Monetary and non-monetary poverty in urban slums in Accra: Combining geospatial data and machine learning to study urban poverty

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Abstract

As Sub-Saharan Africa continues to urbanize, slum populations are growing at 4.5 percent per year. Providing housing to slum dwellers, protecting them from natural disasters and diseases, and connecting them to jobs and services through improved infrastructure are urgent policy issues in many Sub-Saharan African cities. Identifying the location and living conditions of slums is a critical step toward designing effective urban policies. By combining household survey data and census data with high spatial resolution satellite imagery and other geospatial data using multiple methodologies, including machine learning, we attempt to define slums objectively within the city of Accra. Within these defined slum areas, the patterns of monetary and non-monetary poverty are assessed. Poverty rates are estimated at the neighborhood level and indicate that living in slums is strongly correlated with higher monetary poverty, higher fertility among women, and lower school attendance among children. Poverty is more prevalent in communities in areas of lower elevation, which in Accra are generally flood-prone areas. Ethnic, religious, and regional ties are important reasons people live in slums for long periods of time. People born in the community and ethnic majorities are more likely to get jobs in the manufacturing sector, while ethnic minorities, and new migrants tend to get jobs in the wholesale sector in poorer slum communities. Overall, the results indicate a wide range in economic opportunities between slum communities. These results have important policy implications and are crucial to understand the impact of social networks and how they generate economic opportunities in slums so that effective urban policies can be designed.

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1. Introduction

In Sub-Saharan Africa, slum populations are growing at 4.5 percent per year (Marx et al. 2013). Providing slum dwellers with housing, protecting them from natural disasters and diseases, and connecting them to jobs and services through improved infrastructure are urgent policy issues in many African cities. Glaser (2014) argues the challenge of a mega-city in developing countries is weak governance, which reduces a city's ability to address the negative side effects of urbanization. Even though urban planning is critical for providing access to services and coordinating land use planning, building decisions, and investment in infrastructure, many cities have failed to implement effective urban planning because of inadequate financing tools and weak governance (Collier and Venables 2016, Henderson et al. 2016).

Eakin et al. (2017) show that disasters, such as floods and extreme temperatures, caused more than 30,000 deaths per year and estimate economic losses of US$250–300 billion between 1995 and 2015. They emphasize the importance of improved infrastructure and urban planning, as the population is increasingly concentrating in urban areas. Duflo et al. (2012) describe the disease burden arising from the unsanitary living conditions in slums. The prevalence of underweight, stunting, and wasting is reported to be higher in slums (Marx et al. 2013), and improved sanitation contributes to several years of longer life expectancy (Kesztenbaum and Rosenthal 2016). Investment on infrastructure is also essential to ensure that urbanization leads to economic growth (Castells-Quintana 2016).

Expansion of urban slums is not a new phenomenon in Ghana. Marx et al. (2013) recount the 2003 UN-Habitat report which listed Ashaiman in greater Accra as one of the five largest slums in the world. Even though Accra has successfully absorbed massive migrant labor and reduced poverty while experiencing substantial population growth (Molini and Paci 2015), expanding urban slums, deteriorating living conditions, and access to services have become serious problems. Molini et al. (2016) report that Accra has started to see the side effects of rapid urbanization, including congestion, a decline in access to services, and lack of affordable housing. Flood risk has become one of the most pressing problems in Accra, especially for the people who have moved into flood-prone slum communities (Rain et al. 2011). Amoako (2016) points out the population growth in flood-risk informal settlements in Accra is partly due to lack of land management by city authorities. Marinetti et al. (2016) show poor or lacking drainage systems have increased the risk of floods and caused health risks through contaminated overflows, especially in areas where the population is growing rapidly.

Identifying the location and living conditions of slums is a critical step toward designing effective urban policies. In this paper, we combine household survey data and census data with information from high spatial resolution satellite imagery, and then use machine-learning technique to identify and characterize slum areas.

Recently, the use of high spatial resolution satellite imagery in poverty analysis has gained popularity (Donaldson and Storeygard 2016). In order to design effective policies and target public resources to poor areas, it is important to identify the geospatial distribution of population, poverty, and economic activities (Henderson et al. 2016). Conventional methods of data collection, such as population census, are extremely expensive for developing countries to conduct regularly. High-resolution satellite imagery can be both an alternative to traditional data collection, and a great complement to it, as it provides information that is difficult to collect by other means. Satellite imagery has recently become more readily available and the algorithms for extracting information from these images have been developed. The explosion in the availability of high-resolution imagery and recent advances in machine learning (Athey 2017) have opened a new frontier in analysis. High-resolution satellite imagery has been used to estimate poverty rates (Blumenstock 2016, Engstrom et al. 2016, Jean et al. 2016, Watmough et al. 2016), study the distribution of economic activities by lights (Chen and Nordhaus 2011, Henderson et al. 2012, Chen and Nordhaus 2015, Chen 2016, Henderson et al. 2016), urban land use (Burchfield et al. 2006), agricultural productivity (Costinot et al. 2016), pollution (Jayachandran 2009), deforestation (Burgess et al. 2012), and fishing conditions (Axbard 2016), and to identify the location of slums (Graesser et al. 2012, Lopez et al. 2017).[1]

For Ghana, numerous geospatial analyses have been conducted to study slums in the field of geography. Weeks et al. (2007) follow the UN-Habit definition of slums and construct a slum index using the 2000 Population Census. Jankowska (2011) shows strong correlations among the slum index, the flood risk, and environmental degradation. Studies closest to our paper are Engstrom et al. (2015, 2015, 2016), which use the same spatial, structural, and contextual features (e.g., PanTex, Histogram of Oriented Gradients, Line Support Regions, Hough transforms, and others) to map slum areas and examine correlations between geospatial features and population census variables. This paper complements Engstrom et al. (2015, 2015, 2016) in two important ways. First, we introduce population density and elevation in defining slums. As shown in Section 3, population density and elevation are the most important factors in defining slums in Accra. Second, we combine population census and household survey data with geospatial variables to estimate poverty rates at the neighborhood level. We show geospatial features have significant predictive power of poverty rates at the neighborhood level, which is a much smaller area than the areas analyzed by previous studies.

Some economists suggest slums are a transitory phenomenon, as they progressively give way to formal housing as the economy grows (Glaeser 2011). But empirical evidence suggests slums are not always a temporary phenomenon. Slums have been expanding for decades in many countries, and millions of households get trapped in slums for generations (Marx et al. 2013). Marx et al. (2013) claim that slum residents may get trapped in a low-skilled, low-income equilibrium. Gulyani et al. (2014) show slum residents in Nairobi are more educated and are more likely to have wage employment than slum residents in Dakar, but their living conditions and access to infrastructure are worse than slum residents of Dakar.

Understanding the economic opportunities and social ties in slums is important for understanding why people continue living in slums. Overlooking economic opportunities and social networks is a major factor that contributes to failed relocation and slum upgrading projects (Atlaw 2012). Barnhardt et al. (2015) demonstrate that slum residents who moved into improved housing projects in India did not improve income after 14 years, and many of them returned to the

[1] Lopez et al. (2017) use satellite imagery to define slums and detect the expansion of illegal urban settlements in Mexico City. Graesser et al. (2012) also use information from satellite images to characterize formal and informal neighborhoods in Venezuela, Bolivia, and Afghanistan. We also study how geospatial features help us identify slums in Accra and report the results in a separate paper (Engstrom et al. 2017).

original slums. People who moved into the housing project reported isolation from family and caste networks.

We estimate poverty rates at the neighborhood level and show living in slums is strongly correlated with higher monetary poverty, higher fertility among women, and lower school attendance among children. Poverty is more prevalent in communities in areas of lower elevation, which in Accra are generally flood-prone areas. Ethnic majorities and people who were born in the community are more likely to get jobs in the manufacturing sector in wealthier slums. In contrast, ethnic minorities, and new migrants tend to get jobs in the wholesale sector in poorer slum communities. We also show ethnic, religious, and regional ties are important reasons why people keep living in slums. Living in the communities where there are higher percentages of people of the same ethnicities helps people get jobs in construction and agriculture. The chance of getting jobs in the wholesale sector is higher among people who live in the communities with higher percentages of people of their own religions. Overall, the results indicate there is a wide range in economic opportunity between slum communities. These results have important implications for designing effective urban policies, as it is crucial to understand the impact of social networks and how these connections generate economic opportunities in slums.

The main contributions of the paper are 1) definition and identification of slum, and 2) the use of geospatial data for the estimation of poverty rates in small areas. Defining and identifying slums is critically important to examine poverty in slums but it has been a challenge to define and identify slums, as universal definitions of slums do not always apply to local contexts, and objective measures of slums have not been developed. To bridge this knowledge gap, this paper employs innovative methods, including machine learning and geospatial data, to advance the methodology in slum research.

The paper is organized as follows: Section 2 describes the data used in this paper. In Section 3, we define slums and create the slum map. We demonstrate how machine-learning techniques can be applied to define slums objectively, and show how it complements the official slum map produced by UN-Habitat. In Section 4, we estimate poverty rates at the neighborhood level. Section 5 discusses the relationship between slum living, poverty, and economic opportunities. Section 6 discusses policy implications and conclusions.

2. Data

We use three types of data in this study: 1) population census, 2) household data, and 3) geospatial data. All the datasets have location information so we can combine the datasets spatially.

2.1. Population and Housing Census (2010) and Ghana Living Standards Survey 6 (2012)

The 2010 Population and Housing Census gathered information from each household on September 26, 2010. The questionnaire included questions on geographical location of household members, literacy and education, migration, demographic characteristics, economic activities, disability, use of information and communication technology (ICT), fertility, mortality, access to services, and housing conditions. The data was collected in 2,402 enumeration areas (EAs) in Accra Metropolitan Assembly (AMA).

