazard events. The integration of remotely sensed features and census data has mainly been limited to use with spectral information, low-resolution imagery, and within developed areas. With the advent of high resolution imagery and the introduction of spatial features, further research can reveal spatial patterns of population characteristics based on the features that make up the built-up landscape.

Chapter 3: Objectives and Hypothesis

3.1 Research Question

The main research questions that are addressed in this research are 1) can spatial features be quantified to show variations in built-up area within a city, and 2) once these spatial features are quantified, are they related to census-derived population characteristics within a city?

3.2 Hypothesis

This research is guided by the following hypotheses. Spatial features can be extracted from imagery due to geometric and contextual characteristics observed between pixels. These spatial features can then be quantified and aggregated to show variations in built-up areas, as different parts of built-up areas exhibit distinct geometric features, orientations, and shapes that are indicative of building type, size, and land use. However, spatial features singularly do not fully encompass all characteristics of the built-up area or population in question. Therefore, the correlations between spatial features and census-derived variables will be explored to determine the strength and significance of relationships.

3.3 Scope of Work

To address the research questions, the scope of work in this study is as follows. Five spatial features (LSR, PanTex, HoG, LBP, and FT) and spectral information (NDVI and the local means of the original multispectral bands and the composite image) were computed at multiple scales for the study site. These features were then statistically aggregated to neighborhoods, the geospatial unit of analysis. The aggregated spatial features were then correlated with the census-derived population characteristics, also aggregated to the neighborhood level. Significant correlations were analyzed to determine if certain areas of the city exhibit trends in spatial feature occurrence and distribution, and if demographic variables relate to spatial features.

Chapter 4: Methodology

4.1 Study Area

Accra, Ghana is a sub-Saharan city situated along the Gulf of Guinea in West Africa (Figure 5). According to the 2000 Ghanaian census, approximately 1.65 million people were living in 365,550 households within the Accra Metropolitan Assembly (AMA) limits (Ghana Statistical Service 2000). The AMA is the administrative entity responsible for the health, welfare, and governance of the urban population (Engstrom et al. 2013).

The city was first settled by the Ga-Dangme ethnic group, who established Accra as a fishing village. However, when the British moved their colonial headquarters from Cape Coast to Accra in 1877, the city saw substantial growth. The central business district was developed in the urban core near the port, while the peripheral areas in the east were designated as upscale, formal neighborhoods with shady vegetation. The western part of the city has developed more recently, as it served as areas of infill into open areas after Ghana gained its independence in 1957. This area is generally less dense, and follows a more suburban sprawl type of land use, with occasional pockets of commercial land use (Engstrom et al. 2013).

Generally, Accra is a sprawling urban city that is typical of many other coastal African cities. The city has very poor urban planning, as many streets lack names and signs (Engstrom et al. 2013). Neighborhoods within Accra are characterized by different by a diverse population. For instance, many older villages have diverse ethnic groups, some neighborhoods are predominantly receptive areas for in-migrants, and formal neighborhoods are situated in historic military cantonments (Weeks et al. 2007).

In this research, Accra was chosen as the study area for several reasons. The city is currently undergoing rapid urbanization and globalization, and the growth in economic opportunities has led to a huge potential for LCLUC (Lambin et al. 2001, Auch et al. 2004). Additionally, since Ghana is one of the few, if not only, West African countries with complete and available demographic census and health survey data, it is an important case study for testing the relationships between urban remote sensing calculations and demographic characteristic estimations.

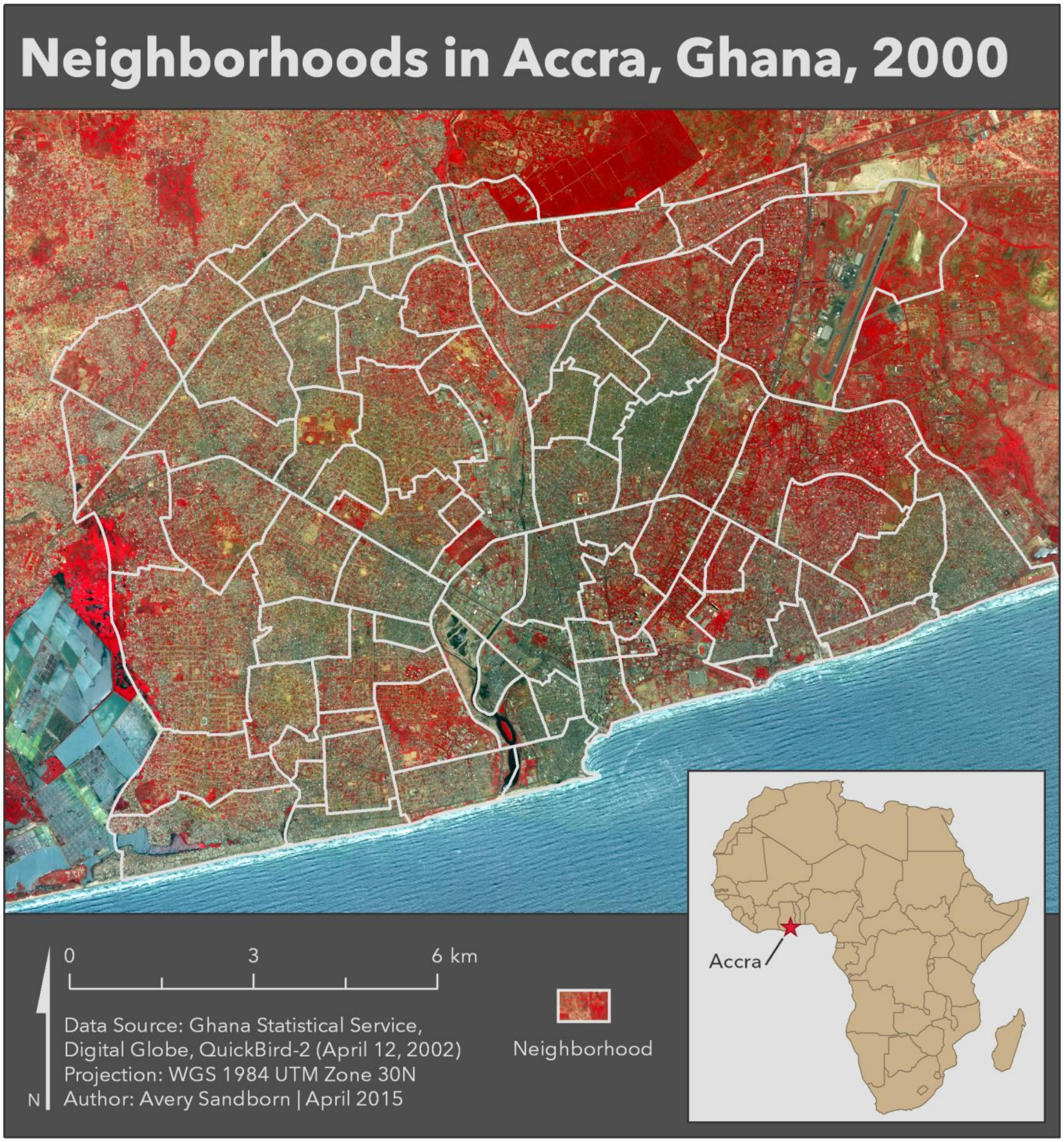

Figure 5: Study Area Map: Study area map of Accra, Ghana, which shows the 2002 QuickBird-2 multispectral imagery (2.44 meter resolution), overlaid with the neighborhood boundaries derived from the 2000 census (full listing of neighborhood names is shown in Appendix A).

4.2 Data Acquisition

This research used a QuickBird-2 multispectral image taken on April 12, 2002. The multispectral dataset includes four bands (blue, green, red, and NIR) has a resolution of 2.44 meters and is cloud free. The image represents a 164 square kilometer portion of Accra, and covers approximately eighty percent of the AMA region. This image was georeferenced using a second order polynomial transformation, 13 ground control points, and a digital elevation model (DEM) created from a merged dataset of Cartosat, ASTER, and splined terrain data.

The 2000 Ghanaian census was obtained from the Ghana Statistical Service (GSS) and contains detailed information about population, housing, education, health, and wealth. There were 31 census variables used in this study and their descriptions can be found in Table 1. Housing quality and tenure measurements include information about structural quality, utility access, and tenancy types. Education measurements include information regarding literacy and secondary education. Health measurements include information related to fertility, mortality, and cooking fuel. Social and economic characteristics were measured by examining migrant activities and employment status.

Finally, the *Slum Index* is a continuous variable that is based on United Nations (UN) definition of a slum. According to the UN, slums are defined as lacking one of the following five criteria: durable housing, sufficient living area, access to improved water, access to improved sanitation, and secure tenure (UN Habitat 2006/2007). This variable was created by calculating the number of UN-defined slum criteria that each household met (using variables already estimated in the Ghanaian census), and then aggregating this data up to the spatial analysis unit. This slum index variable accounted for the relativity of vulnerability, as a neighborhood that meets just one criterion is considered to be significantly better off than a neighborhood that suffers from all five criteria (Weeks et al. 2007).

The records in the original census dataset were compiled at the enumeration area (EA) level. These EAs are the equivalent spatial unit to a census tract in the United States and contain about one thousand people per EA. These EA units were originally available only as hand drawn maps, but were digitized into a geographic information system (GIS) format and spatially georeferenced to the satellite imagery (Engstrom et al. 2011). Although the EA is the basic spatial analytical unit, the neighborhood plays a larger role in differentiating where populations live. This is due to the fact that they are delineated according to socio-economic characteristics, rather than the arbitrary lines demarcated by the EA. Therefore, the EA units were aggregated from 1724 EAs into 108 neighborhoods for analysis (Engstrom et al. 2013). For this study, only neighborhoods that were fully covered by the QuickBird-2 image were included in the analysis, reducing the number to 75 neighborhoods (shown in Appendix A).

Variable Name	Description
Population	Total number of people
Households	Total number of households
Population Density	Population Density
Housing Density	Housing Density
Dependents	Number of dependents (under 5 years old or over 55 years old)
Children	Number of people under 15 years old
Informal Sector	Number of workers in the informal sector
Do Not Work	Percent of people who do not work
Not Literate	Number of people who are not literate (15 years old to 24 years old)
Women Not Educated	Percent of women who are not secondary educated
Fertility	Number of children born to women (z-score)
Infant Mortality	Number of infant mortalities
Not Single Family	Number of households that are not a single family domicile
Renting	Number of households where tenancy is renting
Rent-free	Number of households where tenancy is rent-free
Perching	Number of households where tenancy is perching
Biofuel	Number of households that use charcoal, wood, or palm leaves as primary source of cooking fuel
Non-separate Cooking Space	Number of households with non-separate cooking space
No Electricity	Number of households that do not use electricity as primary lighting source
Unimproved Water	Number of households that do not have piped water as main water source
Unimproved Sanitation	Number of households where main toilet is in a separate house, public center, or bucket pan
No Liquid Waste Collection	Number of households where liquid waste is not collected in sewer
No Solid Waste Collection	Number of households where solid waste is not collected in sewer
Worst Floor	Number of households where floor is constructed out of mud or Earth material
Worst Wall	Number of households where wall is constructed out of mud brick, packing cases, palm, or thatch
Worst Roof	Number of households where roof is constructed out of thatch, palm, bamboo, mud brick, or wood
Born Outside EA	Number of people born outside the current EA
Not in Accra 5 Years Ago	Percent of people who were not in Accra five years prior
Immigrant	Number of people who were not born in Ghana
Ga-Dangme	Number of people who identify with the Ga-Dangme ethnic group
Slum Index	Average number of UN-defined slum criteria met

Table 1: Census Variables: 2000 Census-derived demographic indicators and their descriptions.

4.3 Data Processing

4.3.1 Spatial Feature Extraction

Each spatial feature was computed with each combination of block and scale size. Because spatial features are based on groups of pixels, block and scale size are important components for determining the most effective way to calculate the spatial features (Figure 6). Block size represents the pixel size at which the output feature will be aggregated to. In order to effectively measure a neighborhood's spatial features, block sizes that were closest to 15m were used (Graesser et al. 2012). In this case, block sizes of 4 and 8 allowed for 9.76 meter and 19.52 meter resolution outputs, respectively. Scale size, also referred to as window size, represents the area from which the spatial feature extracts contextual information from, or how many pixels the spatial feature calculation will consult. Scale sizes of regular octaves 8 (19.52 meter), 16 (39.04 meter), and 32 (78.08 meter) were used to compute the spatial features. Ultimately, the use of two block sizes and three scale sizes resulted in six calculations for each spatial feature (block 4 and scale 8, block 4 and scale 16, etc.). This block/scale combination set-up then acted as a moving window that computed spatial feature output for every set of pixels in the entire raster dataset (Graesser & Long 2015).

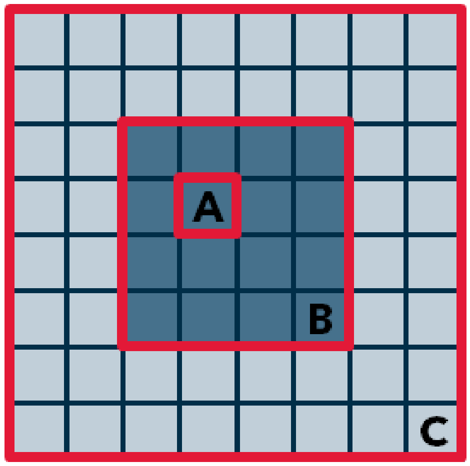

Figure 6: Block and Scale Size: A) Pixel size of 2.44 meter, B) block size of 4 (9.76 meter), and C) scale size of 8 (19.52 meter).

A python library for feature extraction called MapPy was used to calculate spatial feature outputs at each of the six block/scale combinations (Graesser & Long 2015). Each spatial feature (as described in section 1.2) returned between one and four output layers. LSR returned three layers, which were 1) the sum of line lengths, 2) the mean of line lengths, and 3) the line variance. PanTex and NDVI each returned only one layer, which represented the local mean of the specific index. Both HoG and LBP returned four layers describing their respective histograms: 1) histogram mean, 2) histogram variance, 3) histogram skew, and 4) histogram kurtosis. FT returned two layers which were 1) the mean of the radial profile and 2) the variance of the radial profile. Finally, the local means of each of the original multispectral bands and the original multispectral composite were also computed, and returned one layer each.

4.3.2 Correlation Coefficients

Once all spatial features were computed, the descriptive statistics were calculated for each of the spatial feature outputs by neighborhood. Each pixel in the output spatial feature layer represented the value extracted by the spatial feature for that pixel block.

Specifically, zonal statistics (average, standard deviation, and sum) summarized the values of the spatial feature output pixel blocks within the neighborhood shapefile, and exported the data to a readable database table format. The values in the zonal statistics table represented the aggregated neighborhood statistics for the 74 neighborhoods included in this study.

