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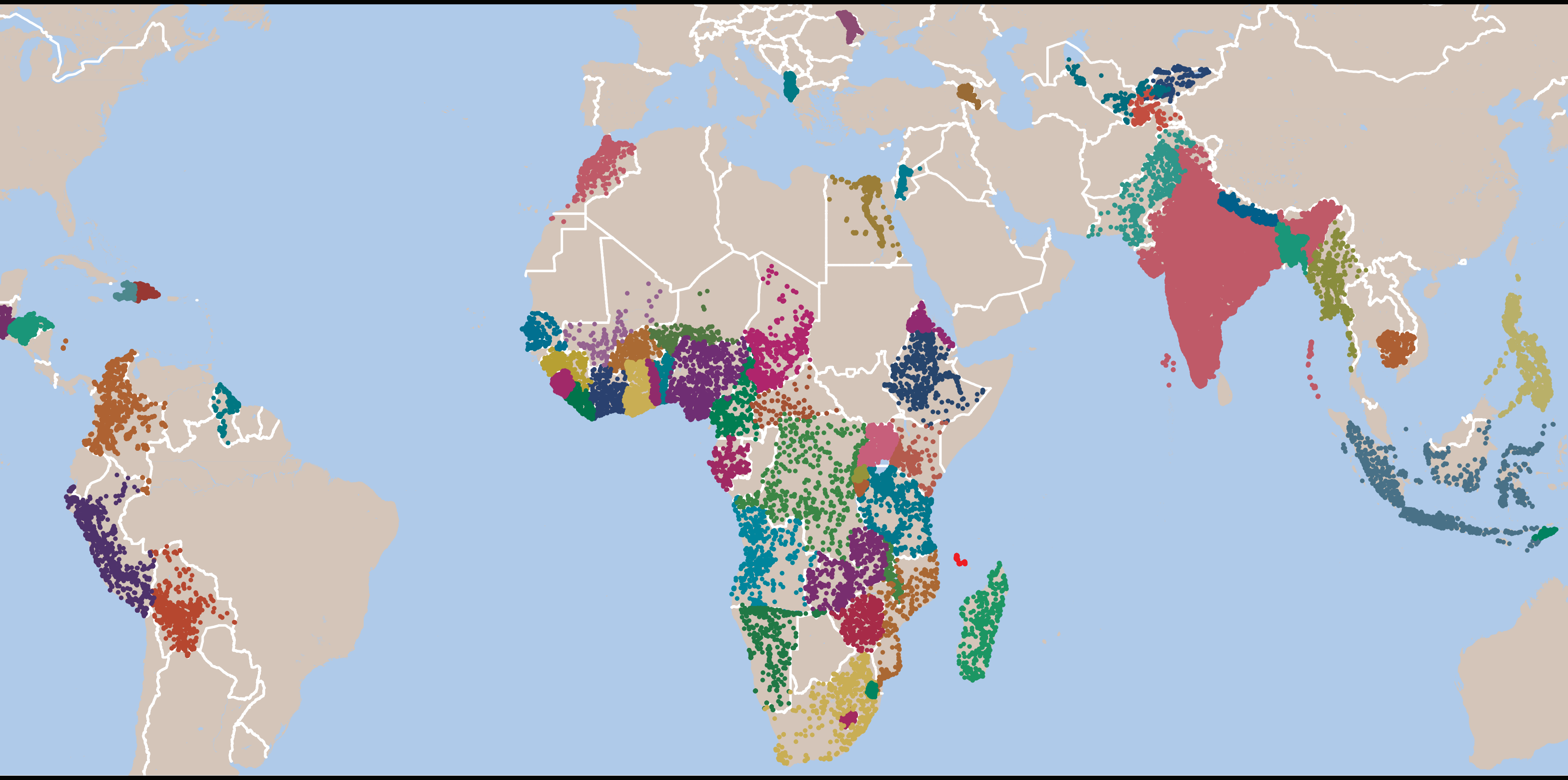
GEOSPATIAL COVARIATES: PROXIES FOR MAPPING URBAN-RELATED INDICATORS

DHS SPATIAL ANALYSIS REPORTS 19



SEPTEMBER 2020

This publication was produced for review by the United States Agency for International Development (USAID). The report was prepared by Thomas D. Fish, Bradley Janocha, Trinadh Dontamsetti, and Benjamin K. Mayala.

DHS Spatial Analysis Reports No. 19

Geospatial Covariates: Proxies for Mapping Urban-Related Indicators

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September 2020

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Acknowledgments: The authors would like to thank Shireen Assaf, Mahmoud Elkasabi, Luis Machado, and Bill Winfrey for their comments on an earlier version of this report.

Special thanks to Lindsay Mallick for coming to the authors last year with the results of the Haiti portion of two working papers that spawned the idea for this study.

Editor: Diane Stoy
Document Production: Joan Wardell and Natalie Shattuck

This study was conducted with support from the United States Agency for International Development (USAID) through The DHS Program (#720-OAA-18C-00083). The views expressed are those of the authors and do not necessarily reflect the views of USAID or the United States Government.

The DHS Program assists countries worldwide in the collection and use of data to monitor and evaluate population, health, and nutrition programs. Additional information about The DHS Program can be obtained from ICF, 530 Gaither Road, Suite 500, Rockville, MD 20850 USA; telephone: +1 301-407-6500, fax: +1-301-407-6501, email: info@DHSprogram.com, Internet: www.DHSprogram.com.

Recommended citation:

Fish, Thomas D., Bradley Janocha, Trinadh Dontamsetti, and Benjamin K. Mayala. 2020. *Predicting Geospatial Covariates: Proxies for Mapping Urban-Related Indicators*. DHS Spatial Analysis Reports No. 19. Rockville, Maryland, USA: ICF.

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PREFACE

The Demographic and Health Surveys (DHS) Program is one of the principal sources of international data on fertility, family planning, maternal and child health, nutrition, mortality, environmental health, HIV/AIDS, malaria, and health services.

The DHS Spatial Analysis Reports supplement other DHS reports and respond to the increasing interest in a spatial perspective on demographic and health data. The principal objectives of all DHS report series are to provide information for policy formulation at the international level and to examine individual country results in an international context.

The topics in this series are selected by The DHS Program in consultation with the U.S. Agency for International Development. A range of methodologies are used, including geostatistical and multivariate statistical techniques.

It is hoped that the DHS Spatial Analysis Reports series will be useful to researchers, policymakers, and survey specialists, particularly those who work in low and middle-income countries, and will enhance the quality and analysis of survey data.

Sunita Kishor
Director, The DHS Program

ABSTRACT

The enumeration areas selected by The DHS Program are classified as either rural or urban. While this classification often plays a role in the analysis of health outcomes, rurality and urbanicity are not defined by The DHS Program. Instead, official urban and rural classifications are determined by the countries themselves. Lack of consensus about this definition leads to inconsistent classifications of enumeration areas as urban or rural. This inconsistency can impair comparative analyses of urbanicity's relationship to health outcomes. There is no universally accepted taxonomy for urbanicity or rurality, although it is commonly believed that urbanicity models should include both a demographic and spatial dimension. This study uses data from Demographic and Health Surveys (DHS) conducted in three countries in East Africa to study the interaction between urbanicity-related outcomes and geospatial covariates. Specifically, the study sought to determine if urban-correlated indicators can be predicted by various covariates of urbanicity, and to identify the covariates of urbanicity that are more often significant in the prediction of urban-related indicators. A Bayesian model-based geostatistical approach was used to model the relationship between DHS urban-related outcomes and covariates. A spatial model was implemented through a stochastic partial differential equation (SPDE) in the integrated nested Laplace approximation (INLA), and was compared with a Bayesian non-spatial model. Results of the DIC values show the importance of including spatial component in the models.