The Ghana Living Standards Survey Round Six (GLSS 6) was conducted from October 18, 2012 to October 17, 2013. The data covers a nationally representative sample of 16,772 households in 1,200 enumeration areas in the country. Detailed information was collected on demographic characteristics of households, education, health, employment, migration, housing conditions, agricultural production, household enterprises, household expenditure, income, access to financial services, and assets. GLSS 6 data is used as the basis for estimating poverty rates.

2.2. Geospatial data

An image mosaic of Quickbird-2 multispectral (Blue, Green, Red, and Near-Infrared) of the AMA (Accra Metropolitan Assembly) with a spatial resolution of 2.44 m was used as the imagery dataset for this study. The eastern portion of the image was captured on January 13, 2010, and the western portion was captured on February 10, 2010.[2] The imagery was combined together to cover approximately the entire AMA region and was spatially aligned with the census and other geospatial data. From this imagery, spatial and spectral features were calculated. These features represent areas or groups of pixels in which the spatial patterns and spectral values are aggregated to represent the variability within the Enumeration Areas (EAs).3

We calculated seven spatial and spectral features, Line Support Regions (LSR), Histogram of Oriented Gradients (HOG), Linear Binary Pattern Moments (LBPM), PanTex, Fourier Transform (FT), the normalized difference vegetation index (NDVI), and the mean of the four original bands (Blue, Green, Red, and Near Infrared). LSR characterizes lines, length, number, and orientation. HOG captures the spatial distribution of structure orientations. LBPM defines contiguous regions of pixel groups and sorts them into a histogram to characterize their spatial pattern. PanTex is a built up presence index derived from the grey-level co-occurrence matrix (mixed sized building areas). FT examines pattern frequency across an image. NDVI is a measure of vegetation greenness (i.e., abundance, presence or absence and amount of vegetation).

[2] Prior to the analysis, the imagery was mosaicked, orthorectified, and radiometrically corrected.

[3] Each spatial feature was computed with a block size of 4 or 8 and scale size 8, 16, and 32. Because spatial features are based on groups of pixels, block and scale size are important components for determining the area, which the spatial feature represents (Figure 1). Block size represents the pixel size at which the output feature will be aggregated. In order to measure a neighborhood's spatial features effectively, block sizes that were closest to 15 m were used (Graesser et al. 2012). In this case, block sizes of 4 and 8 allowed for 9.76 m and 19.52 m 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 m), 16 (39.04 m), and 32 (78.08 m) 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 et al. 2012).

Each spatial feature returned between one and four output layers.[4] The local means of each of the original multispectral bands return one layer each. The descriptive statistics average, standard deviation, and sum for each of the outputs from the spatial and spectral features were calculated for each EA within the AMA.

Prior studies on Accra find these geospatial variables are significantly correlated with particular variables in population census. Engstrom et al. (2016) report LBPM, HOG, LSR, and Pantex correlate with population density, and NDVI correlates with housing quality. LSR is positively correlated with higher population density, as positive LSR implies areas with more buildings. Engstrom et al. (2015) show positive correlations between Pantex and the percentage of people who were born outside of their neighborhood and the percentage that were not in Accra five years ago, as well as strong negative correlations with the Ga ethnic group, who are the original settlers in Accra. Higher Pantex is associated with mixed sized buildings. It suggests the slums with newer immigrants are characterized by mixed sized buildings.

Elevation data was extracted and estimated using a Digital Elevation Model (DEM). The DEM for this study was created using a stereo pair of Cartosat images to create a digital surface model, which was then tied to observations of elevation from vector tiles provided by the Ghana Department of Lands and Surveys. The resulting DEM has a spatial resolution of 5 m with an estimate of elevation for each grid cell.

3. Defining slums

3.1. UN-Habitat definition of slums

According to the United Nations Program on Human Settlements (UN-Habitat), a slum household is defined as a household lacking one or more of the following five indicators: 1) improved water, 2) improved sanitation, 3) sufficient living area, 4) durable housing, or 5) security of tenure (see the full definition with the corresponding census variables in Table A.1 in the Appendix). However, institutions, access to services, and infrastructure often vary across countries, making it difficult to define applicable criteria of slums universally. Okurut and Charles (2014) conduct surveys in low-income urban slums in Rwanda, Uganda, and Kenya, and show there are considerable differences in sanitation facilities among slums in these three countries. Even within a country, slum conditions vary widely. Bag and Seth (2016) analyze household data collected in slums in Kolkata, Mumbai, and Delhi, and illustrate slum residents in Mumbai use better building materials and have better access to improved water facilities than slum residents in Kolkata and Delhi. The above discussion suggests a definition of slums in one country (or city) may not apply to others. The Ugandan government attempts to combine the UN-Habitat definition of slums with more localized characteristics to reflect the "Ugandan situation" and creates their own definition of slums (Nolan 2015).

[4] 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 LBPM 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.

In 2011, Accra Metropolitan Assembly (AMA) and UN-Habitat (2011) used the UN-Habitat's definition of slums and defined informal settlements in Accra. They identified 78 informal settlements and pockets in Accra, using information from the 2000 Population Census, such as durable housing materials, access to safe water, sanitation, and overcrowding. Figure 2 shows the 2010 Population Census enumeration areas that have their centroid of the polygon within the official slum areas. It is not clear exactly how UN-Habitat used 2000 Population Census data to define slums. Weeks et al. (2007) use the UN-Habit definition of slums and construct a slum index using the 2000 Population Census, giving equal weights to each of the five indicators.[5] However, it is unclear whether each of the five indicators equally contributes to the definition of slums.

There are two important factors that may also contribute to an area being considered a slum, population density and susceptibility to natural hazards. Both the official definition of slums by UN-Habitat and the slum index constructed by Weeks et al. (2007) characterize the presence of slums based on the household and do not account for the number of people living in close proximity to one another. For an area to be considered a slum typically it is overcrowded relative to other portions of the city and thus has a relatively higher population density. Additionally, areas that are susceptible to natural hazards are also more likely to be slum areas because these are less desirable places to live. In the case of Accra, slums have often developed in low-elevation areas because flooding is a major risk in the city. Thus population density and elevation can potentially be an important indicators of slums.

3.2. Slum index

In this section, we develop a machine-learning method to produce a slum index objectively, and compare it with the official slums defined by UN-Habitat (2011). We propose a machine-learning method (random forest), and use the same variables as the UN-Habitat definition of slums from 2010 Population Census (note UN-Habitat uses 2000 Population Census while we use 2010 Population Census), add elevation and population density as explanatory variables, and let the algorithm determine which variables contribute most to the slum index.

Machine learning is an appropriate method of estimation for identifying slums for several reasons. First, unlike other regression methods such as OLS, we do not have to dependent variables for all observation. We can use a small number of observations with initial values to estimate slum index for all other households. Second, we can overcome the problems of what variables to include and their weights in constructing a slum index.

In order to use a machine-learning approach, one needs to have some prior information on the variable of interest (i.e., training data). We first create a dummy variable and assign initial values of 0 to enumeration areas (EAs) in 12 well-known wealthy neighborhoods,[6] and 1 to EAs in 6 well-known slum neighborhoods. The following 12 rich neighborhoods are considered non-slum neighborhoods: North Dzorwulu Residential Area, North Ridge, Airport Hills Residential Area, Dansoman Estate, Kanda Estate, Nyanbia Estates, Airport Residential Area, Cantonments, Dzorwulu Residential Area, East Legon Residential, Roman Ridge, and Tesano. Initial values are

[5] Jankowska (2011) shows correlations among the slum index, flood risk, and environmental degradation.
[6] The neighborhoods are defined by Engstrom et al. (2013).

set at 1 for EAs in six well-known slums: Accra New Town, Jamestown, Korle Dudor, Nima, Sabon Zongo, and Sodom and Gomorah.

There are 9,654 households that are assigned the initial values: 66.5 percent of them live in one of the 6 slum neighborhoods (receiving the initial value of 1), and 33.5 percent of them live in one of the 12 wealthy neighborhoods (receiving the initial value of 0). Bootstrapping metric was used to get a robust estimator of the slum measurement—slum index—for 557,421 households in 100 neighborhoods (or 2,403 EAs) in Accra. Sub-samples of 50 percent data were randomly selected 100 times from the total sample to calculate a slum score for all the 557,421 households. The final slum index was calculated as the slum score average on the EA level.

Figure 3 shows the slum index map created by machine learning (random forest), and Figure 4 shows the contributing variables of the slum index. Elevation, population density, and the number of people per house are the most important variables in constructing the slum index. Slum areas tend to be of low elevation, of high population density, and have many people living per house in Accra. Table A.2 shows the correlation between the slum index and the population census variables, which are used to estimate the slum index. Even though UN-Habitat considers pipe-borne outside dwelling and public tap as improved water sources (implying non-slum characteristics), they are highly correlated with the slum index in Accra. Cement is considered as improved materials for floors (suggesting non-slum characteristics), but the correlation coefficient between the concrete floor and the slum index is higher than the correlation coefficients between the slum index and other floor materials. It confirms we cannot simply apply a universal definition of slums to Accra.

Table 1 compares the official slums defined by UN-Habitat and the slum index we construct. The slum index is significantly higher among the official slum EAs than non-official slum EAs. The mean slum index among official slum EAs is 0.764, while the mean slum index outside of the official slum areas is 0.331. Thus, the slum index is highly correlated with the official slum definition. The EAs within the UN-Habitat's official slums tend to be at lower elevation than official non-slum EAs, and population density is higher among official slum EAs than non-slum EAs.

Among 809 EAs with the slum index above 0.764 (mean slum index of official slum EAs), 196 of them are outside of the UN-Habitat's official slum areas. We compare the EAs which are above the slum index of 0.764 and classified as official slums to those which are above the slum index of 0.764 but not classified as official slums in Table 1. The EAs which are above the slum index of 0.764 but not classified as official slums by UN-Habitat have lower mean slum index and lower population density than the EAs which are classified as official slums. Also, they tend to be at lower elevation than the official slum EAs. The poverty rate estimated in the next section is higher among the EAs which are not included in the official slum map. It is likely that these EAs are relatively new slums areas, and thus, are not included in the UN-Habitat's official slum map, as it was produced using an older population census (2000 Population Census). It implies the slum index we constructed incorporates the new slums, which are not captured with the official slums defined by UN-Habitat.