A correlation coefficient matrix was created via an original python script to measure the strength and direction of the relationships that exist between the zonal statistics of the spatial features and the census data. Due to a fairly large dataset of 75 neighborhoods and an alpha significance level of 0.01, the critical value for correlation coefficients was found to be 0.30. Correlation coefficients greater than +0.50 or less than -0.50 were considered to be strong correlations and correlation coefficients between +0.30 and +0.50 or between -0.30 and -0.50 were considered to be weak correlations.

Chapter 5: Results and Analysis

For this section, each of the strongest output layers for each spatial feature is detailed in the following maps. These maps help to demonstrate what the spatial feature output layers look like, and indicate the spatial trends of the feature output by neighborhood. The spatial feature output returns the specific output layer described in section 4.3.1 at the specified block and scale combination. In the following analysis, the terms "aggregated neighborhood average" and "aggregated neighborhood standard deviation" will be used to describe the summarized spatial feature zonal statistic descriptor for a neighborhood described in section 4.3.2. Analysis entails examining the strongest correlations between the output spatial feature layers and the census-derived indicators (a full listing of strong correlation coefficients can be found in Appendix B).

5.1 Line Support Region (LSR) Results

The LSR output layer that produced the strongest correlation with census-derived population characteristics was line variance. Figure 7 shows the aggregated neighborhood averages of LSR line variance, and shows neighborhoods with more heterogeneous lines (high line variance) tend to be clustered in the western region of the city. These high line variance neighborhoods generally exhibit formal residential characteristics. Neighborhoods with more homogenous lines (less line variance) hug the coastline, which tend to exhibit a single type of land cover (e.g. Chorkor, Jamestown, Sodom & Gomorah, South La Estate). The Airport Residential Area neighborhood stands out among its counterparts as a neighborhood with low line variance in the northeast region of the city.

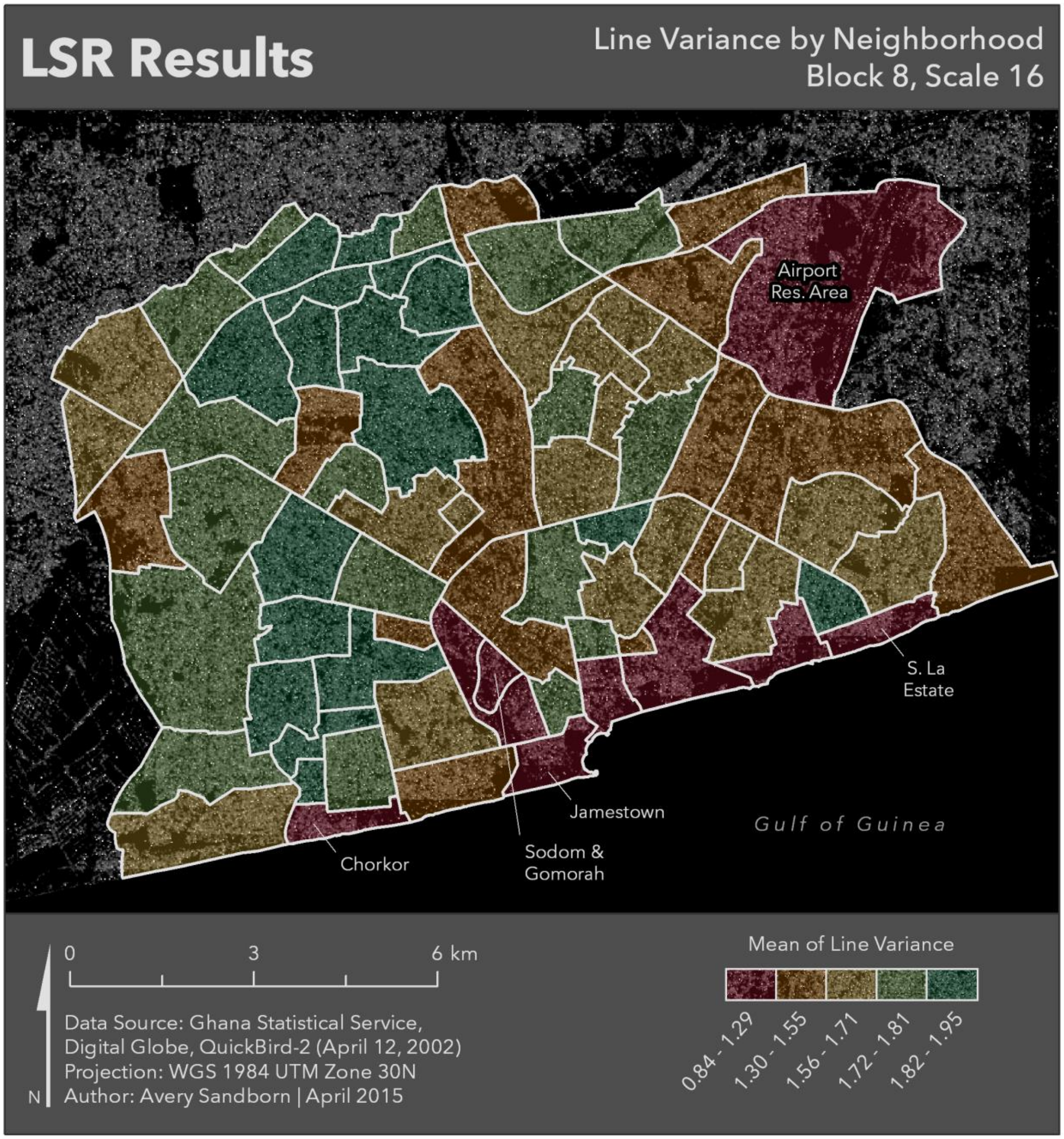

Figure 7: Line Support Region (LSR) Results: This map shows the spatial allocation of line variance (as derived by LSR) for block 8 and scale 16. High values of line variance (shown in green) signify neighborhoods with a high degree of line heterogeneity, while low values of line variance (shown in red) signify neighborhoods with a low degree of line homogeneity.

The strongest demographic indicators that correlated with line variance include *Not Literate* (correlation coefficients ranging from -0.52 to -0.56) and *No Electricity* (correlation coefficients ranging from -0.52 to -0.54). The negative correlations indicate that areas with heterogeneous lines correlate with people who are literate and households that use electricity as their lighting source. LSR line length sum also reveals negative correlations with *Not Literate* and *No Electricity*. Block size did not appear to be a factor in generating strong correlation coefficients; however, a scale size of 8 did not produce any strong correlations with the census data.

These findings suggest possible relationships between line attributes and population characteristics. In general, the LSR results show that neighborhoods with more varied lines correlate with more developed populations. The indicators of literacy and lighting source suggest that more educated and wealthier families live in the formal neighborhoods, while less educated and poorer families live in the coastal informal settlements.

5.2 PanTex Results

One set of PanTex results is shown in Figure 8. These results show the aggregated neighborhood standard deviations of PanTex values within each neighborhood. Taking the standard deviation of the PanTex values in each neighborhood shows how varied the built-up texture measure is within each neighborhood. Higher standard deviations are seen in a few neighborhoods surrounding the perimeter of the AMA region (e.g. Airport Residential Area, East Dzorwulu Residential Area), as well as some neighborhoods in the urban core (e.g. Accra Central, South Industrial Area, Sodom & Gomorah). Lower standard deviations are observed in residential neighborhoods along the coastline (e.g. Chorkor, La, South La Estate), as well as radiating from the urban core (e.g. Nima, North Kaneshie).

These results indicate that buildings sizes and shapes were highly variable in neighborhoods similar to the Airport Residential Area, which makes sense because that neighborhood contains residential houses as well as large commercial buildings on the airport property. Many of the informal residential areas in the city have a small standard deviation in PanTex values, indicating that the buildings in those neighborhoods are all very similar in size and shape.

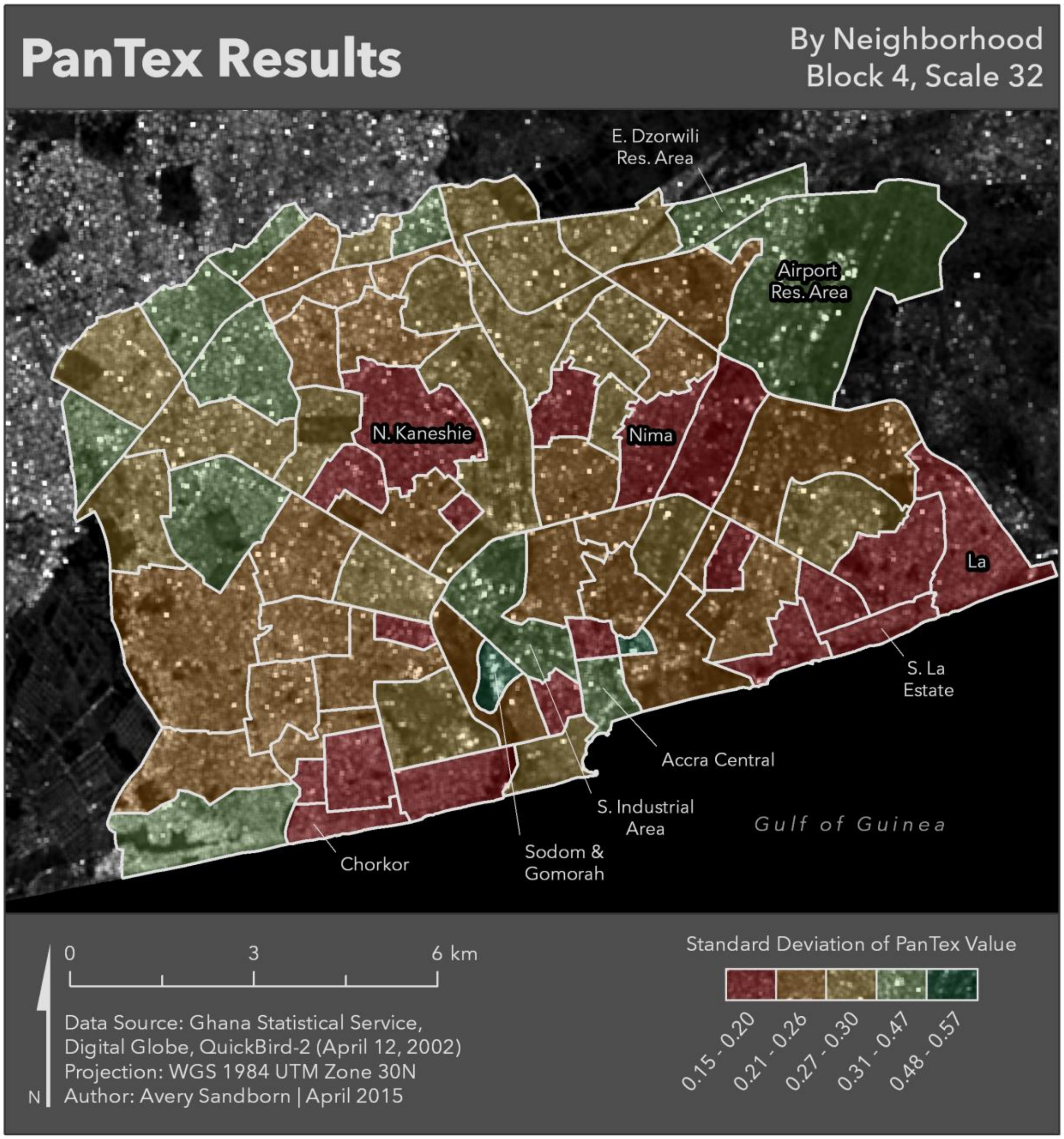

Figure 8: PanTex Results: The PanTex results at block 4 and scale 32 show the standard deviations for the built-up index by neighborhood. High standard deviations (shown in green) indicate that PanTex values are more varied, while low standard deviations (shown in red) indicate that PanTex values are less varied.

Strong positive correlations were observed between PanTex standard deviation and *No Electricity* (correlation coefficients of +0.60), *Born Outside EA* (correlation coefficients ranging from +0.59 to +0.64), and *Not in Accra 5 Years Ago* (correlation coefficients of +0.62). Strong negative correlations were observed between PanTex standard deviations and *Ga-Dangme* (correlation coefficients ranging from -0.52 to -0.59), *Dependents* (correlation coefficients ranging from -0.54 to -0.56) and *Do Not Work* (correlation coefficients of -0.59). Block size did not appear to be a factor in calculating correlation coefficients; however, a scale size of 32 was not as influential as scale sizes 8 and 16.

Together, the census variables of *Born Outside EA*, *Not in Accra 5 Years Ago*, and *Ga-Dangme* suggest a strong spatial trend among migrants and non-migrants. The correlations detected show that immigrants tend to settle in the areas of high PanTex variability, which is spatially associated with the peripheral formal neighborhoods. Non-migrants are shown to reside in the coastline informal settlements, which correspond to the population who identify with the Ga-Dangme ethnic group. This trend follows the traditional settlement patterns of Accra, in which many Ga-Dangme members were historically fishermen and have resided in their coastal villages for hundreds of years, as immigrants tend to settle in other areas of the city (Davies 1967).

A second trend in PanTex standard deviation shows a tendency for non-working populations (*Dependents* and *Do Not Work*) to reside in areas of low building variance. Relating back to Figure 8, these non-working populations coincide with the coastal neighborhoods. From this correlation, a possible relationship can be explored between the working population and the immigrant population.

5.3 Histogram of Oriented Gradients (HoG) Results

Results for the aggregated neighborhood average of HoG histogram skew are displayed in Figure 9. These results show that areas with very positive skew are located in commercial neighborhoods (e.g. Airport Residential Area, Korle Bu Hospital, North Industrial Area, South Industrial Area), while areas with less positive skew (closer to a normal histogram distribution) are located in more informal housing areas (e.g. Accra New Town, Mamobi, Nima). These results also correlate with the aggregated neighborhood average of HoG histogram kurtosis. Areas with high kurtosis are located in the commercial areas as well, whereas areas with low kurtosis are located in the informal housing areas. These HoG results together indicate that areas with high peakedness and non-uniform distribution of orientations are correlated with areas of commercial and formal development, while areas with low peakedness and a more uniform distribution of orientations occur in areas of informal housing.