The results were mixed, but promising. Despite the variability in urbanicity definitions across countries, the relationship between the covariates and the selected DHS outcomes illustrates a pattern across the various countries. Land-use and demographic covariates can be used to help make predictions about the health and demographics of residents living in different enumeration areas (EAs). When women's agricultural employment is the outcome being modeled, nightlights and travel times to hospitals should be included in the model.

ACRONYMS AND ABBREVIATIONS

Admin 1	first subnational administrative level
Admin 2	second subnational administrative level
Admin 3	third subnational administrative level
ANC	antenatal care
DHS	Demographic and Health Survey
DIC	deviance information criterion
EA	enumeration area
ECJRC	European Commission's Joint Research Center
ESA	European Space Agency
EVI	enhanced vegetation index
FP	family planning
GPS	global positioning system
GRUMP	Global Rural - Urban Mapping Project
INLA	integrated nested Laplace approximation
MAE	mean absolute error
MAP	malaria atlas project
MBG	model-based geostatistics
MIS	Malaria Indicator Survey
MODIS	moderate resolution imaging spectroradiometer
NOAA	National Oceanic and Atmospheric Administration
SEDAC	NASA's Socioeconomic Data and Applications Center
SPED	stochastic partial differential equation
SSA	sub-Saharan Africa
UNDESA	United Nations Department of Economic and Social Affairs
WHO	World Health Organization

1 BACKGROUND AND OBJECTIVES

From the very first World Fertility Survey in 1974 to the most recent Demographic and Health Surveys (DHS), urbanicity has been included in datasets used by demographers. Urbanicity, the measure of a geographical area's urban features (Vlahov and Galea 2002), has been found to be a predictive factor in a wide variety of health outcomes including, but not limited to, anemia (Adamu et al. 2017; Jones, Acharya, and Galway 2016), under-5 mortality (Yaya et al. 2019), fertility (Ajaero et al. 2016; Chima and Alawode 2019; Duru et al. 2018), and malnutrition (Fotso 2006; Jones, Acharya, and Galway 2016).

In the DHS Program, enumeration areas (EAs) are classified as either rural or urban. Although this classification often plays a role in the analysis of health outcomes around the world, rurality and urbanicity are not defined by The DHS Program, but by the countries within which it works. The lack of consensus about this definition may lead to an inconsistent classification of EAs as urban or rural, and can impair comparative analyses of urbanicity's relationship to health outcomes. This study will attempt to discover if urban-correlated health and demographic indicators can be predicted by various covariates of urbanicity. Some covariates of urbanicity may be more useful than others when attempting to predict these indicators.

We are not the first group to approach this question. Dorélien, Balk, and Todd (2013) found that urban-rural definitions created by countries performed well when compared to data from the Global Rural—Urban Mapping Project (GRUMP) in 20 surveys between 1990 and 2000. The GRUMP is a dataset that divided areas into urban and rural based on electrification with nightlights collected between 1994 and 1995. In contrast to Dorélien, Balk, and Todd (2013), we view urbanicity as a continuum instead of a binary. In addition, we used a wider array of continuous covariates, including nightlights, to explore the concept.

1.1 Urban-rural Taxonomy

1.1.1 Country-specific definitions

Between countries, there are many different definitions of urban versus rural. Despite lack of a standard definition, patterns for classification emerge when comparing definitions between countries. Country-specific definitions of urbanicity for the three countries used in this study—Burundi, Tanzania, and Uganda—are found in Table 1. These countries were selected for their geographic characteristics (East African countries), as well as their definition of urban areas. The definitions in this study were adapted from the definitions published in the 2018 United Nations World Urbanization Prospectus and the 2018 United Nations Demographic Yearbook (UNDESA 2019, 2018). For a full listing of countries in sub-Saharan Africa (SSA) and their urban definitions, see Table A1 in Appendix A.

The year of the most recent census to each survey used in this study is shown in Table 1. Countries use the census to redesignate EAs as either urban or rural. A longer time between a census and a survey is a known source of error in the urban and rural designations.

Table 1 Definitions used to classify EAs as urban or rural in the study countries

Country	Year of previous census	Definition
Burundi	2008	Commune of Bujumbura
Tanzania	2012	All regional and district headquarters and wards with urban characteristics. Urban wards have above a certain population density and/or a certain percentage of inhabitants in non-agricultural occupations. No specific numerical values of density or employment are identified.
Uganda	2014	Cities, municipalities, and towns with more than 2,000 inhabitants

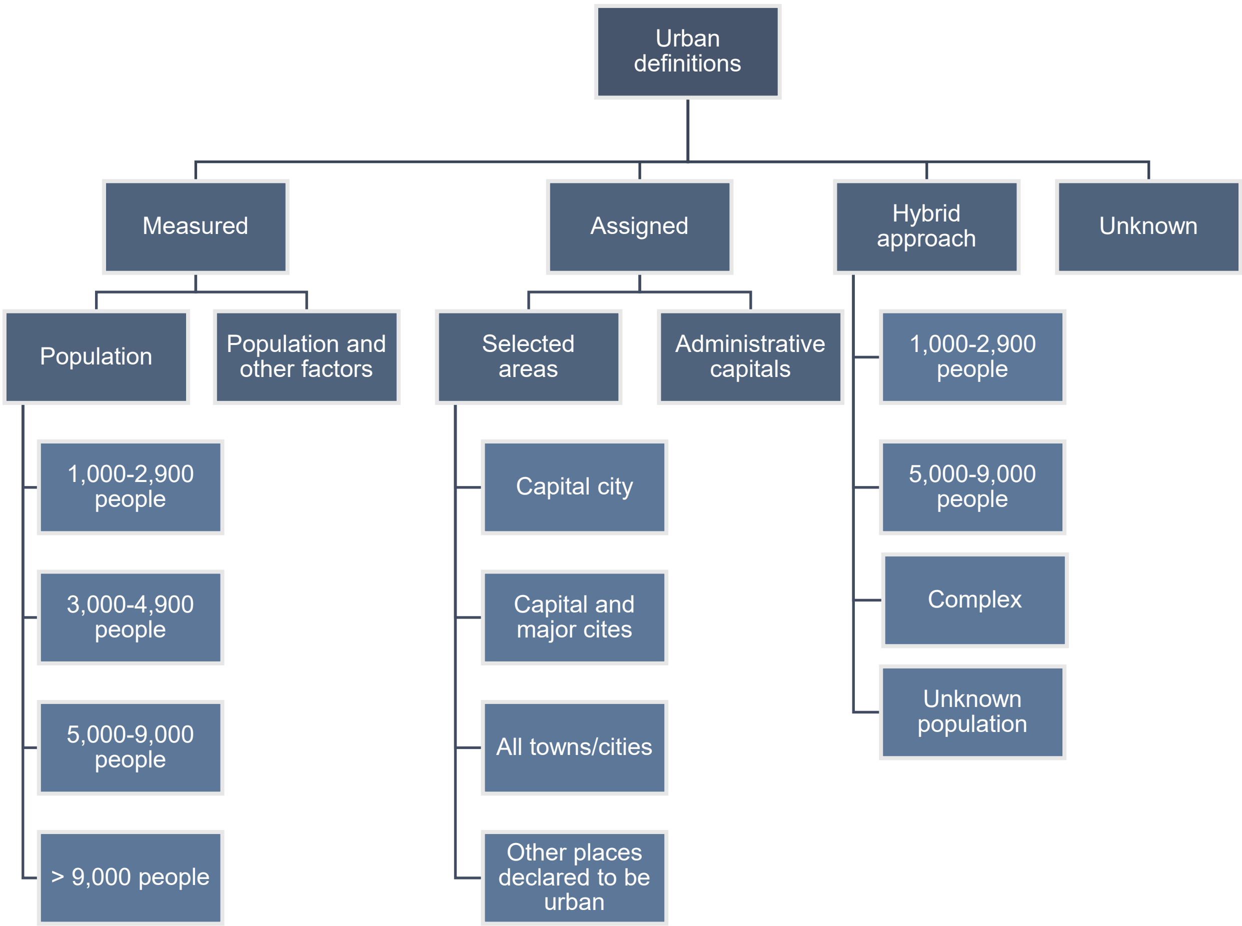
Each of the three countries in this study defines urbanicity differently. Uganda generally relies on the population of small administrative units to determine if the unit is urban or rural. In contrast, Burundi depends on the national legislature to declare a location as urban. Currently the capital of Burundi, Bujumbura, is the only urban location in the country. Tanzania uses a hybrid definition that includes measurable characteristics, as well as a location's role in the country's administration.