4. Estimating poverty at the neighborhood level

In this section, we follow the small-area poverty estimation methodology developed by Elbers et al. (2003) to estimate poverty rates at the neighborhood level. We use neighborhoods defined by Engstrom et al. (2013) as units for small-area poverty estimation. Engstrom et al. (2013) identify 108 neighborhoods covering the entire Accra Metropolitan Assembly (AMA). The neighborhoods represent social-cultural characteristics and identities that are important to local residents and are agglomerations of EAs from the 2000 census.

Using the 2010 Population Census and GLSS 6 data, Ghana Statistical Service (GSS) uses the small-area poverty estimation methodology developed by Elbers et al. (2003) to produce the poverty map at the district level (Ghana Statistical Service 2015). We use the same variables from the 2010 Population and Housing Census and GLSS 6 but add population density and geospatial variables as explanatory variables. Elbers et al. (2003) support the use of satellite imagery in poverty mapping since it allows environmental and communal characteristics to be defined comprehensively and with great precision. We use four types of variables: household level variables from census and survey, EA level variables, neighborhood level variables, and geospatial variables on the EA level. The geospatial variables included in the analysis are LSR, PanTex, HOG, LBPM, FT, NDVI, and the mean of each individual band. This rich set of variables with access to 100 percent census data allows us to estimate poverty rates for small areas of neighborhoods.

There are some limitations in our analysis. GLSS 6 data contains only 852 observations (households) in AMA. This limits the number of variables that can be included in the final model. We cannot include more than 20 out of approximately 580 variables available for analysis. It forces us to use a very conservative model selection procedure.

For model selection, we use a two-step procedure. At the first step, we use a Lasso estimator with Bayesian shrinkage to identify key variables. At the second stage, we select our final model based on stepwise procedure using a p-value as a selection criterion as follows:

(1) $$\beta_{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \underbrace{\frac{1}{2}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{K} x_{ij}\,\beta_j\right)^2}_{Sum\ of\ squared\ residuals} + \underbrace{\lambda \sum_{j=1}^{K}\left|\beta_j\right|}_{Shrinkage\ factor} \right\}$$

where: $i = 1 \ldots . N$ is the number of observations, and

$j = 1 \ldots K$ is the number of parameters to be selected.

The first term in the optimization function is identical to an OLS procedure while the second term controls the number of estimated coefficients β. For the stepwise procedure, we use a very conservative approach by setting a very small significance level of parameters (0.01) to select 15 variables for the second stage regression.

The above regression estimates consumption for the population of 557,421 households living in 100 neighborhoods[7] in the 2010 Population Census, and the poverty rate is estimated as the proportion of people living on less than the national poverty line of 1,314 Ghanaian Cedis per capita. Table 2 contains the regression results.

Results indicate that having any household member engaged in agriculture is positively correlated with the household consumption level, as wealthy households in urban areas tend to have farm estates. Wealthier households tend to use gas as cooking fuels and are less likely to use electricity for cooking. Wealthy individuals live in EAs with a lower percentage of people who are self-employed. Household heads of wealthy households are more likely to be legislators or managers, and less likely to be engaged in crafts and other trade activities. The heads of wealthy households tend to have completed junior secondary school or junior high school. Household size is negatively correlated with per capita consumption. Wealthier households are more likely to be living in the neighborhoods with higher shares of households with mobile phones and tend to have personal computers. The roof of their dwellings are more likely to be made of concrete. Wealthy households do not live in the EAs where people use public dump containers for rubbish disposal.

Two out of 15 of the most important variables in the consumption model are geospatial variables. LSR mean of line lengths at block 4 scale 16 negatively correlates with per capita consumption. The standard deviation of the Kurtosis of HOG at block 4 scale 32 also negatively correlates with per capita consumption. This implies that areas with low variability in building orientations have higher consumption than areas with a large variability of building orientations. The inclusion of the geospatial variables in the regression increased R square by 0.05.

Figure 5 shows the poverty map, and Figure 6 summarizes the distributions of EAs by poverty rates. Since the mean slum index of official slums (defined by UN-Habitat) is around 0.75, we divide EAs into two groups, one with the slum index above 0.75, and one with the slum index below 0.75. EAs with slum index above 0.75 have higher poverty rates than EAs with slum index below 0.75. It suggests EAs with stronger slum characteristics (EAs with the slum index above 0.75) are poorer than EAs with weak slum characteristics (EAs with the slum index below 0.75). However, there are significant variations of poverty rates among EAs with high slum index. In the next section, we take advantage of the variations of poverty rates among slums, and compare socio-economic characteristics and economic opportunities of poorer slums and wealthier slums.

5. Monetary and non-monetary poverty

In this section, we analyze the 2010 Population Census data and investigate whether living in slums is associated with poverty, poorer access to services, lower school attendance, and a children working at a young age. We use both slum index and poverty rates as independent variables in regressions to examine how poverty and living in slums correlate with monetary and non-monetary poverty.

[7] We estimated poverty rates only for 100 neighborhoods out of 108 neighborhoods defined by Engstrom et al. (2013). The geospatial variables are available only for 100 neighborhoods due to the coverage of the satellite imagery.

Table 3 is the summary statistics of Accra residents and correlation coefficients between their characteristics and poverty rates and the slum index. Ga ethnic group tends to live in poorer communities with a higher slum index, while the other three major ethnic groups live in richer communities with lower slum index. For this reason, we treat Ewe, Fante, and Asante ethnic groups as a base and use dummy variables for Ga ethnicity and other ethnic groups in the subsequent regressions. Muslim people tend to live in slum communities with higher poverty rates, while Christians tend to live in wealthier communities with low slum index. People who never attended school, or attended up to primary and middle schools are more likely to live in communities with high slum index and higher poverty rates. In contrast, people who complete more than secondary school tend to live in communities with lower slum index and lower poverty rates. People who were born in towns are more likely to live in communities with higher slum index and higher poverty rates. The number of years of residence in the current community is higher for the people living in communities with higher slum index and higher poverty rates. This signals that some slum residents tend not to move around. It is consistent with the finding by Owusu et al. (2008) that Nima, a well-known slum, is not only a popular destination for migrants, but a place where people choose to live permanently, as migrants tend not to move out of Nima once they settle down. They explain that people stay in Nima because of religious ties, family presence, and economic reasons.

5.1. Monetary poverty in slums

Regression results in Table 4 show the characteristics of household heads who live in communities with higher poverty rates. We use the poverty rate at the neighborhood level as a dependent variable and include characteristics of household heads, as well as slum index, as explanatory variables in the regressions. In the first regression, we include the slum index generated by random forest in Section 3 as an independent variable to examine whether the slum index correlates with urban poverty. In the second regression, we use a dummy variable, which takes the value of 1 if the enumeration area is within the official slums and 0 otherwise, as an explanatory variable. In the third regression, we include elevation as an independent variable to see whether poor areas are concentrated in places at low elevation.

Slum index is highly correlated with poverty rates (see regression (1) in Table 1). However, the official slums are not correlated with poverty (regression (2)). This implies that the slum index is a better indicator of poverty than the officially defined slums. Regression (3) of Table 1 shows lower elevation is also associated with higher poverty. This suggests people who live in low elevation areas, which are often flood prone, are poorer than the people who live in communities at higher elevations. Regression results also suggest household heads who are less educated and informally married tend to live in poorer neighborhoods. Household heads in poorer neighborhoods are more likely to be Ga ethnic group. The variable 'Other Ethnic Group' takes the value of 1 if the household head is not Ga, Ewe, Fante, or Asante. Other ethnic groups are not significantly different from the wealthy majority group (Ewe, Fante, or Asante) in terms of poverty rates. Households have access to electricity regardless of the poverty level of neighborhoods, but households in poorer neighborhoods are less likely to have mobile phones and computers. We examine the characteristics of household heads who were born in slum communities and have been living there since birth. We analyze only these household heads living in the communities with slum index above 0.75. This enables us to compare the people who have been living in the slum neighborhoods since birth against people who were born elsewhere and moved into the slum community. We also explore the characteristics of household heads who have been living in slum communities for many years, and those who lived in the same slum communities 5 years ago. Note that there may be self-selection of migrants from rural areas and these individuals have specific characteristics, which our analysis will pick up. Unfortunately, we cannot distinguish the self-selection effect. However, our analysis is still value for the purpose of comparing long-term slum residents and recent migrants in slums.

In the first regression, we use a dummy variable 'Born in Town' as a dependent variable, which takes the value of 1 if the household head was born in the current community, 0 otherwise.[8] In the second regression, we use the years of residence in the current community as a dependent variable. In the third regression, we use a dummy variable 'lived in the same community 5 years ago' as a dependent variable, which takes the value of 1 if the household head lived in the current community 5 years ago, 0 otherwise. We estimate age fixed-effect regression models to control for the differences that arise from age difference of household heads.

Table 5 summarizes the regression results. Household heads who live in richer slum communities (lower poverty rates) are more likely to reside in the slum communities where they were born, compared with the household heads who live in poorer slums. Lower poverty rates are also correlated with longer residency in the current slum community, and the probability that the household lived in the same community 5 years ago. People who live in the slums they were born in, as well as those who have been living in the current slum communities for many years, tend to live in the communities where the percentage of people who follow the same religion is higher than the average of Accra City (higher than average concentration of people following the same religion). It indicates religious ties are one of the important social factors that explain why people keep living in slums. Ethnic ties are also key factors of long-term slum residency. People who are natives of the slum communities and those who have been living in the current slum communities for many years tend to be living in the neighborhoods where the percentage of people who belong to the same ethnic groups is higher than the average of Accra City. These findings suggest the potential importance of ethnic and religious ties in slums.