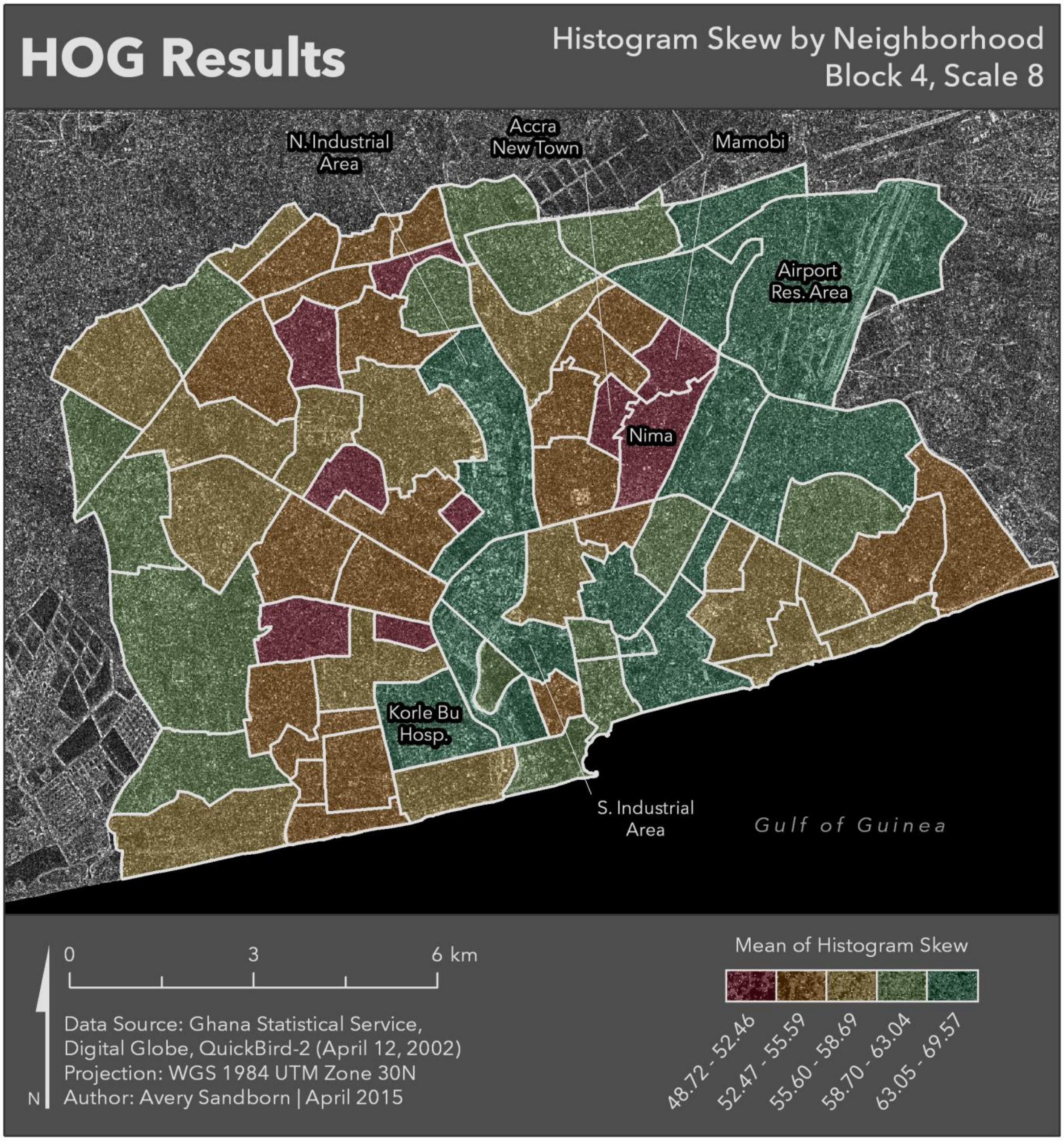

Figure 9: Histogram of Oriented Gradients (HoG) Results: This map shows the histogram skew values for HoG at block 4 and scale 8. Extreme positive values of histogram skew (shown in green) indicate that the majority of orientations the HoG feature detected were binned in one or two bins. Lower positive values of histogram skew (shown in red) indicate that there are a similar number of orientations in all bins, and the histogram represents a more normal distribution.

Strong negative correlations between HoG histogram skew and kurtosis were observed with *Population Density* (correlation coefficients ranging from -0.50 to -0.72), *Housing Density* (correlation coefficients ranging from -0.56 to -0.71), *Children* (correlation coefficients ranging from -0.52 to -0.61), and *No Liquid Waste Collection* (correlation coefficients ranging from -0.51 to -0.52). Both sizes did not appear to be a contributing factor to the correlation coefficients, however, scale size 8 produced stronger correlation coefficients with the census data than scale sizes 16 and 32.

Neighborhoods with positive skew and positive kurtosis exhibit a more uniform spatial layout. For instance, the commercial areas mentioned above all have a very systematic layout, in that their buildings tend to be oriented homogeneously, represented in a histogram by a majority of orientations falling into a small number of bins. Conversely, an informal neighborhood lacks the urban planning aspect of its layout and exhibits a heterogeneous layout. This neighborhood pattern is represented by a less skewed histogram, and a more even distribution of orientations in all bins.

5.4 Local Binary Pattern (LBP) Results

The results shown in Figure 10 represent the aggregated neighborhood average of LBP histogram variance. Neighborhoods that have LBP histograms with more variance signify that there are a similar number of instances of each local pattern occurring in the neighborhood. Neighborhoods with LBP histograms that have less variance signify that local patterns do not occur uniformly in all histogram bins. From the map, commercial areas (e.g. Airport Residential Area, Korle Bu Hospital, Ministries, North Industrial Area) have low variance, indicating that local patterns are not evenly spread. This makes sense, as commercial areas tend to have larger buildings (e.g. warehouses). Informal neighborhoods (e.g. Jamestown, Mamobi, Nima, Sodom & Gomorah) have higher variance.

At the most basic level, a building has four corners and four edges. In the case of a commercial building, the LBP histogram returns four instances in the corner pattern bin, and many instances in the line edge pattern bin, as the buildings are larger and have longer edges in these areas. This leads to high variance in the LBP histogram. Informal settlements reverse this logic, in that the LBP histogram returns four instances in the corner pattern bin, and a small number of instances in the line edge pattern bin, as the buildings are smaller and have shorter edges in these areas. This in turn leads to lower variance in the LBP histogram.

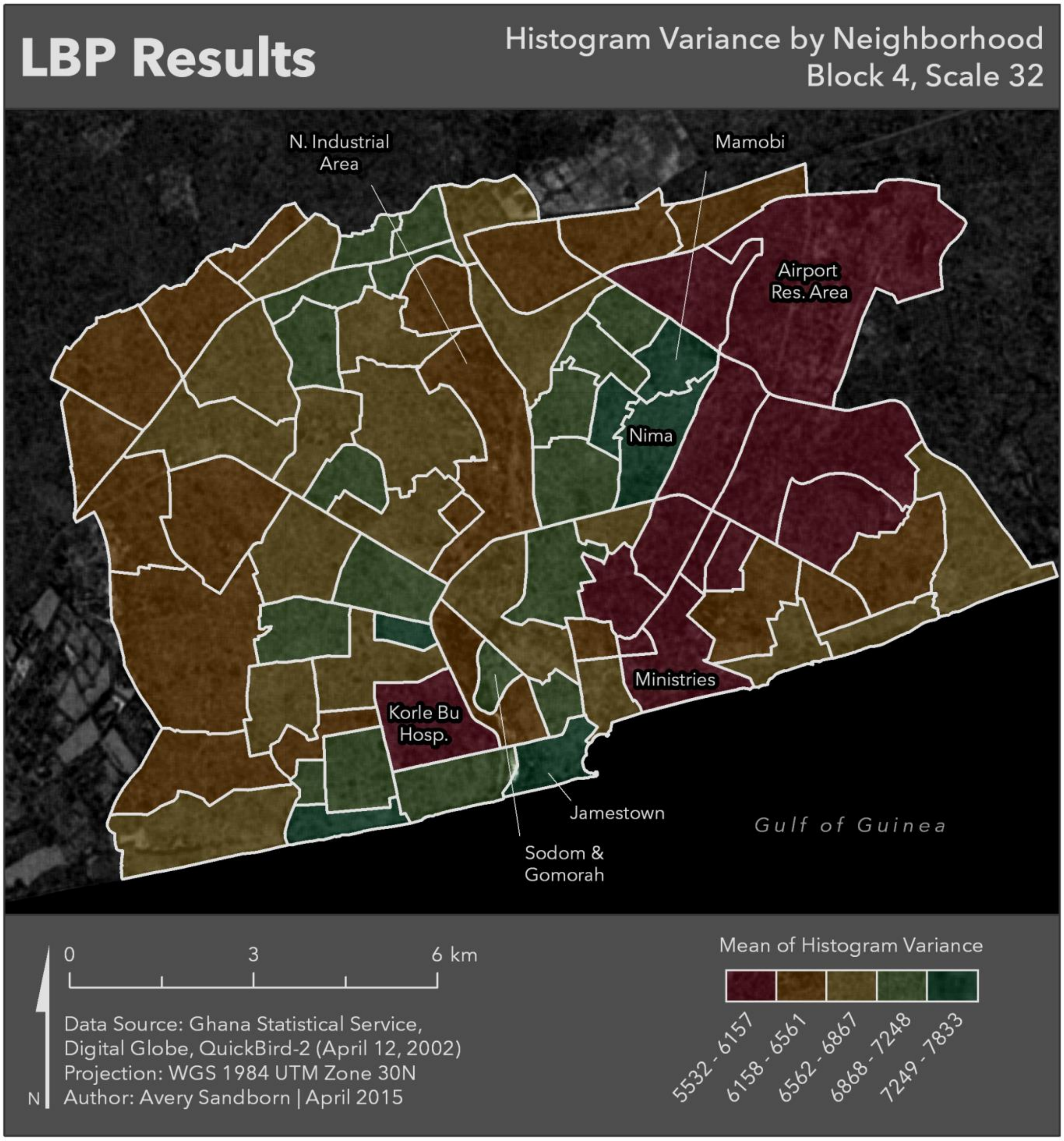

Figure 10: Local Binary Patterns (LBP) Results: This map shows the variance of the histograms detected by LBP at block 4 and scale 32. High LBP histogram variance (shown in green) signifies that there are a similar number of instances of each local pattern in the neighborhood, whereas low LBP histogram variance (shown in red) signifies that local occurrence is not similar in all bins.

LBP histogram variance is very strongly positively correlated with *Population Density*, *Housing Density*, *Biofuel*, *Non Separate Cooking Space*, *No Liquid Waste Collection*, and *Slum Index* (correlation coefficients ranging from +0.71 to +0.85), and strongly positively correlated with *Informal Sector*, *Women Not Educated*, *Not Single Family*, *Unimproved Sanitation*, *No Solid Waste Collection*, *Total Households*, *Total Population*, *Worst Wall*, and *Children* (+0.50 to +0.70). These positive correlations show that LBP may be a strong indicator of population and housing density, informal settlements, and wealth. All combinations of block and scale size generated strong correlation coefficients.

The neighborhoods of low LBP histogram variance tend to be less densely populated areas, which could be due to multiple reasons. One reason may be that many of these areas are commercially zoned, and hence why less people would be living in these land cover zones to begin with. Secondly, other neighborhoods in this category are formal neighborhoods (e.g. Cantonments, Kanda Estate, North Labone Estate), and have access to sewerage services, and more space to live. The neighborhoods that exhibit high LBP histogram variance tend to be densely populated, and lack essential utilities and public services. These areas may tend to have a range of edges, corners, and line ends that make up their informal land cover zones.

5.5 Fourier Transform (FT) Results

The FT output that has the strongest correlations with the census-derived characteristics is the aggregated neighborhood average of the radial profile variance (Figure 11). High values of variance for the radial profile correspond with formal residential neighborhoods in the periphery of the city (e.g. Cantonments, North Labone

Estate, Tesano). Low values of variance for the radial profile correspond with the urban center where many different land uses are converging, and there is a mix of informal settlements and commercial areas (e.g. Accra Central, Jamestown, Sodom & Gomorah).

Higher values of variance for the radial profile of each pixel block and scale correspond to formal neighborhoods. At each specific pixel block and scale, the FT frequencies will be varied more in formal neighborhoods, for example, when the edge of a roof converges with an elongated edge of a road. Contrary, FT frequencies will be less varied at the block and scale level in informal neighborhoods, due to the similar sizes and densely packed nature of informal houses. The two exceptions to this logic are the neighborhoods of Airport Residential Area and Abofu. Both of these neighborhoods have a majority of formal neighborhoods, however also encapsulate a drastically different land cover: the Kotoka International Airport (and surrounding grassy areas) in Airport Residential Area and Achimota Forest Reserve in Abofu. These regions stand out among the other neighborhoods with low radial profile variance because their edges are on a much larger scale than the pixel block, and FT does not detect a noisy power spectrum over a large smooth surface, such as forest or grass.

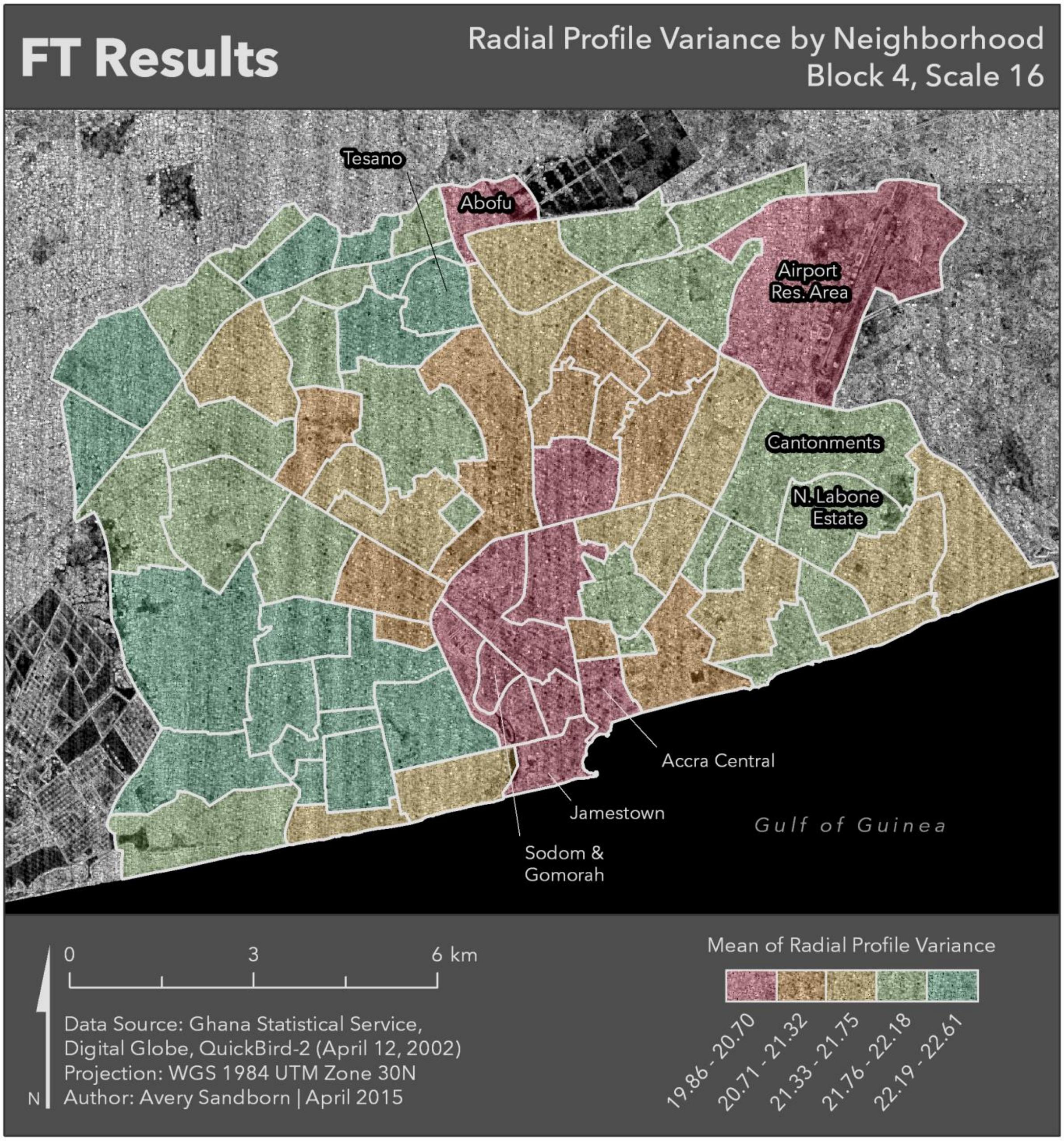

Figure 11: Fourier Transform (FT) Results: FT radial profile variance at block 4 and scale 16 is shown in this map. Higher values (shown in green) indicate a noisier power spectrum with many land cover variations, while lower values (shown in red) indicate a neighborhood with less land cover variations.