The variation in these three countries is representative of a large pattern of classification identified in this study. In countries around the world, localities are classified as urban through either measurement, assignment, a hybrid method, or an unknown definition. Inconsistencies in the methods that determine urbanicity have led to an arbitrary international urban-rural classification system. Figure 1 displays a taxonomy of the various methods used by SSA countries to classify urban areas.

For measurement-based definitions, the decision to designate an area as either urban or rural depends on a published formula. At the most simplistic, such as in Uganda, this uses a population cutoff, with small administrative units above the cutoff classified as urban and the others rural. However, the definitions can be much more complex. In Kenya, for example, there is a population cutoff and criteria for determining the land-use of an administrative unit, which is used for an urban designation. Other common factors used by SSA countries include the occupations of the residents in an administrative unit, as well as population density. Figure A1 in Appendix A shows the countries that use various measurement-based heuristics for their urban definition.

Some countries use assignment-based definitions to define a list of administrative units as urban, while others use a general approach that designates all towns as urban areas. In other countries, such as Chad, the capitals of each administrative unit down to the second subnational administrative level (Admin 2) or the third subnational administrative level (Admin 3) are considered urban. Other countries use a more minimalist approach. In Burundi, only the capital of Bujumbura is classified as urban, while in Rwanda, the capital city and some other major cities are urban. If updated frequently, assignment-based approaches can be just as sensitive, or even more so, to newly urbanizing areas as measurement-based definitions. Figure A2 in Appendix A shows countries that use various assignment-based heuristics for their urban definition.

Figure 1 Classification of urban definitions



The hybrid approach is the final major method that countries use to define urban areas. Countries typically begin with a list of urban areas, which are often administrative capitals or major cities, and then add additional factors that can be as simple as a count or a multi-section definition. The more complex definitions, such as Tanzania's, are difficult to use to determine exactly if an area is urban or rural. Figure A3 in Appendix A shows the countries that use various hybrid heuristics for their urban definition.

1.1.2 Spatial urban-rural classifications

Although there is no universally accepted taxonomy for urbanicity or rurality, the literature reveals two key characteristics that inform the urban-rural delineation. It is commonly believed that urbanicity models should include both a demographic and spatial dimension (Melchiorri et al. 2018). Although these most often are in the form of population density and land use, the datasets vary from study to study. One indicator of land use can be nightlight datasets, which have been strongly correlated with highly developed areas (Yi et al. 2014). Another includes transportation data that can assess accessibility to urban centers (Linard et al. 2012). Localities with high population density and access to more built-up (developed) areas, for example, may be classified as urban.

In contrast, rural localities are not described by distinct characteristics in the literature. Instead, rurality is often defined by its exclusion (Hall, Kaufman, and Ricketts 2006). Urban areas must meet certain population density and land use criteria, while rural localities are those that do not. Although this lack of definition simplifies the delineation process, future studies may consider further characterizing rural locations.

1.2 Study Aims and Objectives

This study examined the agreement and disagreement between different urbanization measures in three East African countries: Burundi, Tanzania, and Uganda. Specifically, the study objectives were to (1) model urban-related indicators using geospatial covariates and determine their relationship to urbanicity, and (2) determine the covariates that are significantly related to the urban-related indicators.

2 DATA

2.1 Survey Data

We used data from three DHS surveys in East Africa: the Burundi 2016-2017 DHS, Tanzania 2015-2016 DHS, and Uganda 2016 DHS. The DHS surveys are nationally representative, household surveys with data on various indicators of population, reproductive health, nutrition, and maternal and child health. These surveys are nationally representative, and are also representative at nationally defined urban-rural residency and at one or more subnational levels.

The surveys in this study range in size from 13,000 to almost 18,000 women, with the largest survey in Uganda and the smallest in Tanzania. Table 2 shows the surveys, type of sample, sample size, and the number of EAs, or clusters, in the sample.

Table 2 Countries in this study

Country	Survey year	Survey type	Sample type	Sample size	Enumeration areas
Burundi	2016-17	DHS	All women age 15-49	17,269	554
Tanzania	2015-16	DHS	All women age 15-49	13,266	608
Uganda	2016	DHS	All women Age 15-49	18,506	696

Figure 2 shows the location of the selected countries. These countries were selected because they are clustered together in East Africa and each county defines urban in a different manner.

Figure 2 Countries included in this study and the surrounding countries

2.2 Urbanicity-related DHS Indicators

In defining urbanicity, we made urban-rural distinctions in order to reveal patterns in data and uncover any potential discrepancies or inequalities. This study's classification of urban and rural areas was assessed by demographic characteristics and health outcomes related to urbanicity. As explained in the subsections below, the literature suggested that family planning (FP), antenatal care (ANC), and occupation may be related to urbanicity in various SSA countries. Table 3 defines these indicators.

Table 3 Indicators in this study

Indicator	Definition	Type
Modern method of FP	Percentage of women who currently use any modern method of family planning	Family planning
4+ ANC visits	Percentage of women with a birth in the last 5 years, who had 4 or more antenatal care visits for most recent birth	Antenatal care
Women's agricultural employment	Percentage of women engaged in agricultural employment	Occupation

2.2.1 Family planning

Two assessments of the Nigeria 2013 DHS found that rural respondents were less likely to use FP methods (Ajaero et al. 2016; Duru et al. 2018). Several different factors may be relevant. It has been suggested that discrepancies in media access between urban and rural areas may lead to discrepancies in FP practices (Chima and Alawode 2019), and that expanding access to cellular phones in rural areas has different effects. In general, given the socioeconomic circumstances of urban life, global fertility rates are lower in cities than in rural areas. In cases where overall fertility rate declines, the rate in urban areas has declined more quickly than in rural locations (Lerch 2019). Although the literature highlights potential factors that might lead to greater FP method use and, by extension, lower fertility rates in urban areas, the use of FP methods in SSA is known to be influenced by many factors.