A Harris-Todaro model (1970) suggests people migrate to urban areas if they believe the expected value of migrating is greater than the economic and non-economic value of remaining. Similarly, one would expect those in better jobs would be likely to remain where they are. Our results are consistent with the predictions of Harris-Todaro model.

5.2. Non-monetary poverty

The discussion in the previous sub-section suggests living in slums does not necessarily mean living in monetary poverty, especially for those who have been living in slums for many years. Nevertheless, living in slums still involves a high prevalence of non-monetary poverty and poor access to services. Table A.2 in the Appendix shows slum index is highly correlated with the use of public toilets. Jenkins and Scott (2007) conduct interviews in slums in Accra, and report that the top reason for not constructing household toilets is limited space (48.4 percent). Even if people can afford the construction of toilets, slum residents are constrained by space. Table 3 shows the use of charcoal for cooking is strongly correlated with slum living. Boadi and

[8] In all regressions, we control for religions.

Kuitunen (2006) report households that use charcoal have a high incidence of respiratory health problems in Accra. Slum residents do not tend to receive the service of rubbish collection and throw liquid waste into gutters (Table 3).

Table 4 illustrates that slum residents are less educated than non-slum residents. However, in order to stop the cycle of poverty, they need to send their children to school. We conduct age fixed effect regressions to examine if children between 6 and 22 years are currently attending school. We include both poverty rates and slum index as explanatory variables to separate the effects of poverty from the effects of living in slums. Regression results presented in Table 6 demonstrate that both poverty and slum living have negative effects on children's school attendance. Children living in poor neighborhoods or slums have lower probability of attending school. Children in female-headed households are less likely to attend school. Disabled children and girls are also less likely to attend school. Marriage is a crucial factor determining school attendance. Children who are already married or informally married stop going to school.

We also examine the determinants of labor force participation among children. Children living in poor neighborhoods are more likely to be working. Married, and female children are more likely to be working. We also run the regressions limiting the data only to children living in the communities with slum index above 0.75. The additional regression results suggest poverty is the major factor limiting a child's school attendance and increasing child labor participation in slums.

Being born in the current community increases the likelihood of attending school and decreases the probability of working. This implies children who moved into the community (children of recent migrants) are less likely to be attending school, as they need to help parents financially by taking up jobs. Policy intervention may be required to make sure children of recent migrants attend school.

As discussed in Section 3, slums are characterized by high population density. It is largely due to migration, but it may also be due to high fertility in slums. We examine the circumstances affecting the number of children, as well as the survival rates of children. Table 7 contains the age-fixed model regression results for women between 18 and 60 years. Poverty rates are not correlated with either the number of children per woman or the survival rate of infants. However, slum index is positively correlated with the number of both female and male children, as well as the total number of children per woman. This suggests women living in slums have significantly more children, after controlling for the poverty level.

Single, informally married, separated, and divorced women have fewer children compared with married women, and the survival rates of their infants are also lower. Educated women and working women have fewer children. Infant mortality, especially for boys, is lower among working women. Disabled women are likely to have fewer children, and their girls' mortality rate is high. The above regression results suggest the population expansion of slums may not be only due to migration but also to a higher birth rate within slums. Weeks et al. (2006, 2010) find that the fertility rate among the Ga ethnic group is significantly higher than other ethnic groups in slums. Our result suggests the fertility rate among the Ga ethnic group is significantly higher than other majority groups, even after controlling for poverty rates and slum living.

5.3. Economic opportunities

Living in slums for long periods of time may be advantageous if that gives people access to better jobs. Jobs in the wholesale, manufacturing, accommodation, transportation, construction, agriculture, and administrative sectors are the most common occupations in slums. We look at socio-economic characteristics and circumstances of job holders in each job category and try to understand the nature of economic opportunities in slums. Table 8 shows the regression results, using dummy variable for each occupation as a dependent variable. Higher slum index is associated with the probability of working in all selected sectors. Poverty rates are positively correlated with the chance of working in the wholesale sector, suggesting wholesale jobs are available in poorer slums. In contrast, people living in richer slums tend to have manufacturing, transportation, and construction jobs. It implies poor slums and rich slums offer different economic opportunities.

Jobs in the wholesale, accommodation, and agricultural sectors are held by people with lower education, since the dummy variables for completing primary, middle, upper secondary, and university are negative for these industries. In contrast, jobs in the manufacturing, transportation, construction, and administrative sectors are held by people with primary or middle school education.

The jobs in the wholesale sector, which are more common in poorer neighborhoods, are likely to be held by women, ethnic minorities, and those who were born outside of the communities. In contrast, manufacturing jobs, which tend to develop in wealthier slums, are more likely to employ the Ga ethnic group, which is the largest ethnic group in Accra, as well as those who were born in the communities. People who don't belong to the top four majority ethnic groups tend not to get manufacturing jobs.

Living in the communities where there are higher percentages of people of the same ethnicity help people get jobs in construction and agriculture, as well as administrative jobs. Living in the communities with people who were born in the same regions increases the probability of getting jobs in agriculture.

Regressions in Table 9 limit the data only for the communities with slum index above 0.75. The regression results suggest people in wealthier slums tend to have jobs in the manufacturing, transportation, and construction sector, while people in poorer slums are employed in the wholesale sector. Ethnic Ga who live in slums have advantages over other ethnic groups in getting jobs in the manufacturing, construction, and agricultural sectors, while other ethnic groups (non-Ga, Ewe, Fante, Asante) are disadvantaged in getting jobs in these sectors.

6. Concluding discussion and policy implications

The findings in this paper indicate living in slums is strongly correlated with higher monetary poverty, higher fertility among women, and low school attendance among children. Poverty is more prevalent in communities in areas of lower elevation, which in Accra are generally flood-prone areas. People born in the community and in ethnic majorities tend to get jobs in the manufacturing, transportation, and construction sectors. These jobs are concentrated in wealthier slums, while ethnic minorities, and new migrants tend to get jobs in the wholesale sector in poorer slum communities. Ethnic, religious, and regional ties are important reasons people live in slums for long periods of time, and the social network helps them get jobs in some sectors. Overall, the results indicate that there is a wide range in economic opportunity between slum communities. These results have important implications for designing effective policies, as it is crucial to understand the impact of social networks and how these connections generate economic opportunities in slums.

Gentilini (2015) affirms that as urban populations increase, it is important to understand how safety nets work in urban areas. Our findings suggest that new migrants and ethnic minorities are disadvantaged in the job market, as they do not have access to the social network which can help them gain employment in the manufacturing, transportation, and construction sectors. In addition, their children tend to start working at young ages instead of attending school so they can support their family financially.

Low school attendance among children of slum residents may also be due to high costs of education and lack of access to schools in slum areas. Adam (2013) reports that public schools in slums are overcrowded, and there is often no private school nearby. Low school attendance will deprive children of future human capital. It can be mitigated with urban safety nets that are conditional on school attendance.

Women in slums tend to have more children, creating more pressure for the local government to provide education to children of slum residents. High fertility of women deprives them of future human capital and empowerment, so female empowerment programs could be an effective policy intervention.

The results of this study suggest people keep living in slums for economic opportunities and for the social network that helps them get jobs, thus, relocation of slum residents may not be a sensible policy option for the local government. Gulyani and Bassett (2007) show infrastructure investment is an effective slum upgrading strategy. Galiani, Gertler et al. (2016) report upgrading slum dwellings has positive impacts on overall housing conditions, reported happiness, and the quality of life. We do not discuss life satisfaction in this study, but it is important to extend this research to study life satisfaction as living in slums involves various risks, including floods, lack of basic services, and higher non-monetary poverty.

Enhancing land tenure security may be an effective policy intervention to give people an incentive to invest in their dwellings and develop businesses.[9] Field (2005), Nakamura (2016), and Galiani and Schargrodsky (2010) show strengthening tenure security in urban slums has a significant effect on residential investment in Peru, India, and Argentina. Gulyani and Talukdar (2010) find tenure security and infrastructure access strongly impact creation and success of microenterprises in urban slums in Nairobi. We do not discuss tenure security in this paper as data on tenure security is not available. However, it is important to investigate how weak tenure security and perceived risk of eviction impact the incentive to invest on dwelling and household enterprises.

Besides contributing new findings on monetary and non-monetary poverty in urban slums, our

[9] Besley (1995) finds security of tenure motivates farmers to invest in land in Ghana.

paper makes a methodological contribution to small-scale estimation of poverty. We combine population census and household survey data with geospatial variables to estimate poverty rates at the neighborhood level, which is a much smaller area than the areas analyzed by earlier studies. There are some limitations to our analytical method. As the household data contains only 852 observations, we cannot include more than 20 explanatory variables in the regression, even though we have around 580 variables available for estimation. We use a Lasso estimator to reduce the number of explanatory variables. The resulting poverty rates are sensitive to the explanatory variables selected for estimation. In order to overcome this problem and ensure that we obtain robust estimations of poverty rates, we will try alternative model selection methods and compare results of estimations.

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Table 1: Relationship between slum index and official slums

	No of EAs	Mean slum index	Elevation	Population density	Poverty rate
Non-Official Slums	1,419	0.331	24.6	17,391	0.034
Official Slums	983	0.764***	21.9***	43,085***	0.044***
EAs with slum index above 0.764					
	No of EAs	**Mean slum index**	**Elevation**	**Population density**	**Poverty rate**
Non-Official Slums	196	0.886	14.4	40,093	0.063
Official Slums	613	0.926***	20.0***	53,591***	0.054***

*** Significant at 1%.

Table 2: Poverty map consumption model

Variable description	Coefficient
Constant	6.9885***
Any household member engaged in agriculture	0.3611***
Cooking fuel used in household: gas	0.2380***
Cooking fuel used in household: electricity	-0.2509***
Average share of self-employed with employees, EA level	-0.9238***
Household head occupation is legislator/manager	0.4483***
Household head occupation is craft and related trades workers	-0.1175**
Household's head education level JSS/JHS	1.0195**
Log of household size	-0.3892***
Share of households with access to mobile phone, neighborhood level	2.2412***
M_LSR_BD_BGR_121	-0.1418***
Share of people with no schooling in household	-0.2446**
Household has a PC	0.2522***
Roof of the household's dwelling is made of concrete/other	0.4064***
Share of households with rubbish disposal: public dump (container), EA level	-0.2988***
S_HOG_BD_BGR_134	-0.0971***
Observations	846
R squared	0.45

Dependent variable is log per capita consumption.