FT radial profile variance is negatively correlated with *Not Literate* (correlation coefficients ranging from -0.53 to -0.61), *Slum Index* (correlation coefficients ranging from -0.54 to -0.60), *Unimproved Sanitation* (correlation coefficients ranging from -0.52 to -0.58), *Biofuel* (correlation coefficients ranging from -0.54), and *Women Not Educated* (correlation coefficients ranging from -0.53 to -0.54). These correlations follow the logic above, in which neighborhoods with high radial profile variance (formal neighborhoods) correspond with higher levels of education and better living conditions. Block 8 and scale 8 produced weaker results than block 4 and scales 16 and 32.

5.6 Normalized Difference Vegetation Index (NDVI) Results

The spatial layout of the aggregated neighborhood average of NDVI is very distinct and can be seen in Figure 12. High values of NDVI indicate areas of dense vegetation, and are spatially clustered in the eastern portion of the city, which has not developed as fast or as dense as the western portion of the city. Many commercial areas of the city, such as the Airport Residential Area and the Korle Bu Hospital neighborhoods are also areas of densest vegetation, along with the formal neighborhoods of Cantonments, Kanda Estate, and North Labone Estate. Low values of NDVI indicate areas of less dense vegetation, and are heavily clustered in the urban core of Accra (Accra Central, Gbegbeyise, Sodom & Gomorah), as well the coastal neighborhoods. These areas are closely correlated with the UN Habitat defined informal settlement neighborhoods (UN Habitat 2006/2007).

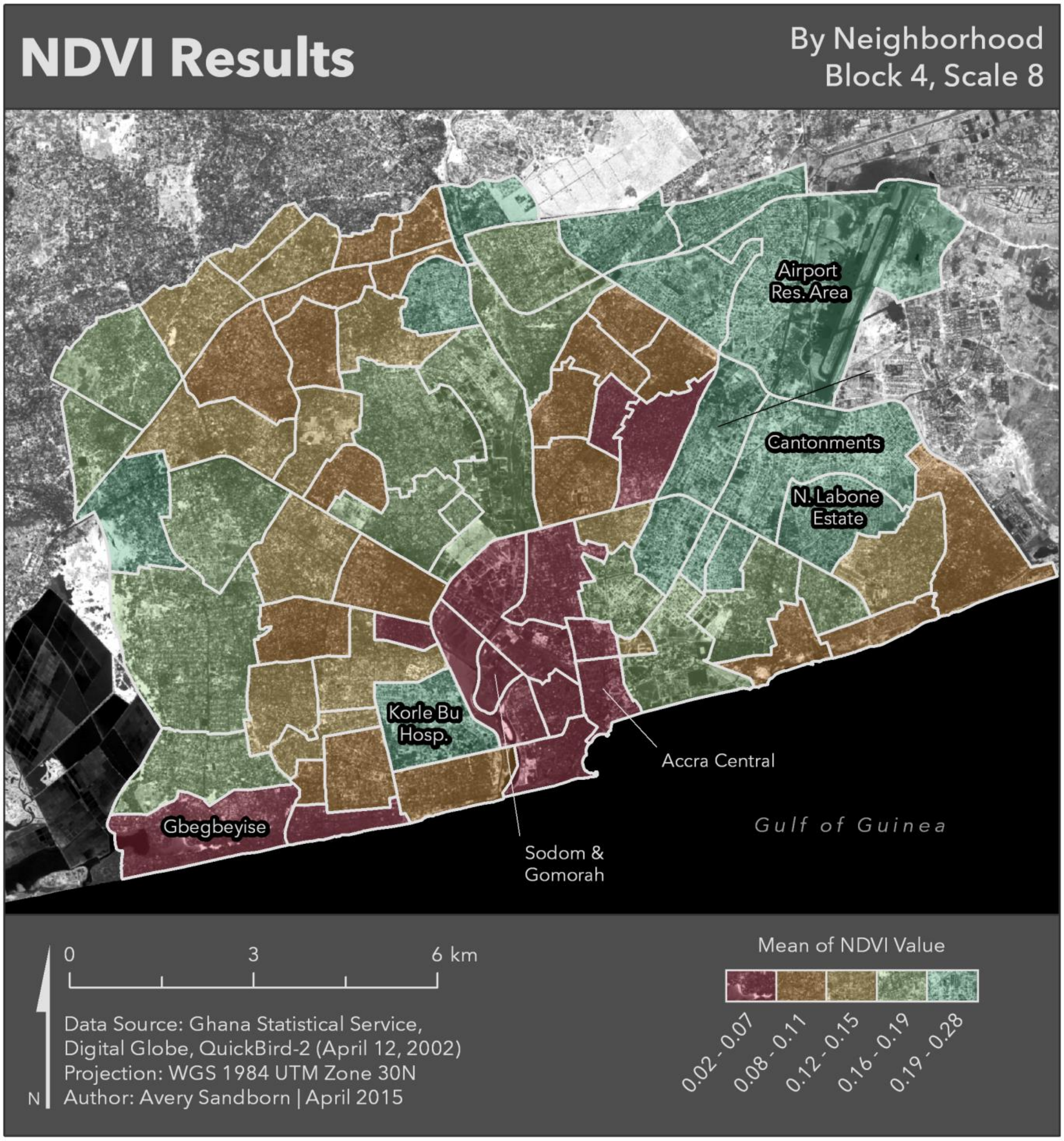

Figure 12: Normalized Difference Vegetation Index (NDVI) Results: NDVI results at block 4 and scale 8 show major differences between neighborhoods with denser vegetation (shown in green) and neighborhoods with less dense vegetation (shown in red).

NDVI results produced many strong correlation coefficients ranging from -0.51 to -0.86 between eleven different census-derived variables. These variables include *Biofuel*, *Non-Separate Cooking Space*, *No Liquid Waste Collection*, *Not Single Family*, *Slum Index*, *Unimproved Sanitation*, *Population Density*, *Housing Density*, *Informal Sector*, *Women Not Educated*, and *No Solid Waste Collectio*n. For NDVI results, there was not a significant differentiation between certain block and scale sizes.

These results imply that households with better building materials, utility infrastructure, and education are living in more vegetated neighborhoods. This also allows for a more spread out lifestyle in which neighbors are not as close in proximity to one another, as portrayed through the population and housing density variables. These results also provide a strong foundation for the case that much of the wealthier and healthier populations live in the periphery of the city, while the vulnerable populations live in the urban core (Engstrom et al. 2011, Stow et al. 2012).

5.7 Mean Results

The aggregated neighborhood average results for band 3 (red) are displayed in Figure 13 and the aggregated neighborhood average results for the local mean of the original QuickBird-2 multispectral image are displayed in Figure 14. Vegetation tends to have a lower percentage of reflectance in the red wavelength, a slightly higher reflectance in the green wavelength, and extremely high reflectance in the NIR band (Ridd 1995). Neighborhoods with high red reflectance are shown to correlate with dense informal housing neighborhoods (e.g. Chorkor, Gbegbeyise), while areas with lower red reflectance are shown to correlate with formal housing neighborhoods (e.g. Abofu, Cantonments, Roman Ridge). This trend is exaggerated in Abofu, since part of the

Achimota Forest Reserve is encompassed in the neighborhood. The multispectral composite results follow a similar trend, in that neighborhoods with high local means are correlated with informal settlement areas.

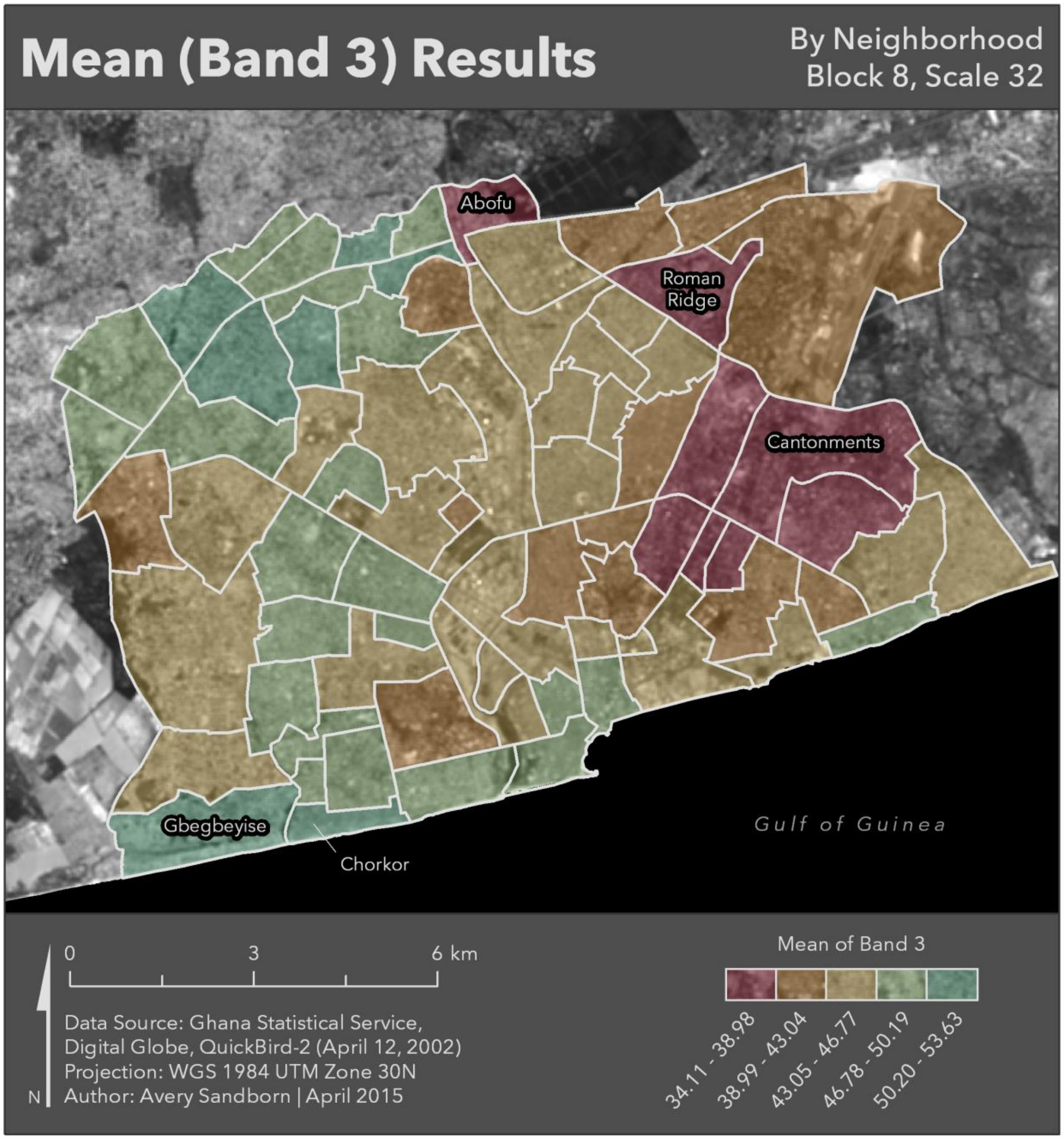

Figure 13: Mean (Band 3) Results: This map shows the local mean of band 3 (red) of the original multispectral dataset at block 8 and scale 32. High values of local mean (shown in green) indicate that band 3 exhibits high reflectance, whereas band 3 exhibits low reflectance where the local mean value is low (shown in red).