2.2.2 Antenatal care

The literature describes a difference in ANC between urban and rural EAs, and also suggests a difference in some associated factors (Adewuyi et al. 2018). Some factors may differentiate urban areas from rural, while others may be common between the two. In their analysis of data from the Nigeria 2013 DHS, Adewuyi et al. found that ANC underutilization in both urban and rural EAs was significantly associated with parents' lack of education and the distance to the nearest health facility. Socioeconomic factors, and more specifically education and wealth, have been found to be primary causes of disparities in urban-rural ANC prevalence (Afulani 2015). However, this does not necessarily account for urbanicity's spatial component. Distance to the nearest health facility, in contrast, does account for this (Kyei, Campbell, and Gabrysch 2012). Distance to the nearest health facility may be a significant factor in ANC underutilization in both urban and rural EAs, although the average distances are expected to differ greatly between rural and urban areas.

2.2.3 Occupation

Of all the DHS demographic information collected, the most useful for this study is the respondents' employment status. While rural populations are not limited to agricultural work, it is rare for urban residents to leave their city or residence to work on farms (Tacoli, McGranahan, and Satterthwaite 2015). It is more common to define urban areas by their characteristics and rural areas by exclusion. Areas that have a heavy dependence on employment in agriculture may be considered rural because they cannot be urban (UNDESA 2017). In contrast, since employment related to resource extraction is not indicative of either urban or rural, other demographic factors must be considered.

2.3 Spatial Covariates

In addition to the DHS indicators, we assembled geospatial covariates data layers, which were obtained from publicly available remote sensing sources. The geospatial covariates were selected for their potential to predict various DHS indicator outcomes and for their ability to measure urbanicity in terms of demographic trends and land use (Alegana et al. 2015; Gething et al. 2015; Linard, Tatem, and Gilbert 2013, Santé et al., 2010). Table 4 describes the geospatial covariates in our analysis. The selected covariates are population data, land use data, or physical geography data.

Table 4 Spatial covariates used to develop the models in this study

Name	Category	Years	Resolution	Units	Source
WorldPop global mosaic	Population	2015	1km	Population count	WorldPop
Global human built-up grid (BUILT)	Land use	2014	1km	Land use index	ECJRC
Travel times to hospitals	Land use	2018	1km	Minutes	Alegana et al. 2018
VIIRS day/night band nightlights	Land use	2015	15 arcsec	Radiance value	NOAA
Travel times to populated places	Land use	2015	1km	Minutes	MAP
Elevation	Physical geography	1999	1km	Meters	NOAA
Enhanced vegetation index	Physical geography	2015	5km	Vegetation index	MODIS

2.3.1 Population data

In selecting population density data, this study considered the criteria by Leyk et al. (2019). In assessing a dataset's appropriateness for use, this study sought data that was thematically, spatially, and temporally relevant. The study used a single population dataset, the WorldPop Global Mosaic. Of the population datasets we reviewed, such as the UN-Adjusted Population Density and Global Human Settlement Model, the WorldPop Global Mosaic included the best mixture of temporal, spatial, and modeling attributes.

2.3.2 Land use data

Ancillary data such as land cover and settlement extent dramatically improve the quality of population data (Leyk et al. 2019), and can also help to delineate urban and rural areas. This study used four different land use raster covariates. The most straightforward dataset we utilized was the Global Human Built-Up Grid (BUILT), which is a unitless index of urbanicity based on satellite imagery. The BUILT dataset is a primary component of the Global Human Settlement Model (GHS-SMOD) that uses land use and population to define urban areas. The literature suggested that GHS-SMOD is highly effective in determining population density and urbanicity (Leyk et al. 2019; Melchiorri et al. 2018). However, the inclusion of population in our model prevented us from being able to use GHS-SMOD due to the inclusion of population in the creation of GHS-SMOD.

In addition, we also considered other data that could indirectly measure land use. As mentioned in Section 1.1, nightlights and transportation infrastructure have been used as indicators of urban land use (Linard et al. 2012; Yi et al. 2014). Although nightlight data have been found to misclassify rural areas as urban (Zhang and Seto 2013), the Urban Light Index has been shown to be a good indicator to use when classifying urban development (Yi et al. 2014). Transportation infrastructure was included in our model through the inclusion of travel times to populated places from Weiss et al. (2018). The locations of health facilities are another potential indicator of land use. This study used a layer of travel times to hospitals from Alegana et al. (2018) to capture the distance of clusters from hospitals.

2.3.1 Physical geography data

The physical geography of a location is an additional source of covariates when creating spatial models. Two of the attributes commonly used are vegetation and terrain. The enhanced vegetation index (EVI) is a satellite imagery-based measurement of tree cover, grass, and shrubbery in a location. The amount of vegetation has been shown to decrease as urbanicity increases (Zhao, Liu, and Zhou 2019; Gui et al. 2019). Elevation is one of the covariates The DHS Program uses to create its modeled surfaces (Gething et al. 2015).

3 METHODS

3.1 Indicator Preparation

The DHS indicators in this study were calculated in accordance with *The DHS Guide to Statistics* (Croft et al. 2018) and the indicator code published by The DHS Program (The DHS Program 2020). The employment outcomes used in the study are not based on existing DHS indicators, but were calculated from the number of women age 15-49 in the 12 months before the survey who were employed by the occupation group (*v171*) variable in the standard DHS recode. The variable contains nine possible codes to describe an individual's field of employment. We defined agricultural employment as women who participate in either paid or subsistence agriculture (codes 4 or 5).

This definition is not perfect. Any work within the past 12 months in a field counts as employed. In addition, those residents who engage in fishing for money or subsistence are counted within their respective agricultural categories. Despite these imperfections, the categorizations were useful for our analysis.

3.2 Spatial Covariates Processing

The raw covariate datasets in this analysis came from a myriad of data sources, and have different spatial references, projections, extents, and dimensions as seen in Table 4**.** To make these useful in our models, we used the *raster* and *shapefiles* packages in the R software (R Core Team 2019) to (1) re-project to the same coordinate reference system (the standard World Geodetic System 1984), (2) crop and mask to an extent that encompassed the boundaries of the study area, and (3) resample with bilinear interpolation to the same spatial resolution used in the modeling.

For each extraction, we used the publicly available EA locations published by The DHS Program. The GPS location of the center of each cluster is recorded during either the fieldwork or the listing stage of the survey. Those locations are processed to verify that they are within the correct administrative units. To protect the confidentiality of our respondents, the locations are displaced through a process called geo-masking or geo-scrambling. Each cluster was displaced from the actual location by up to 2 kilometers (for urban points) and 10 kilometers (for rural points). We ensured that during the displacement procedure, the point did not move between large administrative units. More information about the displacement procedure used can be found in Burgert et al. (2013).