Table 3: Summary statistics of Accra residents

	% of household heads	Correlation coefficients	
		Slum index	Poverty
Top 4 ethnic groups			
Ga	23.6	0.069***	0.100***
Ewe	16.6	-0.484***	-0.099***
Fante	10.8	-0.095***	-0.066***
Asante	8.5	-0.076***	-0.053***
Religion			
Christian	76.5	-0.185***	-0.160***
Muslim	13.6	0.237***	0.202***
Other	9.9	-0.010**	-0.006

Education	% of household heads	Correlation coefficient	
		Slum index	Poverty
Never attended	11.4	0.163***	0.186***
Primary/JSS/JHS (Primary)	22.9	0.189***	0.205***
Middle	24.2	0.037***	0.019***
SSS/SHS/Secondary/Vocational/Post-secondary (Upper secondary)	34.3	-0.029***	-0.094***
Bachelor degree/Post Grad (University)	7.19	-0.170***	-0.102***

Household heads	Mean	Correlation coefficient	
		Slum index	Poverty
Born in town	40.6%	0.122***	0.052***
Years of residence	25.7	0.109***	0.018***

Cooking fuel	% of households	Correlation coefficient	
		Slum index	Poverty
None	8.6	0.074***	0.111***
Wood	1.1	-0.021***	-0.005
Gas	41.4	-0.297***	-0.229***
Electricity	1.3	-0.061***	-0.033***
Kerosene	1.5	0.028***	0.014***
Charcoal	45.5	0.267***	0.172***
Crop residue	0.1	-0.004	-0.007
Saw dust	0.3	-0.009**	-0.008**
Animal waste	0.1	-0.014***	-0.004
Other	0.3	-0.004	-0.018***

Rubbish disposal	% of households	Correlation coefficient	
		Slum index	Poverty
Collected	56.0	-0.175***	-0.185***
Burned by household	3.6	-0.160***	-0.058***
Public dump (container)	33.2	0.223***	0.130***
Public dump (open space)	5.0	0.040***	0.130***
Dumped indiscriminately	1.1	0.024***	0.116***
Buried by household	0.3	-0.033***	-0.014***
Other	0.8	0.024***	0.033***

Liquid waste disposal	% of households	Correlation coefficient	
		Slum index	Poverty
Through the sewerage system	7.9	-0.169***	-0.089***
Through drainage system into a gutter	26.1	-0.044***	-0.066***
Through drainage into a pit (soak away)	4.0	-0.128***	-0.054***
Thrown onto the street/outside	7.7	-0.080***	0.004
Thrown into gutter	45.4	0.310***	0.112***
Thrown onto compound	8.3	-0.162***	0.013***
Other	0.6	0.021***	0.033***

Table 4: Characteristics of household heads who live in poor neighborhoods

	(1)	(2)	(3)
Slum Index	0.033***		
	(0.009)		
Official Slums		0.007	
		(0.005)	
Elevation			-0.001***
			(0.000)
HH Size	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Age	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Age2	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Primary School	-0.008	-0.010*	-0.009*
	(0.005)	(0.006)	(0.005)
Middle	-0.008*	-0.009**	-0.009**
	(0.004)	(0.005)	(0.004)
Upper Secondary	-0.009*	-0.012**	-0.011**
	(0.005)	(0.005)	(0.005)
University	-0.008*	-0.013**	-0.013***
	(0.004)	(0.005)	(0.004)
Female Headed	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Working	0.004*	0.004*	0.004**
	(0.002)	(0.002)	(0.002)
Disabled	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Born in Town	-0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)
Years of Residence	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Ethnic Ga	0.010***	0.012***	0.007**
	(0.003)	(0.004)	(0.003)
Other Ethnic Groups	0.002	0.003*	0.003*
	(0.002)	(0.002)	(0.002)
Electricity	0.002	0.004	0.003
	(0.003)	(0.003)	(0.003)
Mobile Phone	-0.010**	-0.011**	-0.010**
	(0.005)	(0.005)	(0.004)
Fixed Phone	0.004	0.000	-0.001
	(0.003)	(0.003)	(0.002)
Computer	-0.001	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Internet	-0.003	-0.004	-0.003

	(0.002)	(0.002)	(0.002)
Single	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Informally Married	0.005***	0.007***	0.004*
	(0.002)	(0.002)	(0.002)
Separated	0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)
Divorced	-0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)
Widowed	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Constant	0.053**	0.069***	0.088***
	(0.022)	(0.026)	(0.029)
Observations	55,740	55,740	55,740
R-squared	0.245	0.142	0.270

Standard errors reported in parentheses are clustered by neighborhoods.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Characteristics of household heads who were born in slums, have lived in the slums for many years, or lived in the same community 5 years ago (Slum index>0.75)

	Born in town	Years of residence	Lived in the same community 5 years ago
Poverty Rate	-0.963***	-22.805***	-0.934***
	(0.141)	(3.589)	(0.106)
Elevation	0.001	0.032***	0.001***
	(0.000)	(0.010)	(0.000)
HH Size	0.006***	0.250***	0.005***
	(0.001)	(0.045)	(0.001)
Primary School	0.056***	0.651*	0.026**
	(0.009)	(0.382)	(0.012)
Middle	0.043***	0.992**	0.020**
	(0.010)	(0.448)	(0.008)
Upper Secondary	0.080***	1.164***	0.007
	(0.011)	(0.390)	(0.008)
University	0.058***	-1.010	-0.074***
	(0.021)	(0.778)	(0.019)
Female Headed	0.011	0.383	-0.018***
	(0.007)	(0.245)	(0.006)
Disabled	0.019	1.901***	0.021**
	(0.013)	(0.448)	(0.009)
Ethnic Ga	0.547***	14.200***	0.120***
	(0.010)	(0.409)	(0.013)
Other Ethnic Groups	-0.028***	-1.026***	-0.005
	(0.009)	(0.278)	(0.008)
Same Ethnicity	0.040***	1.500***	0.026***
	(0.009)	(0.313)	(0.007)
Same Religion	0.042***	1.120***	0.010*
	(0.007)	(0.223)	(0.006)
Same Region		0.236	0.003
		(0.261)	(0.006)
Single	0.073***	1.851***	0.008
	(0.010)	(0.322)	(0.010)
Informally Married	0.065***	1.457***	0.023**
	(0.010)	(0.291)	(0.011)
Separated	0.053***	1.768***	0.011
	(0.015)	(0.482)	(0.010)
Divorced	0.013	0.200	-0.010
	(0.013)	(0.553)	(0.011)
Widowed	0.011	2.273***	0.019**
	(0.011)	(0.497)	(0.008)
Constant	0.172***	19.385***	0.798***
	(0.017)	(0.613)	(0.013)
Observations	20,761	20,761	20,761
R-squared	0.241	0.173	0.041

Age fixed-effect model regression results. Standard errors are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: School attendance and working children

	All		Slum index>0.75	
	Attending school	**Working**	**Attending school**	**Working**
Poverty Rate	-1.329***	1.651***	-1.304***	1.703***
	(0.134)	(0.203)	(0.164)	(0.187)
Slum Index	-0.060**	0.033		
	(0.025)	(0.019)		
Female Headed	-0.042***	0.021***	-0.031***	0.014**
	(0.007)	(0.004)	(0.005)	(0.005)
Born in Town	0.055***	-0.066***	0.083***	-0.096***
	(0.011)	(0.012)	(0.013)	(0.017)
Married	-0.127***	0.077***	-0.101***	0.057***
	(0.026)	(0.016)	(0.015)	(0.018)
Informally Married	-0.235***	0.210***	-0.209***	0.199***
	(0.025)	(0.013)	(0.027)	(0.023)
Disabled	-0.072***	0.003	-0.039	-0.002
	(0.014)	(0.013)	(0.024)	(0.017)
Ethnic Ga	0.012**	-0.021***	-0.007	-0.010**
	(0.006)	(0.005)	(0.006)	(0.004)
Other Ethnic Groups	0.005	-0.000	0.014**	0.001
	(0.004)	(0.003)	(0.005)	(0.006)
Female	-0.035***	0.017***	-0.035***	0.019***
	(0.006)	(0.003)	(0.008)	(0.003)
Constant	0.827***	0.095***	0.752***	0.135***
	(0.017)	(0.012)	(0.009)	(0.010)
Observations	68,629	68,629	25,611	25,611
R-squared	0.058	0.059	0.067	0.087

Age fixed-effect model regression results. Standard errors are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Number of children per woman and the survival rates of their infants