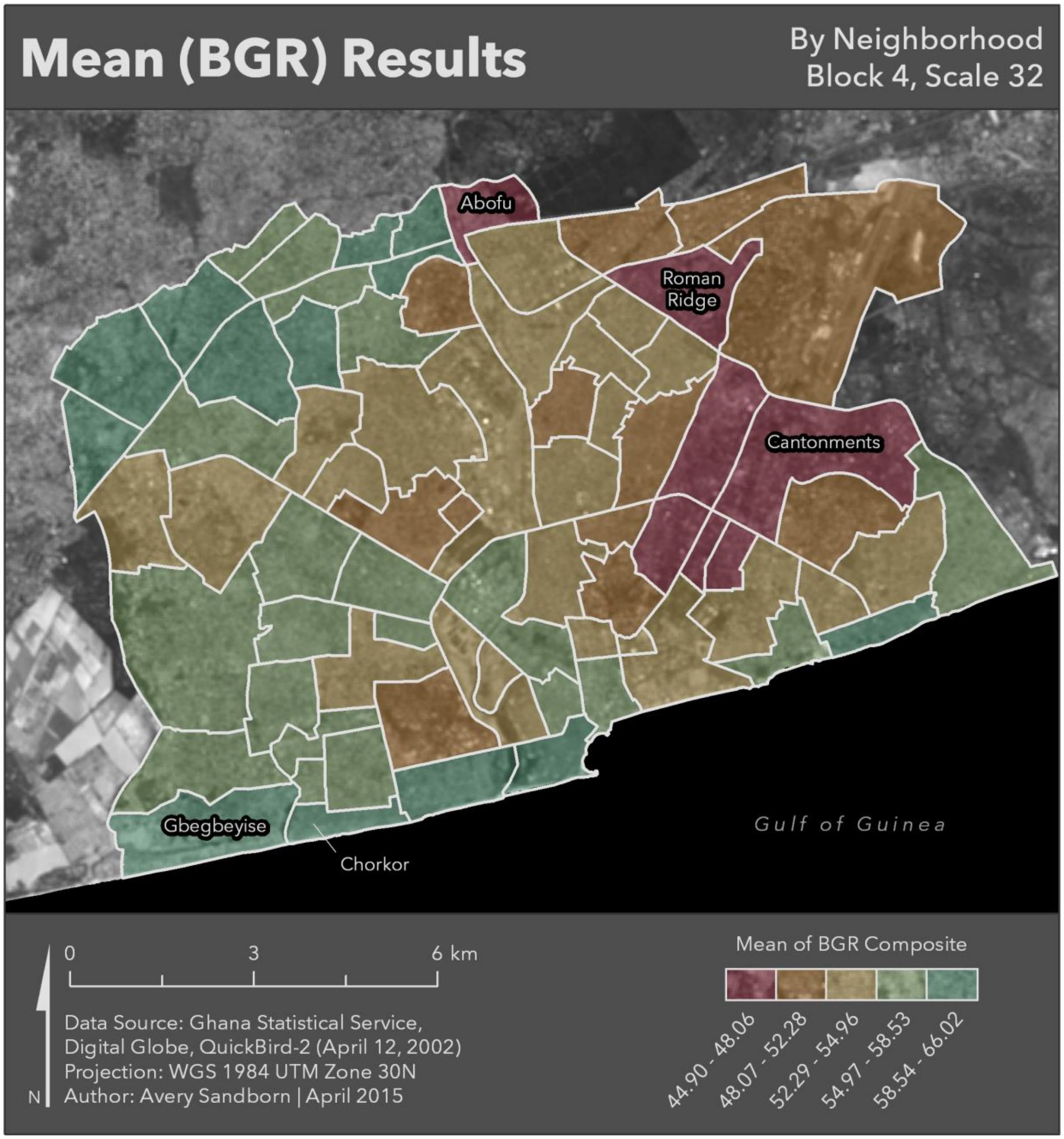

Figure 14: Mean (BGR Composite) Results: This map shows the local mean of the original multispectral composite dataset at block 4 and scale 32. High local mean (shown in green) corresponds with informal residential neighborhoods, and low local mean (shown in red) corresponds with formal residential neighborhoods.

Results indicate that the red band reflectance levels are strongly positively correlated (correlation coefficients ranging from +0.50 to +0.73) with many census-derived indicators: *Informal Sector*, *No Liquid Waste Collection*, *No Solid Waste Collection*, *Biofuel*, *Non-separate Cooking Space*, *Women Not Educated, Not Single Famil*y, and *Rent-free*. The multispectral composite results shared similar strong positive correlations (correlation coefficients ranging from +0.51 to +0.68) with the same census-derived indicators, with the addition of *No Electricity*. Block and scale size were not a contributing factor in calculating correlation coefficients. Similar to NDVI results, Band 3 mean results indicate that neighborhoods with less reflection in the red wavelength exhibit better health and wellness characteristics including better sanitation and education.

Chapter 6: Conclusions

6.1 Summary of Research

The goal of this research was to determine the extent to which spatial features correlate with census-derived demographic characteristics in Accra, Ghana. To test these relationships, five spatial features (LSR, PanTex, HoG, LBP, and FT) and traditional spectral information (NDVI and Mean) were extracted from high spatial resolution imagery, and statistically aggregated to the neighborhood level. These values were then correlated with 31 demographic and housing variables derived from the census.

The strongest correlations observed were between NDVI mean values and building amenity indicators. These results showed strong correlations between neighborhoods with less vegetation and neighborhoods with biofuel cooking fuel, non-separate cooking spaces, and uncollected sewage. Although NDVI revealed the strongest correlations between many census-derived variables, spatial features also displayed comparable correlation coefficients with the census-derived data. Very high correlations, and the most correlations out of any feature, were observed between LBP and census-derived variables. The highest LBP correlations were between LBP histogram variance and population and housing density indicators, illustrating a spatial difference between commercial and residential land use zones.

Some spatial features were also able to reveal additional strong correlations that were not depicted in the NDVI analysis. HoG distribution variables exposed strong correlations between children under 15 years old and informal settlements, while PanTex standard deviation revealed immigrant and ethnic group settlement patterns throughout the city. These discoveries demonstrate the ability for spatial features to enhance traditional remote sensing studies that only utilize spectral information. Block and scale size importance varied between each spatial feature, indicating that careful consideration should be taken to apply the best parameters to the spatial feature computations.

It is important to note, that while spatial features were found to be correlated with census data, this research is contextual and reflects historical and ethnic trends distinctive to Accra. Ultimately, this innovative exploratory analysis suggests possible patterns and trends that can be extracted from built-up areas via satellite imagery, such as line attributes, line variances, and geometric object detection

6.2 Future Work

Although strong correlations were found in this study, this research can and should be applied to other cities to establish universal trends in spatial feature correlations. This research would be particularly helpful in other developing cities where census data is not collected or readily available, and can benefit from remotely sensed population and housing characteristic estimates. Additional analysis may be done in Accra, with more recent imagery, as the 2010 Ghanaian census becomes accessible to researchers.

Dasymetric mapping may help to establish stronger correlations by excluding larger water bodies or heavily commercial areas. In Accra, for instance, neighborhoods such as Gbegbeyise and Korle Lagoon Area have large water bodies, where if they are masked perhaps could increase the correlations between spatial features and population characteristics. Additionally, large commercial infrastructure, such as the Kotoka

International Airport, may have outlier effects within the correlations due to the fact that it is located within the Airport Residential Area neighborhood boundary.

To capture more spatial properties of built-up areas, additional spatial features can be extracted from the imagery. These include Gabor filters that combine Gaussian filters with sinusoids to detect edges (Daugman 1985), Hough Probabilistic Transform which exploits point/line duality to estimate shape parameters (Ballard 1981), and Lacunarity which measures gap distribution (Dong 2000), among others.

Due to the very high correlations demonstrated in the NDVI and LBP outputs, a bivariate regression analysis may be useful in creating a more comprehensive list of correlations between satellite imagery and population characteristics. Additional multivariate regression analysis may show repetition between spatial feature outputs and spectral feature outputs as well. Suggested further research also entails running a land cover classification algorithm on a virtual stack that includes spatial feature outputs, in an effort to aid traditional classification schemes. Finally, this research should be tested in other built-up areas, in an effort to refine spatial feature results and interpretation.

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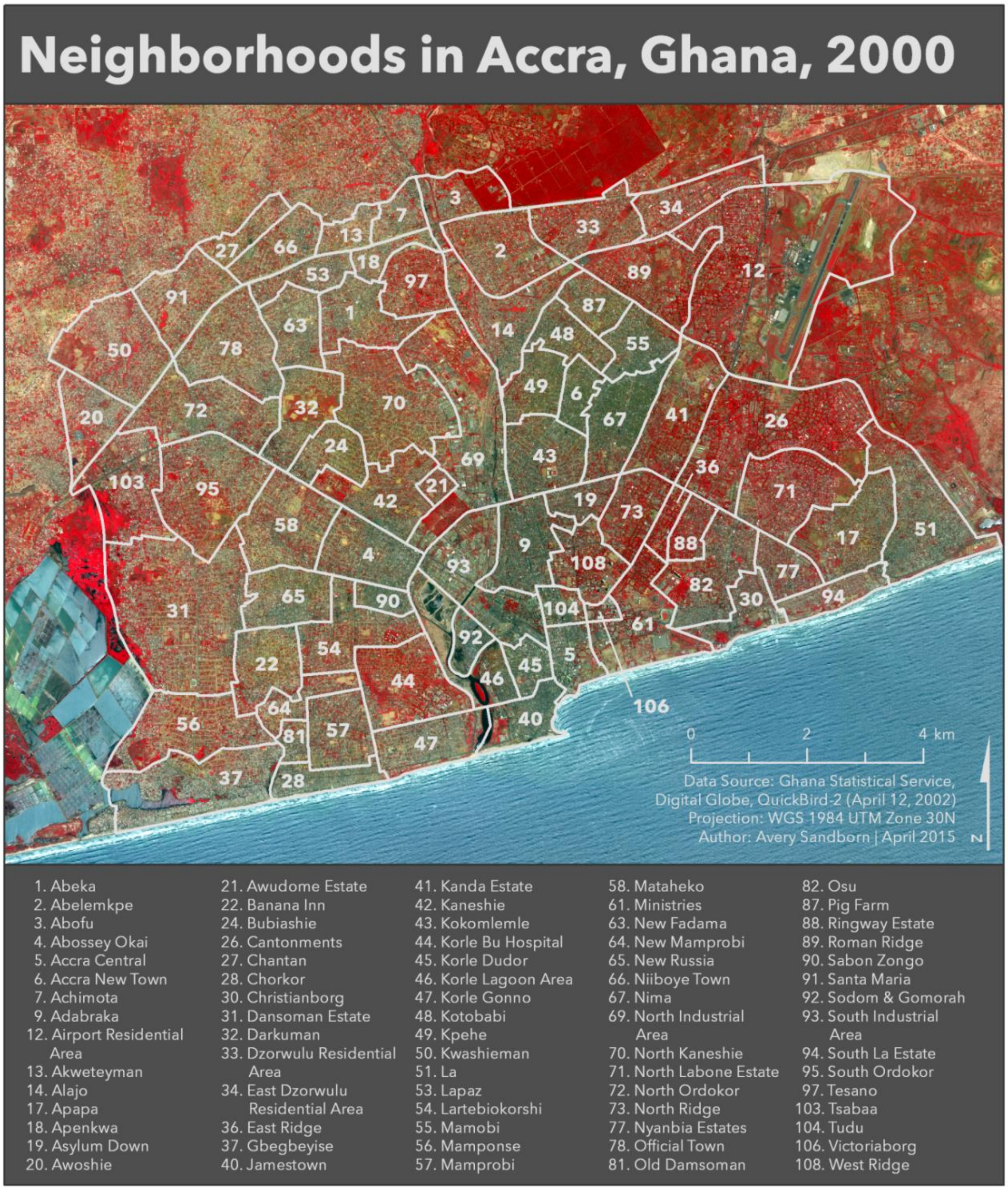
Appendices

Appendix A: Index to Neighborhood Study Area Map.



Appendix B: Spatial Features with Strong Correlations to Census-Derived Data.

Line Support Regions (LSR)

Block	Scale	Output	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
8	32	Line Length Average	Standard Deviation	No Electricity	0.55
8	16	Line Length Average	Standard Deviation	Not Literate	0.54
4	32	Line Length Average	Standard Deviation	No Electricity	0.53
4	16	Line Length Average	Standard Deviation	Not Literate	0.53
8	16	Line Variance	Standard Deviation	Rent-free	0.53
8	16	Line Length Average	Standard Deviation	No Electricity	0.51
4	16	Line Length Average	Standard Deviation	No Electricity	0.51
4	32	Line Length Average	Mean	Population Density	0.50
4	16	Line Length Average	Mean	Rent-free	-0.50
8	32	Line Length Average	Mean	Rent-free	-0.50
8	32	Line Length Sum	Mean	Not Literate	-0.50
8	16	Line Length Average	Mean	Rent-free	-0.51
4	32	Line Length Sum	Mean	No Electricity	-0.52
8	32	Line Variance	Mean	Not Literate	-0.52
4	32	Line Variance	Mean	No Electricity	-0.52
8	32	Line Length Sum	Mean	No Electricity	-0.53
4	16	Line Length Sum	Mean	Not Literate	-0.53
8	32	Line Variance	Mean	No Electricity	-0.53
4	16	Line Length Sum	Mean	No Electricity	-0.53
4	16	Line Variance	Mean	Not Literate	-0.53
8	16	Line Length Sum	Mean	No Electricity	-0.54
4	16	Line Variance	Mean	No Electricity	-0.54
8	16	Line Variance	Mean	No Electricity	-0.54
8	16	Line Length Sum	Mean	Not Literate	-0.54
8	16	Line Variance	Mean	Not Literate	-0.56

PanTex

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Standard Deviation	Born Outside EA	0.64
8	32	Standard Deviation	Born Outside EA	0.63
4	32	Standard Deviation	Not in Accra 5 Years Ago	0.62
8	32	Standard Deviation	Not in Accra 5 Years Ago	0.62
4	16	Standard Deviation	Born Outside EA	0.61
8	32	Standard Deviation	No Electricity	0.60
4	32	Standard Deviation	No Electricity	0.60
8	16	Standard Deviation	Born Outside EA	0.59
4	8	Mean	Informal Sector	0.51
8	8	Mean	Informal Sector	0.50
8	16	Standard Deviation	Ga-Dangme	-0.52
4	16	Mean	Rent-free	-0.52
8	16	Mean	Rent-free	-0.52
4	16	Standard Deviation	Ga-Dangme	-0.52
8	16	Standard Deviation	Dependents	-0.54
4	16	Standard Deviation	Dependents	-0.54
8	8	Mean	Rent-free	-0.54
4	8	Mean	Rent-free	-0.55
8	32	Standard Deviation	Dependents	-0.56
4	32	Standard Deviation	Dependents	-0.56
8	8	Standard Deviation	Ga-Dangme	-0.59
4	8	Standard Deviation	Ga-Dangme	-0.59
4	32	Standard Deviation	Do Not Work	-0.59
8	32	Standard Deviation	Do Not Work	-0.59

Histogram of Oriented Gradients (HoG)