3.2.1 Spatial covariates selection

Covariate selection has been described as one of the most important stages in the spatial modeling process, which has shown to improve model fit and increase the precision of predicted estimates (Craig et al. 2007, Raffalovich et al. 2008). However, other studies have warned that care must be taken in the selection of covariates to decrease the risk of over-fitting, which occurs when more covariates than are necessary are used to fit the model (Babyak 2004; Murtaugh 2009). This can lead to poor predictions because coefficients fitted to these covariates add random variations to subsequent predictions and make replication of findings difficult (Babyak 2004). Numerous methods for selecting the best fitting covariates have been described in previous studies (Austin and Tu 2004; Murtaugh 2009, Craig et al. 2007; Hoeting et al. 2006; Derksen and Keselman 1992). In our analysis, the covariate selection used the following steps:

Step 1 – A univariate logistic regression, nonspatial model was performed using each of the geospatial covariates described in Table 4. We compared the models in terms of the Akaike Information Criterion (AIC) and selected the covariates that had the lowest in AIC in the univariate analysis (Akaike 1974). The AIC is a measure of model fit that penalizes for the number of parameters. A lower AIC, which indicates a better fitting model, is defined by:

$$AIC = -2l(\beta) + 2k$$

Where $\beta = \{\beta_0, \beta_j\}$ are the regression coefficients, l is the maximum value of the likelihood function for the mode, and k is the number of parameters in the model.

Step 2 – Multicollinearity in the data was removed by identifying all pairs of covariates with a Spearmans rank coefficient > |0.75| and eliminating the covariate in each pair with the highest AIC, obtained from Step 1. The problem with multicollinearity is that highly correlated covariates compete for inclusion in the model (Austin and Tu 2004).

3.3 Statistical Analysis

3.3.1 Overview of the modeling approach

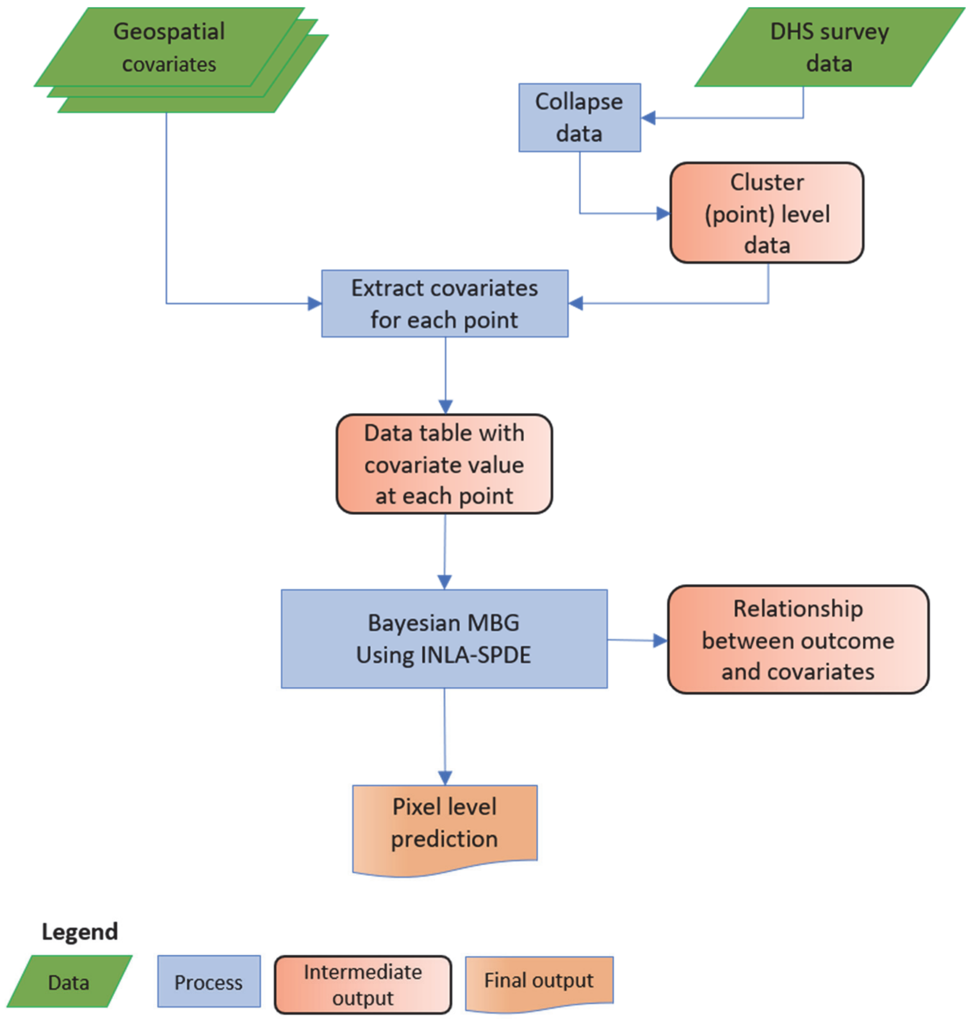
Figure 3 depicts a conceptual overview of the modeling framework used for modeling DHS indicators and the underlying covariates and for producing the gridded pixel estimates. The approach involved the following steps:

Step 1 - We summarized the individual-level DHS survey data to the finest spatial resolution (latitude and longitude) that represented the location of the survey cluster.

Step 2 - The processed geospatial covariates (from the previous section) and the cluster (point) level data were imported into the R environment for statistical computing (R Core Team 2019). We then applied the raster package to extract the corresponding covariate pixel values at each survey cluster point.

Step 3 - The point level data (from Step 2) and their associated geospatial covariates were used in the geospatial (MBG) model in INLA. The outputs of the final model are pixel-level mean estimates at the 5 x 5 km resolution.

Figure 3 Modeling flowchart



3.3.2 Model description

For each indicator of interest, we modeled Y_i, the number of 'positive' individuals among those sampled at cluster location $s_i, i = 1, \ldots n$, using a binomial spatial regression with a logit link function (Banerjee, Carlin, and Gelfand 2014; Diggle and Giorgi 2019). If N_i is the total number of individuals sampled at cluster s_i, the model can be written as:

$$Y_i \sim Binomial(N_i, p_i)$$

$$logit(p_i) = \beta_0 + \beta X_i + \omega_i + \varepsilon_i$$

$$\omega_i \sim GP(0, \Sigma)$$

Where:

- β_0 denotes the intercept,
- p_i is the probability, representing the underlying prevalence at cluster s_i,
- $X_i = (X_{i1,} X_{i2}, \ldots X_{im})$ is the vector of logit-transformed covariates for location s_i,
- $\beta = (\beta_1, \beta_2, \ldots \beta_m)$ vector of regression coefficients
- ω_i is a correlated spatial error term, accounting for spatial autocorrelation between data points, and ε_i is an unstructured random error term known as nugget effect.

The spatial error term ω_i is modeled as Gaussian process with a zero-mean and spatially structured covariance matrix $\sum$.