	Number of children			Percentage of children survived		
	Total	**Female**	**Male**	**Total**	**Female**	**Male**
Poverty Rate	0.029	0.050	-0.020	0.086	-0.037	0.126*
	(0.358)	(0.222)	(0.201)	(0.053)	(0.058)	(0.063)
Slum Index	0.178***	0.093***	0.085***	0.002	0.006	-0.001
	(0.024)	(0.015)	(0.015)	(0.005)	(0.004)	(0.005)
Single	-1.082***	-0.540***	-0.542***	-0.052***	-0.024***	-0.068***
	(0.069)	(0.036)	(0.034)	(0.006)	(0.006)	(0.008)
Informally Married	-0.115***	-0.065***	-0.050***	-0.016***	-0.008**	-0.022***
	(0.027)	(0.017)	(0.018)	(0.004)	(0.004)	(0.005)
Separated	-0.346***	-0.155***	-0.191***	-0.018***	-0.021***	-0.017***
	(0.059)	(0.036)	(0.030)	(0.005)	(0.005)	(0.006)
Divorced	-0.425***	-0.203***	-0.222***	-0.022***	-0.012**	-0.028***
	(0.052)	(0.030)	(0.030)	(0.004)	(0.005)	(0.006)
Widowed	0.061	0.021	0.040	-0.018***	-0.012	-0.028***
	(0.037)	(0.029)	(0.028)	(0.006)	(0.007)	(0.006)
Primary School	-0.374***	-0.185***	-0.189***	0.007*	0.010**	0.008
	(0.029)	(0.016)	(0.017)	(0.004)	(0.004)	(0.005)
Middle	-0.469***	-0.239***	-0.230***	0.008*	0.013**	0.005
	(0.042)	(0.025)	(0.025)	(0.005)	(0.005)	(0.005)
Upper Secondary	-0.817***	-0.406***	-0.412***	0.003	0.010*	0.003
	(0.057)	(0.029)	(0.031)	(0.005)	(0.005)	(0.006)
University	-0.942***	-0.470***	-0.472***	-0.009	0.008	-0.007
	(0.071)	(0.036)	(0.038)	(0.009)	(0.008)	(0.010)
Disabled	-0.159***	-0.062**	-0.097***	-0.009	-0.029***	-0.002
	(0.038)	(0.025)	(0.028)	(0.006)	(0.006)	(0.008)
Working	-0.063***	-0.024**	-0.039***	0.007**	0.004	0.010**
	(0.017)	(0.011)	(0.010)	(0.003)	(0.003)	(0.004)
Ethnic Ga	0.090***	0.042***	0.048***	0.005	0.006	0.002
	(0.017)	(0.012)	(0.010)	(0.003)	(0.004)	(0.004)
Other Ethnic Groups	-0.004	0.002	-0.006	0.003	0.005	0.000
	(0.014)	(0.012)	(0.009)	(0.003)	(0.003)	(0.004)
Born in Town	0.006	0.001	0.005	-0.004	-0.003	0.002
	(0.014)	(0.009)	(0.010)	(0.003)	(0.003)	(0.003)
Constant	2.579***	1.279***	1.300***	0.921***	0.937***	0.914***
	(0.055)	(0.028)	(0.032)	(0.006)	(0.007)	(0.006)
Observations	64,831	64,831	64,831	38,066	29,549	29,317
R-squared	0.125	0.073	0.070	0.006	0.004	0.007

Age fixed-effect model regression results. Standard errors are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Socio-economic characteristics of people working in various sectors

	Wholesale	Manufacturing	Accommodation	Transportation	Construction	Agriculture	Administrative
Poverty Rate	0.450***	-0.358***	-0.038	-0.217***	-0.095***	-0.016	0.003*
	(0.065)	(0.040)	(0.039)	(0.027)	(0.023)	(0.018)	(0.002)
Slum Index	0.048***	0.008**	0.019***	0.008***	-0.007***	0.004**	-0.029*
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.016)
Age	0.017***	-0.001	0.000	0.004***	0.002***	-0.002***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Age2	-0.000***	-0.000	-0.000	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary School	-0.022***	0.039***	-0.057***	0.024***	0.014***	-0.018***	-0.002
	(0.007)	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.001)
Middle	0.001	0.013***	-0.063***	0.019***	0.010***	-0.025***	0.004**
	(0.007)	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
Upper Secondary	-0.085***	-0.016***	-0.077***	-0.009***	0.001	-0.030***	0.008***
	(0.006)	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
University	-0.247***	-0.088***	-0.122***	-0.038***	-0.033***	-0.034***	0.001
	(0.007)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
Female	0.140***	-0.002	0.124***	-0.103***	-0.089***	-0.021***	-0.022***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Disabled	0.004	0.000	0.001	-0.013***	-0.001	0.009**	0.001
	(0.010)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
Ethnic Ga	-0.047***	0.016***	0.006*	0.008***	0.003	0.009***	-0.001
	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Other Ethnic Groups	0.030***	-0.016***	-0.001	0.003	-0.018***	0.001	0.002*
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Born in Town	-0.040***	0.018***	-0.001	-0.004**	0.002	0.011***	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)

Same Ethnicity	-0.006	0.003	-0.001	-0.002	0.004**	0.006***	0.002*
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Same Religion	0.009**	0.002	-0.008***	0.001	-0.001	0.001	-0.003**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Same Region	-0.004	0.002	0.002	0.001	-0.002	0.003***	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	-0.067***	0.191***	0.089***	0.036***	0.052***	0.068***	0.047***
	(0.024)	(0.018)	(0.016)	(0.011)	(0.010)	(0.008)	(0.008)
Observations	84,071	84,071	84,071	84,071	84,071	84,071	84,071
R-squared	0.064	0.014	0.060	0.053	0.049	0.011	0.009

Robust standard errors are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Socio-economic characteristics of people working in various sectors (Slum index >0.75)

	Wholesale	Manufacturing	Accommodation	Transportation	Construction	Agriculture	Administrative
Poverty Rate	0.541***	-0.367***	-0.006	-0.279***	-0.071***	-0.032	-0.022
	(0.074)	(0.045)	(0.045)	(0.031)	(0.026)	(0.020)	(0.017)
Age	0.024***	-0.003**	0.000	0.003***	0.003***	-0.001**	-0.001**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age2	-0.000***	0.000	0.000	-0.000***	-0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary School	-0.010	0.035***	-0.045***	0.022***	0.014***	-0.022***	0.001
	(0.009)	(0.006)	(0.007)	(0.004)	(0.003)	(0.004)	(0.002)
Middle	-0.016	0.022***	-0.052***	0.016***	0.015***	-0.035***	0.006**
	(0.010)	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)	(0.003)
Upper Secondary	-0.061***	-0.007	-0.065***	-0.015***	0.009***	-0.040***	0.010***
	(0.010)	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)	(0.003)
University	-0.240***	-0.094***	-0.102***	-0.044***	-0.024***	-0.040***	-0.005
	(0.015)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)
Female	0.146***	-0.006	0.144***	-0.111***	-0.085***	-0.033***	-0.026***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Disabled	0.027*	0.001	-0.021**	-0.019***	0.001	0.019***	-0.001
	(0.016)	(0.012)	(0.010)	(0.006)	(0.007)	(0.007)	(0.005)
Ethnic Ga	-0.059***	0.020***	0.007	0.007*	0.007*	0.016***	-0.000
	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)
Other Ethnic Groups	0.031***	-0.011**	-0.000	0.005	-0.022***	-0.006***	0.004**
	(0.007)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
Born in Town	-0.061***	0.035***	0.004	-0.008***	0.004	0.012***	0.001
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Same Ethnicity	-0.010	-0.001	-0.005	-0.007*	0.007**	0.009***	0.002
	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
Same Religion	0.003	-0.000	-0.007*	0.002	-0.001	0.002	-0.003*
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)

Same Region	-0.008	0.001	-0.002	0.005*	-0.002	0.007***	0.000
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	-0.165***	0.223***	0.077***	0.066***	0.032**	0.075***	0.047***
	(0.040)	(0.029)	(0.027)	(0.018)	(0.016)	(0.015)	(0.013)
Observations	30,569	30,569	30,569	30,569	30,569	30,569	30,569
R-squared	0.056	0.014	0.065	0.060	0.050	0.020	0.013

Robust standard errors are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1: Block and scale size: A) Pixel size of 2.44 m, B) block size of 4 (9.76 m), and C) scale size of 8 (19.52 m)