Block	Scale	Output	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
8	8	Histogram Skew	Mean	Rent-free	0.66
8	8	Histogram Kurtosis	Mean	Rent-free	0.66
4	16	Histogram Skew	Mean	Rent-free	0.65
8	16	Histogram Skew	Mean	Rent-free	0.65
4	32	Histogram Skew	Mean	Rent-free	0.65
4	8	Histogram Skew	Mean	Rent-free	0.65
4	32	Histogram Kurtosis	Mean	Rent-free	0.65
8	32	Histogram Skew	Mean	Rent-free	0.65
8	32	Histogram Kurtosis	Mean	Rent-free	0.65
4	8	Histogram Kurtosis	Mean	Rent-free	0.65
8	16	Histogram Kurtosis	Mean	Rent-free	0.64
4	16	Histogram Kurtosis	Mean	Rent-free	0.63
8	32	Histogram Variance	Mean	No Electricity	0.63
4	32	Histogram Variance	Mean	No Electricity	0.62
4	16	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.61
4	8	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.60
8	8	Histogram Kurtosis	Standard Deviation	Rent-free	0.60
8	16	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.60
4	8	Histogram Skew	Mean	Not in Accra 5 Years Ago	0.59
4	8	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.59
8	8	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.58
8	32	Histogram Variance	Standard Deviation	Rent-free	0.58
8	16	Histogram Mean	Standard Deviation	No Electricity	0.58
4	32	Histogram Kurtosis	Standard Deviation	Rent-free	0.58
4	16	Histogram Mean	Standard Deviation	No Electricity	0.58
8	16	Histogram Skew	Standard Deviation	No Electricity	0.58
4	32	Histogram Variance	Standard Deviation	Rent-free	0.58
8	16	Histogram Variance	Mean	No Electricity	0.58
8	8	Histogram Skew	Mean	Not in Accra 5 Years Ago	0.58
4	8	Histogram Kurtosis	Standard Deviation	Rent-free	0.58
8	16	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.58
8	8	Histogram Skew	Standard Deviation	Rent-free	0.57
8	8	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.57
8	32	Histogram Mean	Standard Deviation	No Electricity	0.57
8	16	Histogram Kurtosis	Standard Deviation	Rent-free	0.57
4	32	Histogram Mean	Standard Deviation	No Electricity	0.57
4	16	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.57
4	16	Histogram Skew	Standard Deviation	No Electricity	0.57
4	16	Histogram Variance	Mean	No Electricity	0.57
4	16	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.57
8	32	Histogram Kurtosis	Standard Deviation	Rent-free	0.57
8	16	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.57
4	8	Histogram Skew	Standard Deviation	No Electricity	0.56
8	8	Histogram Skew	Standard Deviation	No Electricity	0.56
4	32	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.56
4	16	Histogram Kurtosis	Standard Deviation	Rent-free	0.56
4	8	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.56
4	32	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.55
8	16	Histogram Kurtosis	Standard Deviation	No Electricity	0.55
4	16	Histogram Skew	Mean	Not in Accra 5 Years Ago	0.55
4	8	Histogram Skew	Standard Deviation	Rent-free	0.55
8	32	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	0.55
8	16	Histogram Skew	Standard Deviation	Rent-free	0.55
8	32	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.55
4	32	Histogram Kurtosis	Mean	No Electricity	0.54
8	32	Histogram Kurtosis	Mean	No Electricity	0.54

4	16	Histogram Kurtosis	Standard Deviation	No Electricity	0.54
8	16	Histogram Skew	Mean	Not in Accra 5 Years Ago	0.54
4	32	Histogram Skew	Standard Deviation	Rent-free	0.54
8	16	Histogram Kurtosis	Mean	No Electricity	0.54
8	8	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.54
4	16	Histogram Kurtosis	Mean	No Electricity	0.54
8	32	Histogram Skew	Standard Deviation	Rent-free	0.53
4	32	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.53
4	8	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.53
4	16	Histogram Skew	Standard Deviation	Rent-free	0.53
8	16	Histogram Variance	Mean	Immigrant	0.53
8	32	Histogram Kurtosis	Standard Deviation	Not in Accra 5 Years Ago	0.53
4	16	Histogram Variance	Mean	Immigrant	0.52
4	8	Histogram Kurtosis	Standard Deviation	No Electricity	0.52
8	32	Histogram Skew	Mean	No Electricity	0.52
4	32	Histogram Skew	Mean	No Electricity	0.52
8	8	Histogram Mean	Standard Deviation	Not in Accra 5 Years Ago	0.52
8	8	Histogram Kurtosis	Standard Deviation	No Electricity	0.52
8	16	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.52
4	16	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.51
4	8	Histogram Variance	Standard Deviation	Rent-free	0.51
4	32	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.51
8	16	Histogram Variance	Standard Deviation	Rent-free	0.51
4	16	Histogram Variance	Standard Deviation	Rent-free	0.51
8	32	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.50
8	32	Histogram Skew	Mean	Population Density	-0.50
4	16	Histogram Mean	Standard Deviation	Dependents	-0.50
4	32	Histogram Skew	Mean	Population Density	-0.50
8	32	Histogram Kurtosis	Mean	Population Density	-0.50
4	32	Histogram Kurtosis	Mean	Population Density	-0.51
4	16	Histogram Skew	Standard Deviation	Children	-0.51
8	16	Histogram Mean	Standard Deviation	Population Density	-0.51
4	16	Histogram Mean	Standard Deviation	Population Density	-0.51
8	16	Histogram Skew	Standard Deviation	Children	-0.51
8	8	Histogram Skew	Mean	No Liquid Waste Collection	-0.51
4	32	Histogram Kurtosis	Standard Deviation	Population Density	-0.51
8	32	Histogram Kurtosis	Standard Deviation	Housing Density	-0.51
4	32	Histogram Kurtosis	Standard Deviation	Housing Density	-0.51
8	32	Histogram Kurtosis	Standard Deviation	Population Density	-0.51
8	32	Histogram Skew	Standard Deviation	Children	-0.51
8	16	Histogram Mean	Standard Deviation	Housing Density	-0.51
4	16	Histogram Mean	Standard Deviation	Housing Density	-0.52
4	32	Histogram Skew	Standard Deviation	Children	-0.52
4	8	Histogram Skew	Mean	No Liquid Waste Collection	-0.52
4	16	Histogram Kurtosis	Standard Deviation	Population Density	-0.53
8	8	Histogram Skew	Standard Deviation	Children	-0.53
8	16	Histogram Kurtosis	Standard Deviation	Housing Density	-0.53
4	16	Histogram Kurtosis	Standard Deviation	Housing Density	-0.53
8	32	Histogram Skew	Mean	Children	-0.53
8	16	Histogram Kurtosis	Standard Deviation	Population Density	-0.53
4	32	Histogram Skew	Mean	Children	-0.53
4	8	Histogram Skew	Standard Deviation	Children	-0.54
8	8	Histogram Mean	Standard Deviation	Dependents	-0.54
4	8	Histogram Skew	Standard Deviation	Population Density	-0.54
4	8	Histogram Skew	Standard Deviation	Housing Density	-0.54
8	8	Histogram Skew	Standard Deviation	Housing Density	-0.54
8	8	Histogram Skew	Standard Deviation	Population Density	-0.55
4	8	Histogram Mean	Standard Deviation	Dependents	-0.55
8	16	Histogram Kurtosis	Mean	Housing Density	-0.56

4	16	Histogram Kurtosis	Mean	Housing Density	-0.56
8	32	Histogram Kurtosis	Standard Deviation	Children	-0.57
8	8	Histogram Kurtosis	Standard Deviation	Children	-0.57
4	32	Histogram Kurtosis	Standard Deviation	Children	-0.57
8	16	Histogram Skew	Mean	Children	-0.57
8	16	Histogram Kurtosis	Mean	Population Density	-0.57
4	16	Histogram Kurtosis	Mean	Population Density	-0.57
4	16	Histogram Kurtosis	Standard Deviation	Children	-0.58
4	16	Histogram Skew	Mean	Children	-0.58
4	8	Histogram Kurtosis	Standard Deviation	Children	-0.58
8	16	Histogram Kurtosis	Standard Deviation	Children	-0.58
8	8	Histogram Kurtosis	Mean	Children	-0.58
8	16	Histogram Kurtosis	Mean	Children	-0.58
8	8	Histogram Skew	Mean	Children	-0.58
4	16	Histogram Kurtosis	Mean	Children	-0.59
8	16	Histogram Skew	Mean	Housing Density	-0.59
8	32	Histogram Kurtosis	Mean	Children	-0.59
4	16	Histogram Skew	Mean	Housing Density	-0.59
4	32	Histogram Kurtosis	Mean	Children	-0.60
4	8	Histogram Kurtosis	Standard Deviation	Housing Density	-0.60
4	8	Histogram Kurtosis	Standard Deviation	Population Density	-0.60
8	8	Histogram Kurtosis	Standard Deviation	Housing Density	-0.60
4	8	Histogram Skew	Mean	Children	-0.61
4	8	Histogram Kurtosis	Mean	Children	-0.61
8	8	Histogram Kurtosis	Standard Deviation	Population Density	-0.61
8	16	Histogram Skew	Mean	Population Density	-0.61
4	16	Histogram Skew	Mean	Population Density	-0.61
8	8	Histogram Kurtosis	Mean	Housing Density	-0.66
8	8	Histogram Kurtosis	Mean	Population Density	-0.68
4	8	Histogram Kurtosis	Mean	Housing Density	-0.68
8	8	Histogram Skew	Mean	Housing Density	-0.69
4	8	Histogram Kurtosis	Mean	Population Density	-0.69
4	8	Histogram Skew	Mean	Housing Density	-0.71
8	8	Histogram Skew	Mean	Population Density	-0.71
4	8	Histogram Skew	Mean	Population Density	-0.72

Local Binary Patterns (LBP)

Block	Scale	Output	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Histogram Variance	Mean	Population Density	0.85
8	32	Histogram Variance	Mean	Population Density	0.85
4	32	Histogram Variance	Mean	Housing Density	0.84
4	16	Histogram Variance	Mean	Population Density	0.84
8	32	Histogram Variance	Mean	Housing Density	0.84
8	16	Histogram Variance	Mean	Population Density	0.84
4	16	Histogram Variance	Mean	Housing Density	0.83
8	16	Histogram Variance	Mean	Housing Density	0.83
8	8	Histogram Skew	Mean	Population Density	0.82
4	8	Histogram Skew	Mean	Population Density	0.82
8	8	Histogram Kurtosis	Mean	Population Density	0.82
4	8	Histogram Kurtosis	Mean	Population Density	0.82
4	8	Histogram Variance	Mean	Biofuel	0.82
8	8	Histogram Variance	Mean	Biofuel	0.81
4	8	Histogram Variance	Mean	Population Density	0.81
8	8	Histogram Skew	Mean	Housing Density	0.81
4	8	Histogram Skew	Mean	Housing Density	0.81
8	8	Histogram Variance	Mean	Population Density	0.81
4	8	Histogram Kurtosis	Mean	Housing Density	0.81
8	8	Histogram Kurtosis	Mean	Housing Density	0.81

4	16	Histogram Variance	Mean	Biofuel	0.80
4	8	Histogram Variance	Mean	Housing Density	0.80
8	16	Histogram Variance	Mean	Biofuel	0.80
8	8	Histogram Variance	Mean	Housing Density	0.80
4	8	Histogram Variance	Mean	Non-separate Cooking Space	0.79
8	8	Histogram Variance	Mean	Non-separate Cooking Space	0.79
4	16	Histogram Variance	Mean	Non-separate Cooking Space	0.79
4	16	Histogram Skew	Mean	Population Density	0.79
8	16	Histogram Variance	Mean	Non-separate Cooking Space	0.79
8	16	Histogram Skew	Mean	Population Density	0.79
4	16	Histogram Kurtosis	Mean	Population Density	0.79
8	16	Histogram Kurtosis	Mean	Population Density	0.78
4	32	Histogram Variance	Mean	Biofuel	0.78
8	32	Histogram Variance	Mean	Biofuel	0.78
4	16	Histogram Skew	Mean	Housing Density	0.78
8	16	Histogram Skew	Mean	Housing Density	0.78
4	16	Histogram Kurtosis	Mean	Housing Density	0.77
4	32	Histogram Variance	Mean	Non-separate Cooking Space	0.77
8	16	Histogram Kurtosis	Mean	Housing Density	0.77
8	32	Histogram Variance	Mean	Non-separate Cooking Space	0.77
4	32	Histogram Skew	Mean	Population Density	0.77
8	32	Histogram Skew	Mean	Population Density	0.77
4	32	Histogram Kurtosis	Mean	Population Density	0.76
8	32	Histogram Kurtosis	Mean	Population Density	0.76
4	32	Histogram Skew	Mean	Housing Density	0.76
8	32	Histogram Skew	Mean	Housing Density	0.76
8	16	Histogram Variance	Mean	No Liquid Waste Collection	0.75
4	16	Histogram Variance	Mean	No Liquid Waste Collection	0.75
4	32	Histogram Kurtosis	Mean	Housing Density	0.75
8	32	Histogram Kurtosis	Mean	Housing Density	0.75
4	8	Histogram Variance	Mean	No Liquid Waste Collection	0.75
8	8	Histogram Variance	Mean	No Liquid Waste Collection	0.75
4	32	Histogram Variance	Mean	No Liquid Waste Collection	0.75
8	32	Histogram Variance	Mean	No Liquid Waste Collection	0.74
4	8	Histogram Skew	Mean	No Liquid Waste Collection	0.73
4	8	Histogram Skew	Mean	Non-separate Cooking Space	0.73
8	8	Histogram Skew	Mean	No Liquid Waste Collection	0.73
8	8	Histogram Skew	Mean	Non-separate Cooking Space	0.73
4	8	Histogram Skew	Mean	Biofuel	0.73
8	8	Histogram Skew	Mean	Biofuel	0.72
4	8	Histogram Variance	Mean	Slum Index	0.72
4	8	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.72
4	8	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.72
8	8	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.72
8	8	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.72
8	8	Histogram Variance	Mean	Slum Index	0.71
4	8	Histogram Kurtosis	Mean	Biofuel	0.71
8	8	Histogram Kurtosis	Mean	Biofuel	0.71
4	8	Histogram Variance	Mean	Women Not Educated	0.70
4	8	Histogram Skew	Mean	Informal Sector	0.70
8	8	Histogram Skew	Mean	Informal Sector	0.70
8	16	Histogram Variance	Mean	Informal Sector	0.70
4	16	Histogram Variance	Mean	Informal Sector	0.70
4	32	Histogram Variance	Mean	Informal Sector	0.70
8	32	Histogram Variance	Mean	Informal Sector	0.70
4	16	Histogram Skew	Mean	No Liquid Waste Collection	0.70
4	16	Histogram Variance	Mean	Slum Index	0.70
8	8	Histogram Variance	Mean	Women Not Educated	0.69
8	16	Histogram Variance	Mean	Slum Index	0.69