The covariance matrix $\sum$ was modeled using a stationary, isotropic Matérn spatial covariance function (Banerjee et al. 2014), given by:

$$\Sigma(s_i, s_j) = \frac{\sigma^2}{2^{\lambda-1}\Gamma(\lambda)}\left(\kappa d(s_i, s_j)^{\lambda} K_{\lambda}\left(\kappa d(s_i, s_j)\right)\right)$$

Here, $d(s_i, s_j)$ is the distance between the two locations and σ^2 is the spatial process variance. The term K_λ denotes the modified Bessel function of second kind and order $\lambda > 0$, which measures the degree of smoothness. Conversely, $\kappa > 0$ is a scaling parameter related to the spatial range $r = \frac{\sqrt{8\lambda}}{\kappa}$ that is the distance at which the spatial correlation becomes almost null (smaller than 10%). See the example by Lindgren, Rue, and Lindström (2011) for a detailed description.

3.3.2 Model implementation

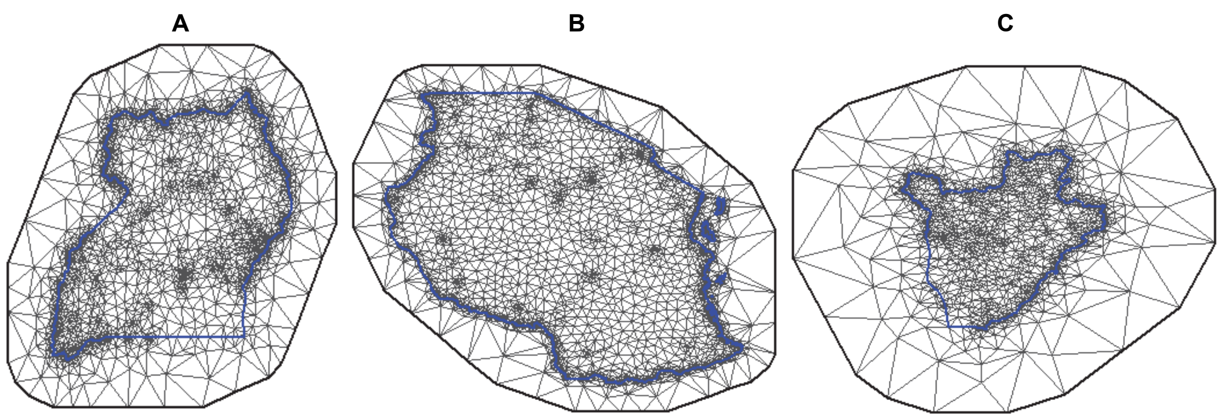
The model was implemented through a stochastic partial differential equations (SPDE) approach in the integrated nested Laplace approximation (INLA) algorithm as applied in the R-INLA package (Rue, Martino, and Chopin 2009). The INLA approach has an advantage of providing fast, reliable calculations of posterior marginal distributions as compared to Markov Chain Monte Carlo algorithms, which are known to have problems of convergence and dense covariate matrices that increase the computational time (Cameletti et al. 2013, Rue, Martino, and Chopin 2009, Blangiardo and Cameletti 2015). We developed and fitted two models: (1) model with covariates and a spatial component (the full model), and (2) a model with covariates and no spatial component (nonspatial). The goodness of fit of the two models was compared using the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002), which considers the fit of the data but penalizes models that are very complex. The model with the lowest DIC value was determined as the best fit.

The SPDE approach approximates the Gaussian process (GP) as a Gaussian Markov Random Field (GMRF), which allow us to define a grid on spatial data by creating a constrained refined Delaunay triangulation (usually called a mesh) over the study region. With this approach, observations are treated as initial vertices for the triangulation. Further vertices are then added or removed to satisfy triangulation quality constraints defined by three parameters: (1) cutoff, (2) offset and (3) maximum edge (Blangiardo and Cameletti. 2015; Lindgren, Rue, and Lindstrom. 2011).

We constructed a finite elements mesh for the SPDE approximation to the GP regression with a simplified polygon boundary. We specified a cutoff value to avoid building too many small triangles around the clustered data locations. We set an offset value that defined how far the mesh should be extended in the inner part (within areas where predictions are required) and the outer part (outside the area where predictions are required). The maximum edge value specified the maximum allowed edge length of the triangle in the inner domain and the outer extension. The inner maximum edge value was small enough to allow the triangulation to support functions with small enough features, and typically smaller than the spatial correlation range of the model (Lindgren, Rue, and Lindstrom. 2011). Figure 4 provides an example of the finite mesh used for modeling.

Estimates for each indicator were generated by taking 1000 draws from the posterior predictive distribution. Pixel level estimates that covered the modeling country were produced at a high spatial resolution of 5 x 5 km. More details about this approach can be found in Mayala et al. (2019).

Figure 4 INLA mesh triangulation for Uganda (A), Tanzania (B) and Burundi (C), with the blue line representing the country boundary



3.3.3 Contribution of covariates to the model

To determine which covariates contributed the most to the estimated prevalence of each outcome, we used pixel values of the surface map and covariates. We resampled the surface map and covariate raster layers to a 5 x 5 km spatial resolution to extract pixel values at each point grid. Next, we used R software to compute the percentage contribution of each covariate to the model.

4 RESULTS

4.1 Covariate Selection

Figure 5 is the correlation matrix that shows spearman rank correlation coefficients for the Burundi datasets. Negative correlations are shaded red, and positive correlations are blue. The strength of the correlation is indicated by squares and red or blue color saturation. The definition of each variable (y-axis) and its coded counterpart (upper x-axis) are defined per comparison. The correlation coefficients were less than |0.70|. Therefore, all seven covariates were included in the analysis. Correlation coefficients for Tanzania and Uganda are presented in Appendix B.

Figure 5 Correlation matrix for covariates

4.2 Model Results

Posterior means and their corresponding 95% Bayesian credible intervals for each covariate and model are listed in Tables D1 through D6 in Appendix D. The deviance information criterion (DIC) values are listed in Table D in Appendix D. For ease of interpretation, each outcome is interpreted separately by using the INLA results and the prediction surfaces outputted by the spatial model.

4.2.1 Women's agricultural employment

Tables 5 to 7 show the posterior means and their corresponding 95% Bayesian credible intervals for each country model for women's agricultural employment. In all three pairs of spatial and nonspatial models, nightlights and travel times to hospitals are significant. Negative associations were found with nightlights, while positive associations were found with travel times to hospitals. The spatial model in Uganda (Table 7) found a significant positive association with BUILT. Both the spatial and nonspatial model in Tanzania (Table 6), and the Burundi nonspatial model (Table 5) had negative associations between BUILT and women's agriculture employment.

Of the six models, the spatial model for Burundi found the smallest number of significant covariates (nightlights and travel times to hospitals). The nonspatial model for Burundi found the most significant covariates of all the models for women's agricultural employment, with only travel times to populated locations found to not be significant. The only pair of models of the six to find more significant covariates in the spatial model than the nonspatial model was Uganda. Travel times to populated locations and BUILT were found to be not significant in the nonspatial model and significant in the spatial model.