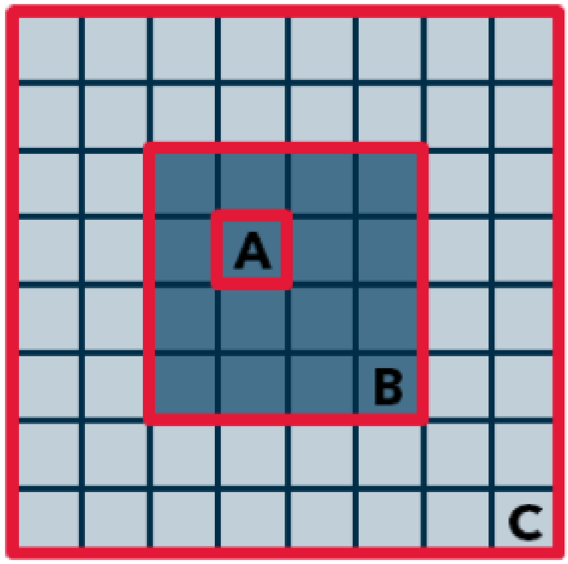


Figure 2: Official slum map

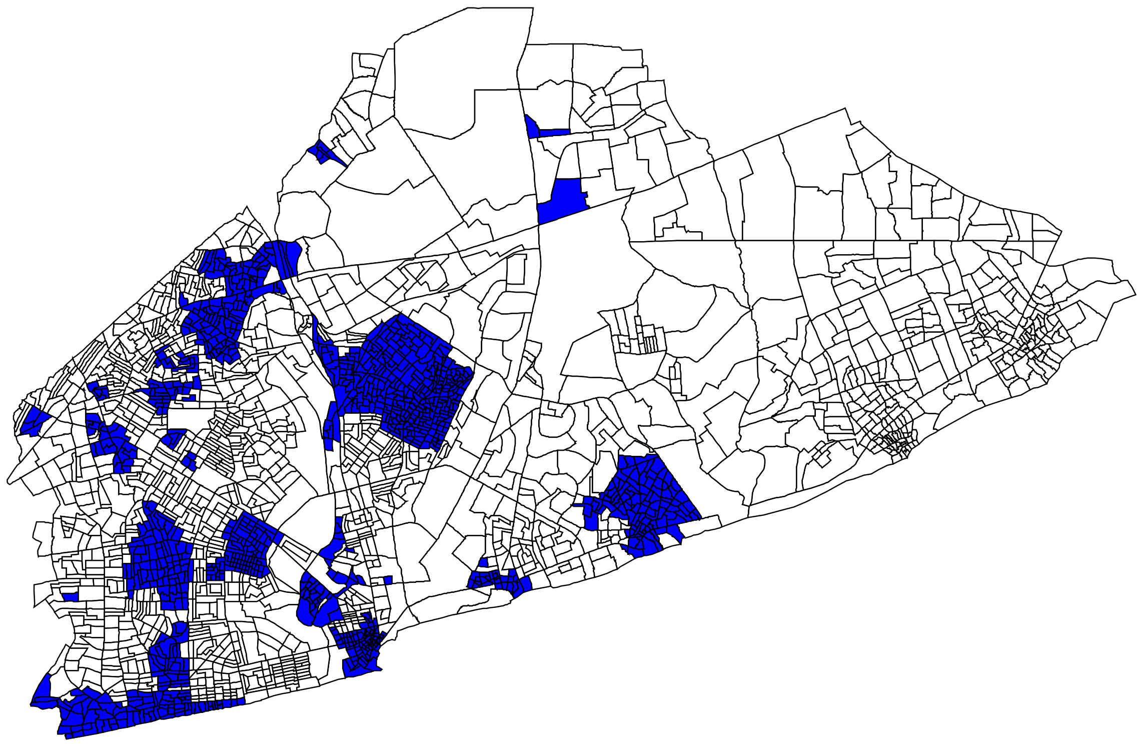


Figure 3: Slum map (Random Forest)

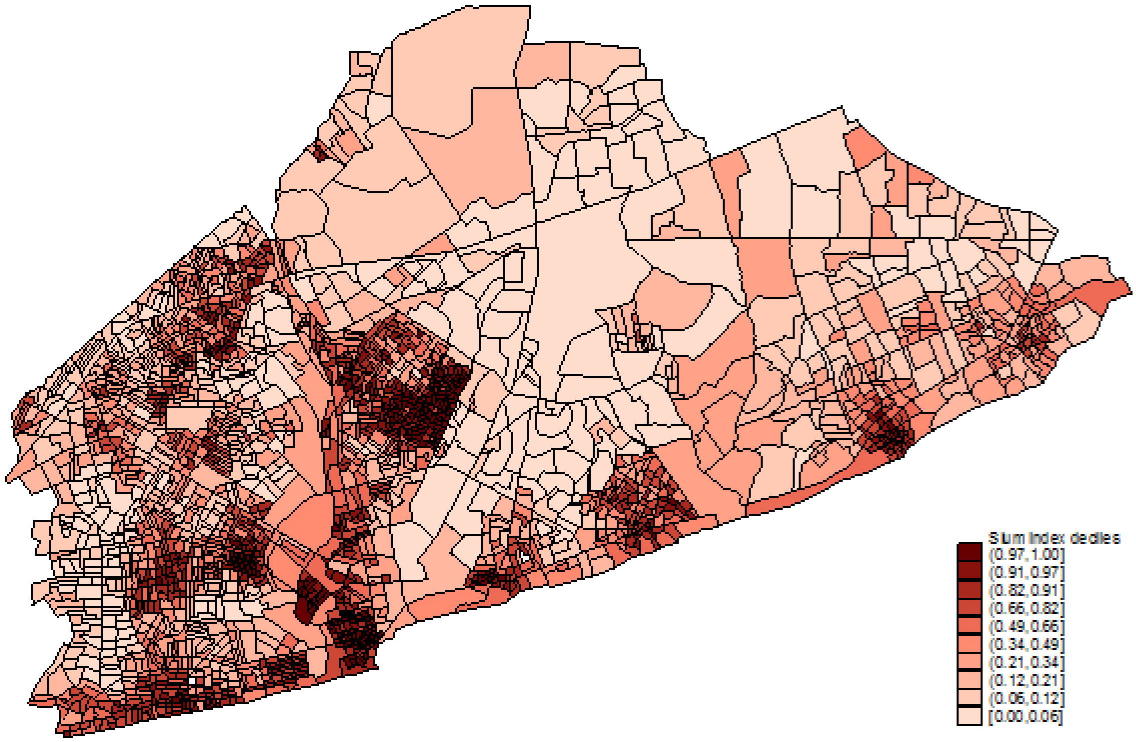


Figure 4: Contributing indicators in constructing slum index (random forest)