8	16	Histogram Skew	Mean	No Liquid Waste Collection	0.69
4	8	Histogram Kurtosis	Mean	Informal Sector	0.69
8	8	Histogram Kurtosis	Mean	Informal Sector	0.69
4	8	Histogram Variance	Mean	Informal Sector	0.69
8	8	Histogram Variance	Mean	Informal Sector	0.68
4	16	Histogram Variance	Mean	Women Not Educated	0.68
4	16	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.68
4	16	Histogram Skew	Mean	Non-separate Cooking Space	0.68
8	16	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.68
8	16	Histogram Variance	Mean	Women Not Educated	0.68
8	16	Histogram Skew	Mean	Non-separate Cooking Space	0.68
4	16	Histogram Skew	Mean	Informal Sector	0.68
4	32	Histogram Skew	Mean	No Liquid Waste Collection	0.68
8	16	Histogram Variance	Mean	Not Single Family	0.68
8	32	Histogram Skew	Mean	No Liquid Waste Collection	0.68
4	16	Histogram Variance	Mean	Not Single Family	0.68
8	16	Histogram Skew	Mean	Informal Sector	0.68
8	8	Histogram Variance	Mean	Not Single Family	0.67
4	8	Histogram Variance	Mean	Unimproved Sanitation	0.67
4	8	Histogram Variance	Mean	Not Single Family	0.67
4	16	Histogram Skew	Mean	Biofuel	0.67
8	8	Histogram Variance	Mean	Unimproved Sanitation	0.67
4	16	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.67
8	16	Histogram Skew	Mean	Biofuel	0.67
8	16	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.67
4	32	Histogram Variance	Mean	Slum Index	0.67
4	32	Histogram Skew	Mean	Informal Sector	0.67
8	32	Histogram Variance	Mean	Slum Index	0.67
4	32	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.67
8	32	Histogram Kurtosis	Mean	No Liquid Waste Collection	0.66
8	32	Histogram Skew	Mean	Informal Sector	0.66
4	32	Histogram Variance	Mean	Not Single Family	0.66
8	32	Histogram Variance	Mean	Not Single Family	0.66
4	16	Histogram Kurtosis	Mean	Informal Sector	0.66
4	32	Histogram Variance	Mean	Women Not Educated	0.66
4	8	Histogram Skew	Mean	Not Single Family	0.66
8	16	Histogram Kurtosis	Mean	Informal Sector	0.66
4	32	Histogram Skew	Mean	Non-separate Cooking Space	0.66
8	32	Histogram Variance	Mean	Women Not Educated	0.66
4	16	Histogram Kurtosis	Mean	Biofuel	0.66
8	32	Histogram Skew	Mean	Non-separate Cooking Space	0.66
8	8	Histogram Skew	Mean	Not Single Family	0.66
8	16	Histogram Kurtosis	Mean	Biofuel	0.65
4	32	Histogram Kurtosis	Mean	Informal Sector	0.65
8	32	Histogram Kurtosis	Mean	Informal Sector	0.65
4	8	Histogram Kurtosis	Mean	Not Single Family	0.65
4	32	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.65
4	32	Histogram Skew	Mean	Biofuel	0.65
8	8	Histogram Kurtosis	Mean	Not Single Family	0.65
8	32	Histogram Kurtosis	Mean	Non-separate Cooking Space	0.65
8	32	Histogram Skew	Mean	Biofuel	0.64
4	16	Histogram Variance	Mean	Unimproved Sanitation	0.64
8	16	Histogram Variance	Mean	Unimproved Sanitation	0.64
4	32	Histogram Kurtosis	Mean	Biofuel	0.63
4	16	Histogram Skew	Mean	Not Single Family	0.63
8	32	Histogram Kurtosis	Mean	Biofuel	0.63
8	16	Histogram Skew	Mean	Not Single Family	0.63
4	16	Histogram Kurtosis	Mean	Not Single Family	0.62
8	16	Histogram Kurtosis	Mean	Not Single Family	0.62

4	32	Histogram Skew	Mean	Not Single Family	0.62
8	32	Histogram Skew	Mean	Not Single Family	0.61
8	32	Histogram Variance	Mean	Unimproved Sanitation	0.61
4	32	Histogram Kurtosis	Mean	Not Single Family	0.61
8	8	Histogram Variance	Mean	No Solid Waste Collection	0.60
4	32	Histogram Variance	Mean	Unimproved Sanitation	0.60
8	32	Histogram Kurtosis	Mean	Not Single Family	0.60
8	16	Histogram Variance	Mean	No Solid Waste Collection	0.60
4	8	Histogram Variance	Mean	No Solid Waste Collection	0.60
4	16	Histogram Variance	Mean	No Solid Waste Collection	0.60
4	8	Histogram Skew	Mean	Women Not Educated	0.59
8	8	Histogram Skew	Mean	Women Not Educated	0.59
4	8	Histogram Skew	Mean	Slum Index	0.59
8	32	Histogram Variance	Mean	No Solid Waste Collection	0.59
4	32	Histogram Variance	Mean	No Solid Waste Collection	0.58
8	8	Histogram Skew	Mean	Slum Index	0.58
4	8	Histogram Kurtosis	Mean	Women Not Educated	0.58
8	8	Histogram Kurtosis	Mean	Women Not Educated	0.58
4	8	Histogram Kurtosis	Mean	Slum Index	0.57
4	8	Histogram Skew	Mean	No Solid Waste Collection	0.57
8	8	Histogram Kurtosis	Mean	Slum Index	0.57
8	8	Histogram Skew	Mean	No Solid Waste Collection	0.57
4	32	Histogram Variance	Mean	Households	0.56
8	32	Histogram Variance	Mean	Households	0.56
4	8	Histogram Kurtosis	Mean	No Solid Waste Collection	0.56
4	32	Histogram Skew	Standard Deviation	Not Literate	0.56
4	16	Histogram Variance	Mean	Households	0.55
8	8	Histogram Kurtosis	Mean	No Solid Waste Collection	0.55
8	16	Histogram Variance	Mean	Households	0.55
8	32	Histogram Skew	Standard Deviation	Not Literate	0.55
4	32	Histogram Variance	Mean	Population	0.55
8	32	Histogram Variance	Mean	Population	0.55
4	32	Histogram Kurtosis	Standard Deviation	Not Literate	0.55
4	8	Histogram Skew	Mean	Households	0.54
4	16	Histogram Variance	Mean	Population	0.54
8	16	Histogram Variance	Mean	Population	0.54
4	16	Histogram Skew	Mean	No Solid Waste Collection	0.54
4	8	Histogram Kurtosis	Mean	Households	0.54
8	32	Histogram Kurtosis	Standard Deviation	Not Literate	0.54
8	16	Histogram Skew	Mean	No Solid Waste Collection	0.54
8	8	Histogram Skew	Mean	Households	0.54
8	8	Histogram Kurtosis	Mean	Households	0.54
4	8	Histogram Skew	Mean	Population	0.54
4	8	Histogram Kurtosis	Mean	Population	0.54
4	16	Histogram Skew	Mean	Women Not Educated	0.53
4	8	Histogram Variance	Mean	Households	0.53
8	8	Histogram Skew	Mean	Population	0.53
8	8	Histogram Kurtosis	Mean	Population	0.53
8	16	Histogram Skew	Mean	Women Not Educated	0.53
8	8	Histogram Variance	Mean	Households	0.53
4	16	Histogram Skew	Mean	Households	0.53
4	16	Histogram Skew	Mean	Slum Index	0.53
4	16	Histogram Kurtosis	Mean	No Solid Waste Collection	0.53
8	16	Histogram Skew	Mean	Slum Index	0.53
4	16	Histogram Kurtosis	Mean	Households	0.53
8	16	Histogram Kurtosis	Mean	No Solid Waste Collection	0.52
4	8	Histogram Kurtosis	Mean	Children	0.52
8	16	Histogram Skew	Mean	Households	0.52
4	16	Histogram Kurtosis	Mean	Women Not Educated	0.52

4	32	Histogram Skew	Mean	No Solid Waste Collection	0.52
8	8	Histogram Skew	Mean	Children	0.52
4	16	Histogram Skew	Mean	Population	0.52
4	8	Histogram Skew	Mean	Children	0.52
8	32	Histogram Skew	Mean	No Solid Waste Collection	0.52
8	8	Histogram Kurtosis	Mean	Children	0.52
4	16	Histogram Kurtosis	Mean	Population	0.52
8	16	Histogram Kurtosis	Mean	Households	0.52
8	16	Histogram Kurtosis	Mean	Women Not Educated	0.52
8	16	Histogram Skew	Mean	Population	0.52
4	32	Histogram Skew	Mean	Households	0.52
4	8	Histogram Variance	Mean	Population	0.52
8	16	Histogram Kurtosis	Mean	Population	0.52
4	16	Histogram Kurtosis	Mean	Children	0.52
4	16	Histogram Skew	Mean	Children	0.52
4	32	Histogram Kurtosis	Mean	Households	0.52
8	32	Histogram Skew	Mean	Households	0.52
8	16	Histogram Skew	Mean	Children	0.52
8	16	Histogram Kurtosis	Mean	Children	0.52
8	8	Histogram Variance	Mean	Population	0.52
4	32	Histogram Skew	Mean	Population	0.52
8	32	Histogram Kurtosis	Mean	Households	0.51
4	16	Histogram Kurtosis	Mean	Slum Index	0.51
4	32	Histogram Kurtosis	Mean	Population	0.51
8	32	Histogram Skew	Mean	Population	0.51
8	16	Histogram Kurtosis	Mean	Slum Index	0.51
4	32	Histogram Kurtosis	Mean	No Solid Waste Collection	0.51
4	32	Histogram Kurtosis	Mean	Children	0.51
8	8	Histogram Skew	Standard Deviation	Not in Accra 5 Years Ago	0.51
8	32	Histogram Kurtosis	Mean	Population	0.51
8	32	Histogram Kurtosis	Mean	No Solid Waste Collection	0.51
4	32	Histogram Skew	Mean	Children	0.51
4	32	Histogram Skew	Mean	Women Not Educated	0.51
8	16	Histogram Variance	Mean	Worst Wall	0.51
8	32	Histogram Skew	Mean	Women Not Educated	0.51
8	32	Histogram Kurtosis	Mean	Children	0.51
4	16	Histogram Variance	Mean	Worst Wall	0.51
4	8	Histogram Skew	Mean	Unimproved Sanitation	0.51
4	32	Histogram Variance	Mean	Worst Wall	0.51
8	32	Histogram Skew	Mean	Children	0.51
8	32	Histogram Variance	Mean	Worst Wall	0.51
4	32	Histogram Variance	Mean	Children	0.51
8	32	Histogram Skew	Mean	Slum Index	0.51
4	32	Histogram Skew	Mean	Slum Index	0.50
4	32	Histogram Kurtosis	Mean	Women Not Educated	0.50
8	8	Histogram Skew	Mean	Unimproved Sanitation	0.50
8	32	Histogram Kurtosis	Mean	Women Not Educated	0.50
8	32	Histogram Variance	Mean	Children	0.50
4	8	Histogram Skew	Mean	Rent-free	-0.50
8	32	Histogram Variance	Mean	Not in Accra 5 Years Ago	-0.51
4	32	Histogram Variance	Mean	Not in Accra 5 Years Ago	-0.51
4	32	Histogram Skew	Mean	Rent-free	-0.51
8	32	Histogram Skew	Mean	Rent-free	-0.51
8	8	Histogram Skew	Mean	Rent-free	-0.51
4	16	Histogram Skew	Mean	Rent-free	-0.52
4	8	Histogram Kurtosis	Mean	Rent-free	-0.52
8	16	Histogram Skew	Mean	Rent-free	-0.52
8	8	Histogram Kurtosis	Mean	Rent-free	-0.52
8	32	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.52

8	32	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.53
8	16	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.53
4	32	Histogram Kurtosis	Mean	Rent-free	-0.53
8	8	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.53
8	32	Histogram Kurtosis	Mean	Rent-free	-0.53
4	8	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.53
4	8	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.53
8	8	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.53
8	16	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.53
4	16	Histogram Kurtosis	Mean	Rent-free	-0.53
4	32	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.53
4	16	Histogram Kurtosis	Mean	Not in Accra 5 Years Ago	-0.53
4	32	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.53
8	16	Histogram Kurtosis	Mean	Rent-free	-0.53
4	16	Histogram Skew	Mean	Not in Accra 5 Years Ago	-0.54
8	8	Histogram Kurtosis	Standard Deviation	Population Density	-0.61
8	8	Histogram Kurtosis	Standard Deviation	Housing Density	-0.62
4	8	Histogram Kurtosis	Standard Deviation	Population Density	-0.62
4	8	Histogram Kurtosis	Standard Deviation	Housing Density	-0.63
8	8	Histogram Skew	Standard Deviation	Population Density	-0.69
8	8	Histogram Skew	Standard Deviation	Housing Density	-0.69
4	8	Histogram Skew	Standard Deviation	Population Density	-0.70
4	8	Histogram Skew	Standard Deviation	Housing Density	-0.71

Fourier Transform (FT)

Block	Scale	Output	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Radial Profile Mean	Mean	Informal Sector	0.54
8	32	Radial Profile Mean	Mean	Informal Sector	0.53
4	16	Radial Profile Mean	Mean	Informal Sector	0.53
8	16	Radial Profile Mean	Mean	Informal Sector	0.52
8	16	Radial Profile Variance	Mean	Unimproved Sanitation	-0.52
8	8	Radial Profile Variance	Mean	Not Literate	-0.53
8	32	Radial Profile Variance	Mean	Women Not Educated	-0.53
8	32	Radial Profile Variance	Mean	Biofuel	-0.54
4	16	Radial Profile Variance	Mean	Slum Index	-0.54
4	32	Radial Profile Variance	Mean	Women Not Educated	-0.54
4	16	Radial Profile Variance	Mean	Unimproved Sanitation	-0.55
4	32	Radial Profile Variance	Mean	Biofuel	-0.55
4	8	Radial Profile Variance	Mean	Not Literate	-0.55
8	32	Radial Profile Variance	Mean	Unimproved Sanitation	-0.56
8	32	Radial Profile Variance	Mean	Not Literate	-0.57
4	32	Radial Profile Variance	Mean	Not Literate	-0.57
8	32	Radial Profile Variance	Mean	Slum Index	-0.58
8	16	Radial Profile Variance	Mean	Not Literate	-0.58
4	32	Radial Profile Variance	Mean	Unimproved Sanitation	-0.58
4	32	Radial Profile Variance	Mean	Slum Index	-0.60
4	16	Radial Profile Variance	Mean	Not Literate	-0.61

NDVI

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Sum	Non-separate Cooking Space	-0.52
8	32	Sum	Non-separate Cooking Space	-0.52
4	16	Sum	Non-separate Cooking Space	-0.52
8	8	Standard Deviation	Informal Sector	-0.52
8	16	Sum	Non-separate Cooking Space	-0.52
4	8	Sum	Non-separate Cooking Space	-0.52
8	8	Sum	Non-separate Cooking Space	-0.52