Table 5 **Posterior estimates (mean and 95% CI) of the women's agricultural employment models, Burundi**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	1.4576	(-0.4746, -0.3502)	0.9617	(0.9114, 1.0108)
Travel time to a populated place	0.0936	(-0.0759, 0.2633)	0.0451	(-0.0078, 0.0988)
Nightlights	**-0.5874**	**(-0.8824, -0.3187)**	**-1.0173**	**(-1.2316, -0.8229)**
Elevation	0.1101	(-0.1061, 0.3261)	**0.1635**	**(0.1129, 0.214)**
EVI	-0.168	(-0.3595, 0.0229)	**-0.2351**	**(-0.2884, -0.1819)**
BUILT	0.0143	(-0.1056, 0.1333)	**-0.0874**	**(-0.131, -0.0437)**
Population	-0.1001	(-0.2802, 0.0796)	**-0.407**	**(-0.5025, -0.3113)**
Travel time to a hospital	**0.1746**	**(0.0118, 0.3375)**	**0.1913**	**(0.142, 0.2411)**
Spatial parameter variance	1.7722	(1.4212, 2.1986)		
Range	0.2138	(0.1565, 0.2779)		

Table 6 **Posterior estimates (mean and 95% CI) of the women's agricultural employment models, Tanzania**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-0.2045	(-0.5082, 0.0989)	-0.4112	(-0.4746, -0.3502)
Travel time to a populated place	**0.4782**	**(0.2731, 0.6834)**	**0.4249**	**(0.3715, 0.479)**
Nightlights	**-0.7003**	**(-0.943, -0.4671)**	**-1.0669**	**(-1.2548, -0.8853)**
Elevation	**0.4098**	**(0.1994, 0.6202)**	**0.2424**	**(0.1863, 0.2986)**
EVI	0.0897	(-0.0515, 0.2312)	-0.0025	(-0.0507, 0.0457)
BUILT	**-0.515**	**(-0.7223, -0.3172)**	**-0.3794**	**(-0.5258, -0.2442)**
Population	0.2005	(-0.0244, 0.4211)	-0.0232	(-0.247, 0.1937)
Travel time to a hospital	**0.5092**	**(0.3839, 0.6348)**	**0.2705**	**(0.2215, 0.3197)**
Spatial parameter variance	2.7425	(2.1089, 3.5590)		
Range	0.1909	(0.1337, 0.2565)		

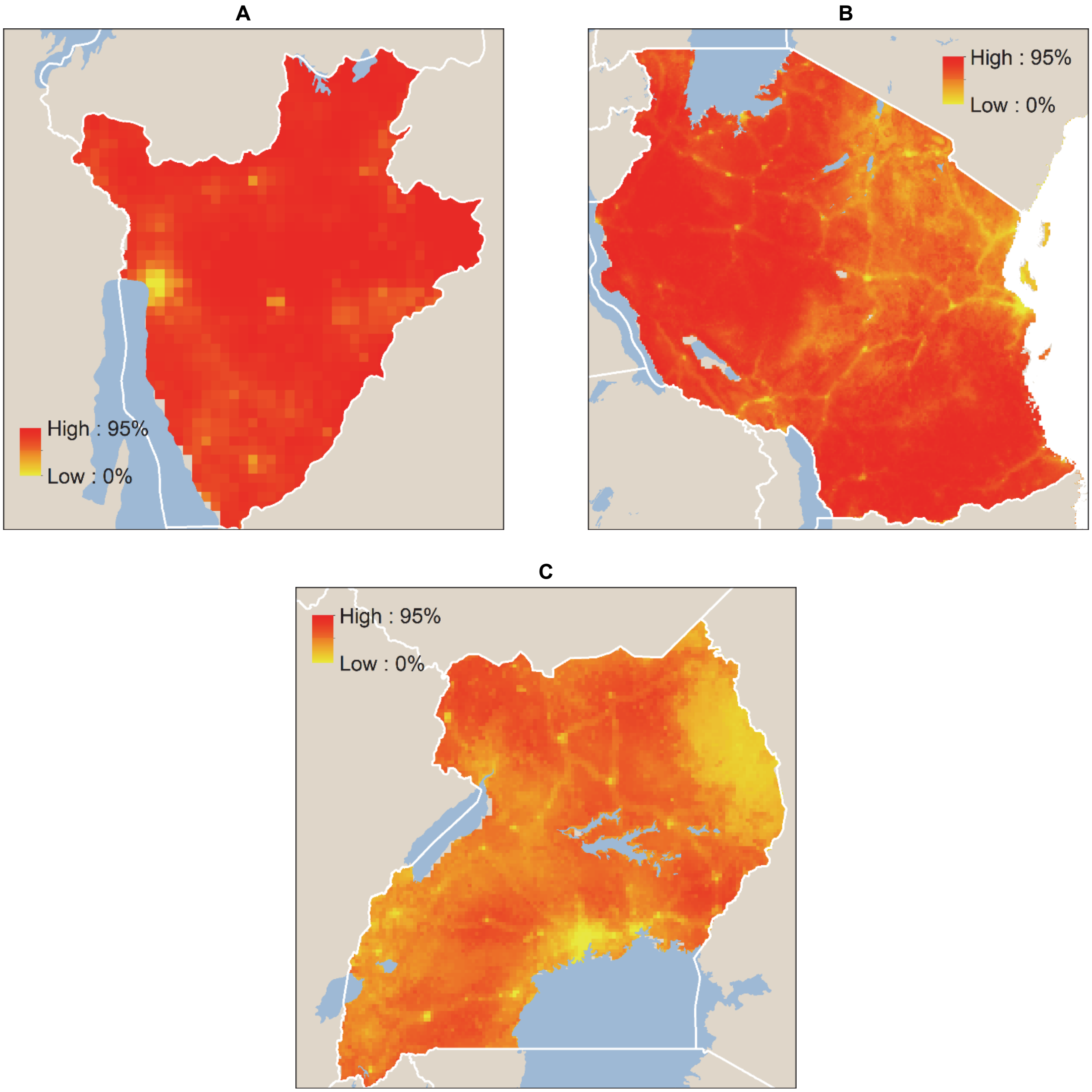
Table 7 **Posterior estimates (mean and 95% CI) of the women's agricultural employment models, Uganda**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-0.9173	(-1.2120, -0.6235)	-1.0251	(-1.1087, -0.9453)
Travel time to a populated place	**0.45**	**(0.2872, 0.6128)**	0.0186	(-0.0288, 0.0659)
Nightlights	**-0.6443**	**(-1.0303, -0.2695)**	**-1.46**	**(-1.7677, -1.1576)**
Elevation	-0.187	(-0.3182, -0.0558)	0.0269	(-0.0082, 0.0619)
EVI	**0.4159**	**(0.2378, 0.5944)**	**-0.1284**	**(-0.1732, -0.0837)**
BUILT	**0.6811**	**(0.3862, 0.9745)**	-0.1078	(-0.3396, 0.1069)
Population	**-0.8458**	**(-1.1417, -0.563)**	**-0.9973**	**(-1.2165, -0.7846)**
Travel time to a hospital	**0.1324**	**(0.0161, 0.2486)**	**0.1465**	**(0.108, 0.1851)**
Spatial parameter variance	1.1933	(0.9186, 1.5315)		
Range	0.3342	(0.2452, 0.4401)		

The DIC values from spatial and nonspatial models were compared. Table D7 in Appendix D shows that the each of the spatial (full) models had a lower DIC value than its corresponding nonspatial value. Thus, the model with spatial component generally improved the model performance.