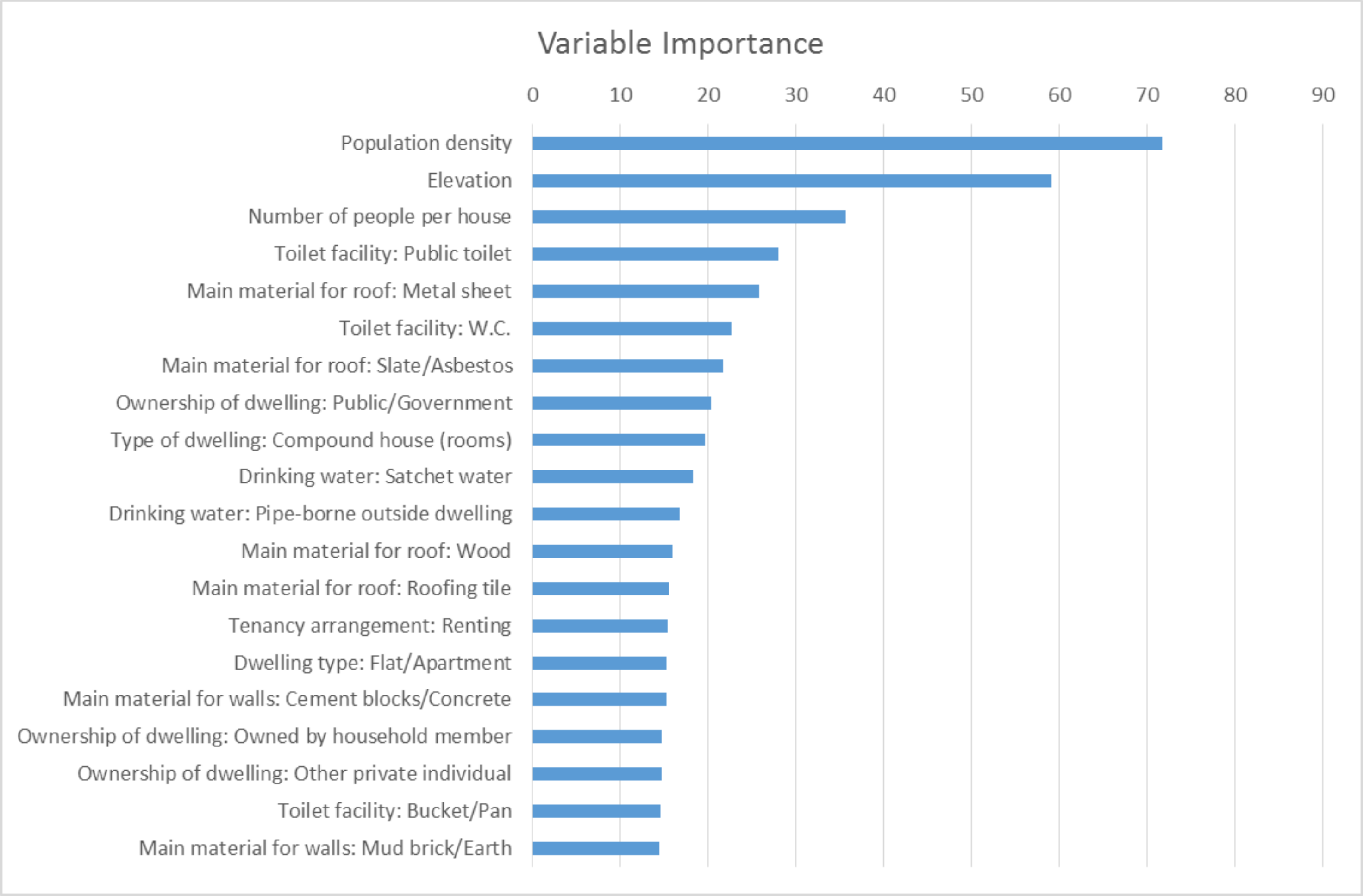


Figure 5: Poverty map

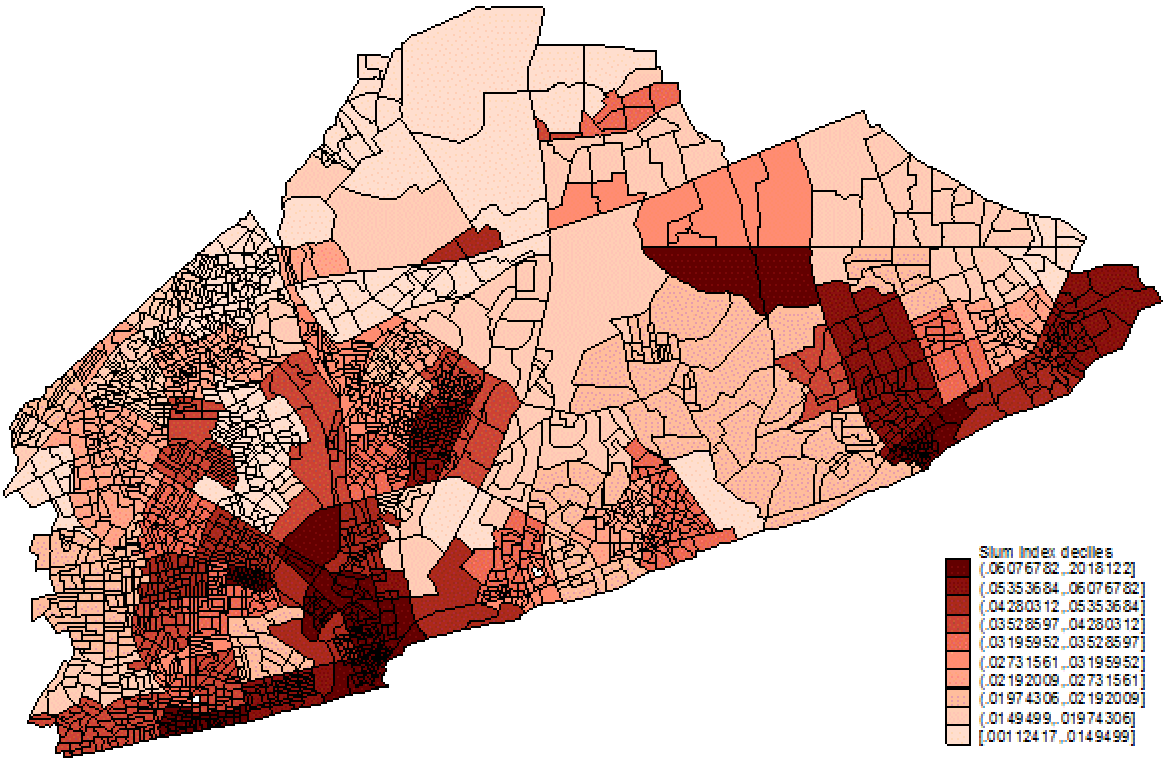
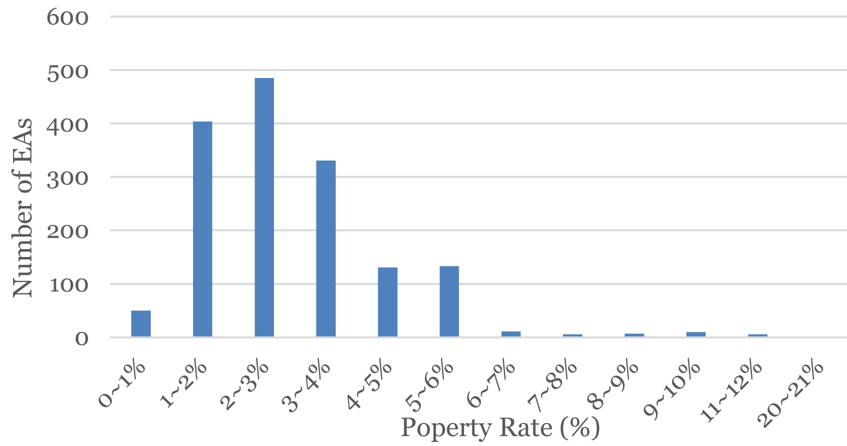


Figure 6: Number of EAs by poverty rates

1) Slum index>0.75

2) Slum index<0.75



Appendix

Table A.1: UN Habitat's definition of slums and corresponding variables in Ghana Population Census

Characteristic/Indicator	Definition	Census variable
1) Access to water / Improved drinking water sources	A household has improved drinking water supply if it uses water from sources that include: - piped water into dwelling, plot or yard; - public tap/ stand pipe; - tube well/borehole; - protected dug well; - protected spring; - rain water collection.	**H09a:** What is the main source of drinking water for the household? 01 Pipe-borne inside dwelling 02 Pipe-borne outside dwelling 03 Public tap/Standpipe 04 Borehole/Pump/Tube well 05 Protected well 06 Rain water 07 Protected spring 08 Bottled water 09 Sachet water 10 Tanker supply/Vendor provided 11 Unprotected well 12 Unprotected spring 13 River/Stream 14 Dugout/Pond/Lake/Dam/Canal 15 Other (Specify)
Access to improved sanitation facilities / Improved sanitation facilities	A household is considered to have access to improved sanitation if it uses: - flush or pour flush to piped sewer system, septic tank or pit latrine; - pit latrine with slab; - composting toilet; - ventilated improved pit latrine. - the excreta disposal system is considered improved if it is private or shared by a reasonable number of households.	**H13a: TOILET FACILITIES** What type of toilet facility is usually used by the household? 1 No facility (e.g. bush/beach/field) (GO TO H14) 2 W.C. 3 Pit latrine 4 KVIP 5 Bucket/Pan 6 Public toilet (e.g. WC, KVIP, Pit, Pan) (GO TO H14) 7 Other (Specify)
Durable housing / a. Location b. Permanency of structure	A house is considered durable if it's built on a non-hazardous location. Hazardous sites include: - geologically unstable areas (landslide/earthquakes and flood areas); - garbage dumpsites; - high industrial pollution areas; - unprotected high risk zones (e.g. railroads, airports, energy transmission lines).	N/A
	Permanency of a housing structure is determined by: - quality of construction (materials used for wall, floor and roof); - compliance with local building codes, standards and bylaws.	**H02: OUTER WALL** What is the main material of the outer walls of this dwelling? 01 Mud bricks/earth 02 Wood 03 Metal sheet/slate/asbestos 04 Stone 05 Burnt bricks 06 Cement blocks/concrete

Characteristic/Indicator	Definition	Census variable
		07 Landcrete 08 Bamboo 09 Palm leaves/Thatch 10 other **H03: FLOOR** What is the main material of the floor of this dwelling? 1 Earth/Mud 2 Cement/Concrete 3 Stone 4 Burnt bricks 5 Wood 6 Vinyl tiles 7 Ceramic/Porcelain/Granite/Marble tiles 8 Terrazzo/ 9 Other (Specify) **H04: ROOF** What is the main material used for the roof? 1 Mud/Mud bricks/Earth 2 Wood 3 Metal sheet 4 Slate/Asbestos 5 Cement/Concrete 6 Roofing Tiles 7 Bamboo 8 Thatch/Palm leaves or Raffia 9 Other (Specify) **H01: TYPE OF DWELLING** In what type of dwelling does the household live? 01 Separate house 02 Semi-detached house 03 Flat/Apartment 04 Compound house (rooms) 05 Huts/Buildings (same compound) 06 Huts/Buildings (different compounds) 07 Tent 08 Improvised home (kiosk, container) 09 Living quarters attached to office/shop 10 Uncompleted building 11 Other (Specify)
Overcrowding / Sufficient living area	A house has sufficient living area for household members if not more than three members share the same room.	**H07b:** How many of the rooms are used for sleeping? > 2 is bad
Security of tenure / Security tenure	Households have secure tenure when they have effective protection against forced evictions through:	**H06: OWNERSHIP TYPE** Who owns the dwelling? 1 Owned by household member

Characteristic/Indicator	Definition	Census variable
	- evidence of documentation (formal title deed to either land or residence or both); - *de facto* or perceived protection against eviction.	2 Being purchased (e.g. Mortgage) 3 Relative not household member 4 Other private individual 5 Private employer 6 Other private agency 7 Public/Government ownership 8 Other (Specify)

Source: UN-Habitat GUO data, 2010.

Table A.2: Correlation coefficients between slum index and census variables

	UN-HABITAT definition of slums	Correlation coefficient
Access to water / Improved drinking water sources		
01 Pipe-borne inside dwelling		-0.176
02 Pipe-borne outside dwelling		**0.124**
03 Public tap/Standpipe		**0.115**
04 Borehole/Pump/Tube well		-0.007
05 Protected well		0.009
06 Rain water		-0.006
07 Protected spring		0.004
08 Bottled water	X	-0.076
09 Sachet water	X	0.007
10 Tanker supply/Vendor provided	X	-0.011
11 Unprotected well	X	-0.012
12 Unprotected spring	X	0.004
13 River/Stream	X	0.005
14 Dugout/Pond/Lake/Dam/Canal	X	0.006
Toilet facilities		
1 No facility (e.g. bush/beach/field)	X	-0.034
2 W.C.		-0.412
3 Pit latrine		-0.044
4 KVIP		-0.063
5 Bucket/Pan	X	**0.123**
6 Public toilet (e.g. WC, KVIP, Pit, Pan)	X	**0.421**
Outer wall		
01 Mud bricks/earth	X	**0.107**
02 Wood	X	**0.083**
03 Metal sheet /slate/asbestos		0.020
04 Stone		0.019
05 Burnt bricks		0.006
06 Cement blocks/concrete		-0.120
07 Landcrete		0.039
08 Bamboo	X	0.003
09 Palm leaves/Thatch	X	-0.018
Floor		
1 Earth/Mud	X	-0.038
2 Cement/Concrete		**0.166**
3 Stone		0.001
4 Burnt bricks		-0.017
5 Wood	X	**0.025**
6 Vinyl tiles		-0.086

	UN-HABITAT definition of slums	Correlation coefficient
7 Ceramic / Porcelain / Granite/Marble tiles		-0.110
8 Terrazzo/		-0.165
Roof		
1 Mud/Mud bricks/Earth	X	-0.021
2 Wood	X	**0.035**
3 Metal sheet		**0.239**
4 Slate/Asbestos		-0.196
5 Cement/Concrete		-0.085
6 Roofing Tiles		-0.093
7 Bamboo	X	0.003
8 Thatch/Palm leaves or Raffia	X	0.002
Dwelling type		
01 Separate house		-0.238
02 Semi-detached house		-0.087
03 Flat/Apartment		-0.198
04 Compound house (rooms)		**0.329**
05 Huts/Buildings (same compound)	X	0.012
06 Huts/Buildings (different compounds)	X	**0.015**
07 Tent	X	-0.005
08 Improvised home (kiosk, container)	X	-0.008
09 Living quarters attached to office/shop	X	-0.040
10 Uncompleted building	X	-0.071
Ownership type		
1 Owned by household member		0.008
2 Being purchased (e.g. Mortgage)		0.009
3 Relative not household member		**0.081**
4 Other private individual	X	**0.031**
5 Private employer	X	-0.065
6 Other private agency	X	-0.022