4	8	Standard Deviation	Not Single Family	-0.52
4	8	Standard Deviation	Informal Sector	-0.53
8	8	Standard Deviation	Not Single Family	-0.53
4	32	Standard Deviation	Housing Density	-0.54
8	32	Standard Deviation	Housing Density	-0.54
8	8	Standard Deviation	No Liquid Waste Collection	-0.54
4	8	Standard Deviation	No Liquid Waste Collection	-0.55
4	32	Standard Deviation	Population Density	-0.56
8	32	Standard Deviation	Population Density	-0.56
8	8	Standard Deviation	Biofuel	-0.58
4	8	Standard Deviation	Biofuel	-0.58
8	8	Standard Deviation	Non-separate Cooking Space	-0.59
4	8	Standard Deviation	Non-separate Cooking Space	-0.60
4	16	Standard Deviation	Housing Density	-0.63
8	16	Standard Deviation	Housing Density	-0.63
4	32	Mean	No Solid Waste Collection	-0.65
4	16	Mean	No Solid Waste Collection	-0.65
4	8	Mean	No Solid Waste Collection	-0.65
4	16	Standard Deviation	Population Density	-0.65
8	16	Standard Deviation	Population Density	-0.65
8	32	Mean	No Solid Waste Collection	-0.65
8	16	Mean	No Solid Waste Collection	-0.65
8	8	Mean	No Solid Waste Collection	-0.65
4	8	Standard Deviation	Housing Density	-0.70
8	8	Standard Deviation	Housing Density	-0.70
8	16	Mean	Women Not Educated	-0.70
8	8	Mean	Women Not Educated	-0.71
4	16	Mean	Women Not Educated	-0.71
4	8	Mean	Women Not Educated	-0.71
8	32	Mean	Women Not Educated	-0.71
4	8	Mean	Informal Sector	-0.71
4	16	Mean	Informal Sector	-0.71
4	32	Mean	Women Not Educated	-0.71
8	8	Mean	Informal Sector	-0.71
8	16	Mean	Informal Sector	-0.71
4	32	Mean	Informal Sector	-0.71
8	32	Mean	Informal Sector	-0.71
4	8	Standard Deviation	Population Density	-0.72
8	8	Standard Deviation	Population Density	-0.72
8	16	Mean	Housing Density	-0.74
8	32	Mean	Housing Density	-0.74
8	8	Mean	Housing Density	-0.74
4	16	Mean	Housing Density	-0.74
4	8	Mean	Housing Density	-0.74
4	32	Mean	Housing Density	-0.74
8	16	Mean	Population Density	-0.75
8	32	Mean	Population Density	-0.75
8	8	Mean	Population Density	-0.75
4	16	Mean	Population Density	-0.75
4	32	Mean	Population Density	-0.75
4	8	Mean	Population Density	-0.75
4	32	Mean	Unimproved Sanitation	-0.75
4	16	Mean	Unimproved Sanitation	-0.75
4	8	Mean	Unimproved Sanitation	-0.75
8	32	Mean	Unimproved Sanitation	-0.75
8	32	Mean	Slum Index	-0.75
4	32	Mean	Slum Index	-0.75
8	16	Mean	Unimproved Sanitation	-0.75
8	16	Mean	Slum Index	-0.75

8	8	Mean	Unimproved Sanitation	-0.75
4	16	Mean	Slum Index	-0.75
8	8	Mean	Slum Index	-0.75
4	8	Mean	Slum Index	-0.75
4	32	Mean	Not Single Family	-0.78
8	32	Mean	Not Single Family	-0.78
4	16	Mean	Not Single Family	-0.78
4	8	Mean	Not Single Family	-0.78
8	16	Mean	Not Single Family	-0.78
8	8	Mean	Not Single Family	-0.78
4	32	Mean	No Liquid Waste Collection	-0.81
4	16	Mean	No Liquid Waste Collection	-0.81
4	8	Mean	No Liquid Waste Collection	-0.81
8	16	Mean	No Liquid Waste Collection	-0.81
8	32	Mean	No Liquid Waste Collection	-0.81
8	8	Mean	No Liquid Waste Collection	-0.81
4	32	Mean	Non-separate Cooking Space	-0.85
4	16	Mean	Non-separate Cooking Space	-0.85
8	32	Mean	Non-separate Cooking Space	-0.85
8	16	Mean	Non-separate Cooking Space	-0.85
4	8	Mean	Non-separate Cooking Space	-0.85
8	8	Mean	Non-separate Cooking Space	-0.85
8	16	Mean	Biofuel	-0.86
4	32	Mean	Biofuel	-0.86
8	32	Mean	Biofuel	-0.86
4	16	Mean	Biofuel	-0.86
8	8	Mean	Biofuel	-0.86
4	8	Mean	Biofuel	-0.86

Mean (BGR)

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Mean	Informal Sector	0.68
4	8	Mean	Informal Sector	0.68
4	16	Mean	Informal Sector	0.68
8	32	Mean	Informal Sector	0.68
8	16	Mean	Informal Sector	0.67
8	8	Mean	Informal Sector	0.67
8	8	Mean	No Solid Waste Collection	0.67
4	8	Mean	No Solid Waste Collection	0.67
8	16	Mean	No Solid Waste Collection	0.67
4	16	Mean	No Solid Waste Collection	0.67
8	32	Mean	No Solid Waste Collection	0.67
4	32	Mean	No Solid Waste Collection	0.66
8	8	Mean	No Liquid Waste Collection	0.66
4	8	Mean	No Liquid Waste Collection	0.66
4	16	Mean	No Liquid Waste Collection	0.66
8	16	Mean	No Liquid Waste Collection	0.66
4	32	Mean	No Liquid Waste Collection	0.66
8	32	Mean	No Liquid Waste Collection	0.66
8	8	Mean	Biofuel	0.62
8	32	Mean	Biofuel	0.62
8	16	Mean	Biofuel	0.62
4	8	Mean	Biofuel	0.61
4	16	Mean	Biofuel	0.61
4	32	Mean	Biofuel	0.61
8	8	Mean	Non-separate Cooking Space	0.61
8	16	Mean	Non-separate Cooking Space	0.61
8	32	Mean	Non-separate Cooking Space	0.61

4	8	Mean	Non-separate Cooking Space	0.61
4	16	Mean	Non-separate Cooking Space	0.61
4	32	Mean	Non-separate Cooking Space	0.61
4	16	Standard Deviation	No Electricity	0.55
8	16	Standard Deviation	No Electricity	0.55
8	8	Standard Deviation	No Electricity	0.55
4	8	Standard Deviation	No Electricity	0.54
8	16	Standard Deviation	Rent-free	0.53
4	16	Standard Deviation	Rent-free	0.53
4	32	Standard Deviation	No Electricity	0.52
8	32	Standard Deviation	No Electricity	0.52
8	8	Standard Deviation	Rent-free	0.52
4	8	Standard Deviation	Rent-free	0.52
8	32	Mean	Women Not Educated	0.51
8	8	Mean	Women Not Educated	0.51
4	32	Mean	Women Not Educated	0.51
8	16	Mean	Women Not Educated	0.51
4	8	Mean	Women Not Educated	0.51
4	16	Mean	Women Not Educated	0.51

Mean (Band 1)

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Mean	Informal Sector	0.63
4	8	Mean	Informal Sector	0.62
4	8	Mean	No Liquid Waste Collection	0.62
4	16	Mean	Informal Sector	0.62
4	16	Mean	No Liquid Waste Collection	0.62
8	8	Mean	No Liquid Waste Collection	0.62
4	32	Mean	No Liquid Waste Collection	0.62
4	8	Mean	No Solid Waste Collection	0.62
8	32	Mean	Informal Sector	0.62
8	16	Mean	No Liquid Waste Collection	0.62
4	16	Mean	No Solid Waste Collection	0.62
8	16	Mean	Informal Sector	0.62
8	8	Mean	No Solid Waste Collection	0.62
8	8	Mean	Informal Sector	0.62
8	32	Mean	No Liquid Waste Collection	0.62
8	16	Mean	No Solid Waste Collection	0.62
4	32	Mean	No Solid Waste Collection	0.62
8	32	Mean	No Solid Waste Collection	0.62
4	8	Mean	Biofuel	0.60
4	16	Mean	Biofuel	0.60
4	32	Mean	Biofuel	0.60
8	8	Mean	Biofuel	0.60
8	16	Mean	Biofuel	0.60
8	32	Mean	Biofuel	0.60
4	16	Standard Deviation	No Electricity	0.60
8	8	Standard Deviation	No Electricity	0.60
8	8	Mean	Non-separate Cooking Space	0.59
4	8	Mean	Non-separate Cooking Space	0.59
4	16	Mean	Non-separate Cooking Space	0.59
8	16	Mean	Non-separate Cooking Space	0.59
8	16	Standard Deviation	No Electricity	0.59
4	32	Mean	Non-separate Cooking Space	0.59
8	32	Mean	Non-separate Cooking Space	0.59
4	8	Standard Deviation	No Electricity	0.59
4	32	Standard Deviation	No Electricity	0.56
8	32	Standard Deviation	No Electricity	0.56

Mean (Band 2)

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Mean	Informal Sector	0.65
4	8	Mean	Informal Sector	0.65
4	16	Mean	Informal Sector	0.65
8	32	Mean	Informal Sector	0.65
8	16	Mean	Informal Sector	0.65
8	8	Mean	Informal Sector	0.65
4	8	Mean	No Solid Waste Collection	0.65
8	8	Mean	No Solid Waste Collection	0.65
4	16	Mean	No Solid Waste Collection	0.65
8	16	Mean	No Solid Waste Collection	0.64
8	32	Mean	No Solid Waste Collection	0.64
4	32	Mean	No Solid Waste Collection	0.64
8	8	Mean	No Liquid Waste Collection	0.64
4	8	Mean	No Liquid Waste Collection	0.63
4	16	Mean	No Liquid Waste Collection	0.63
8	16	Mean	No Liquid Waste Collection	0.63
4	32	Mean	No Liquid Waste Collection	0.63
8	32	Mean	No Liquid Waste Collection	0.63
8	8	Mean	Biofuel	0.59
8	32	Mean	Biofuel	0.59
8	16	Mean	Biofuel	0.59
4	8	Mean	Biofuel	0.59
4	32	Mean	Biofuel	0.58
4	16	Mean	Biofuel	0.58
8	8	Mean	Non-separate Cooking Space	0.58
8	16	Mean	Non-separate Cooking Space	0.58
8	32	Mean	Non-separate Cooking Space	0.58
4	8	Mean	Non-separate Cooking Space	0.58
4	16	Mean	Non-separate Cooking Space	0.58
4	32	Mean	Non-separate Cooking Space	0.58
4	16	Standard Deviation	No Electricity	0.57
8	16	Standard Deviation	No Electricity	0.57
8	8	Standard Deviation	No Electricity	0.56
4	8	Standard Deviation	No Electricity	0.56
4	32	Standard Deviation	No Electricity	0.54
8	32	Standard Deviation	No Electricity	0.54
4	16	Standard Deviation	Rent-free	0.52
8	16	Standard Deviation	Rent-free	0.52
8	8	Standard Deviation	Rent-free	0.51
4	8	Standard Deviation	Rent-free	0.51

Mean (Band 3)

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
8	32	Mean	Informal Sector	0.73
4	32	Mean	Informal Sector	0.73
8	8	Mean	No Liquid Waste Collection	0.73
4	8	Mean	Informal Sector	0.73
4	16	Mean	Informal Sector	0.73
8	16	Mean	Informal Sector	0.73
8	16	Mean	No Liquid Waste Collection	0.73
8	32	Mean	No Liquid Waste Collection	0.73
8	8	Mean	Informal Sector	0.73
4	16	Mean	No Liquid Waste Collection	0.73
4	8	Mean	No Liquid Waste Collection	0.73

4	32	Mean	No Liquid Waste Collection	0.72
8	8	Mean	No Solid Waste Collection	0.70
8	16	Mean	No Solid Waste Collection	0.70
8	32	Mean	No Solid Waste Collection	0.70
4	8	Mean	No Solid Waste Collection	0.70
4	16	Mean	No Solid Waste Collection	0.70
4	32	Mean	No Solid Waste Collection	0.70
8	8	Mean	Biofuel	0.68
8	32	Mean	Biofuel	0.68
8	16	Mean	Biofuel	0.68
4	8	Mean	Biofuel	0.68
4	16	Mean	Biofuel	0.68
4	32	Mean	Biofuel	0.67
8	8	Mean	Non-separate Cooking Space	0.67
8	16	Mean	Non-separate Cooking Space	0.67
8	32	Mean	Non-separate Cooking Space	0.67
4	8	Mean	Non-separate Cooking Space	0.67
4	16	Mean	Non-separate Cooking Space	0.67
4	32	Mean	Non-separate Cooking Space	0.67
8	32	Mean	Children	0.58
4	32	Mean	Children	0.58
8	8	Mean	Children	0.58
8	16	Mean	Children	0.58
4	8	Mean	Children	0.58
4	16	Mean	Children	0.58
8	32	Mean	Women Not Educated	0.56
8	8	Mean	Women Not Educated	0.56
8	16	Mean	Women Not Educated	0.55
4	8	Mean	Women Not Educated	0.55
4	32	Mean	Women Not Educated	0.55
4	16	Mean	Women Not Educated	0.55
8	8	Mean	Not Single Family	0.55
8	16	Mean	Not Single Family	0.55
4	8	Mean	Not Single Family	0.55
4	16	Mean	Not Single Family	0.55
8	32	Mean	Not Single Family	0.55
4	32	Mean	Not Single Family	0.55
8	16	Standard Deviation	Rent-free	0.51
4	16	Standard Deviation	Rent-free	0.50
4	16	Standard Deviation	Housing Density	-0.50
8	16	Standard Deviation	Population Density	-0.52
4	16	Standard Deviation	Population Density	-0.53
8	8	Standard Deviation	Housing Density	-0.55
4	8	Standard Deviation	Housing Density	-0.57
8	8	Standard Deviation	Population Density	-0.58
4	8	Standard Deviation	Population Density	-0.60

Mean (Band 4)

Block	Scale	Zonal Statistic	Census-Derived Indicator	Correlation Coefficient
4	32	Mean	Not Single Family	-0.52
4	8	Mean	Not Single Family	-0.52
4	16	Mean	Not Single Family	-0.52
8	32	Mean	Not Single Family	-0.52
8	16	Mean	Not Single Family	-0.52
8	8	Mean	Not Single Family	-0.52
8	16	Mean	Not Literate	-0.53
8	8	Mean	Not Literate	-0.53
8	32	Mean	Not Literate	-0.53

4	16	Mean	Not Literate	-0.54
4	8	Mean	Not Literate	-0.54
4	32	Mean	Not Literate	-0.54
4	8	Mean	Slum Index	-0.54
4	16	Mean	Slum Index	-0.54
4	32	Mean	Slum Index	-0.54
8	16	Mean	Slum Index	-0.54
8	8	Mean	Slum Index	-0.54
8	32	Mean	Slum Index	-0.54
8	8	Mean	Housing Density	-0.60
4	8	Mean	Housing Density	-0.61
8	16	Mean	Housing Density	-0.61
4	16	Mean	Housing Density	-0.61
8	32	Mean	Housing Density	-0.61
4	32	Mean	Housing Density	-0.61
8	8	Mean	Population Density	-0.61
4	8	Mean	Population Density	-0.61
8	16	Mean	Population Density	-0.61
4	16	Mean	Population Density	-0.61
8	32	Mean	Population Density	-0.61
4	32	Mean	Population Density	-0.61
4	8	Mean	Unimproved Sanitation	-0.73
8	32	Mean	Unimproved Sanitation	-0.73
4	16	Mean	Unimproved Sanitation	-0.73
4	32	Mean	Unimproved Sanitation	-0.73
8	16	Mean	Unimproved Sanitation	-0.73
8	8	Mean	Unimproved Sanitation	-0.73