Model surface prevalence maps for Burundi, Tanzania and Uganda were created with the spatial (full) models. Figure 6 (A to C) shows a large proportion of its area with high proportion of women in agricultural employment. However, there are areas in each country that have much lower predicted agricultural employment. When compared with known cities by using a base layer such as Google maps (not shown here), the areas of low agricultural employment (urban cities) almost perfectly align with populated areas. This is most clear in Burundi but can also be seen in Tanzania and Uganda. The lines between cities almost perfectly align with known highways in both countries. The only unknown effect seen in the prediction surfaces in the contiguous area of low predicted agricultural employment in the northeast part of Uganda, which was roughly Karamoja in the 2016 Uganda DHS.

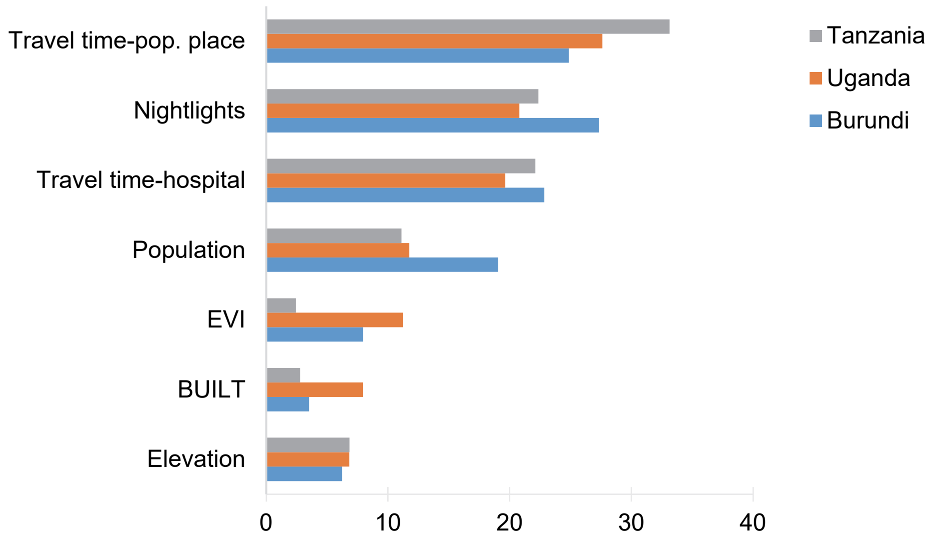
Figure 6 Estimated prevalence of women's agricultural employment; (A) Burundi, (B) Tanzania, and (C) Uganda



4.2.2 Relative importance of covariates

Figure 7 depicts the relative covariate importance for women's agriculture employment. The results indicate that travel time to populated locations contributed most to the models, followed by nightlights and travel time to a hospital. Further results are presents in Appendix C.

Figure 7 Percentage contribution of the covariates for women's agricultural employment

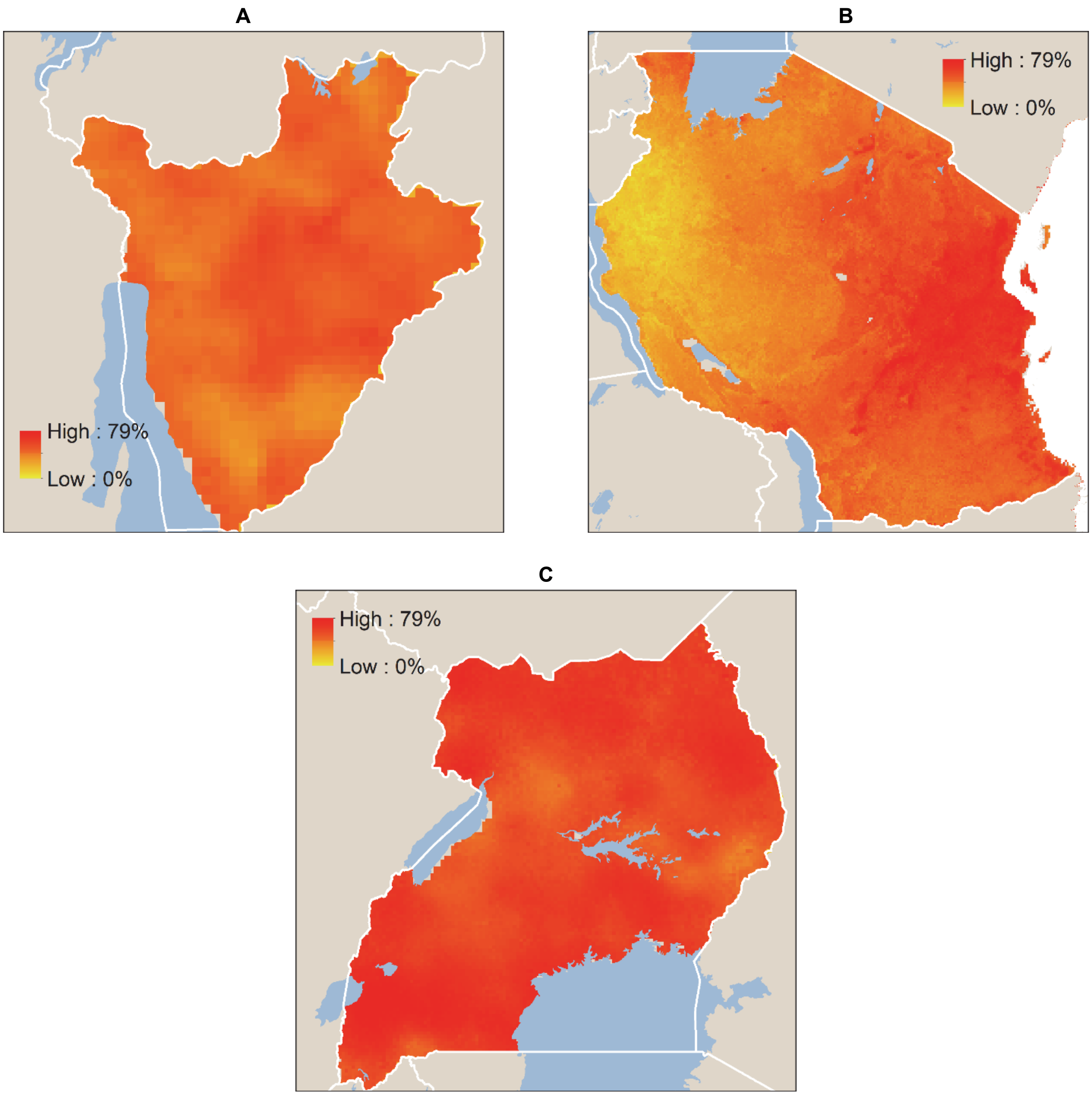


4.2.3 4+ ANC visits

Table D1 through Table D3 in Appendix D shows the posterior means and their corresponding 95% Bayesian credible intervals for each country model for 4+ ANC visits. The Burundi spatial model found that none of the covariates were significant, and there are no covariates that are significant in all six models. Even if the Burundi spatial model is excluded, there is no agreement between the models over which covariates have an association with women attending 4 or more ANC visits. The nonspatial model for Burundi and the nonspatial model for Tanzania both found that EVI had a significant association with our outcome. However, the model for Tanzania found EVI to have a positive association, while the model for Burundi found it to have a negative association. One spatial model found more significant covariates that its corresponding nonspatial model. The spatial model for Uganda found that nightlights and population were significant, with nightlights having a negative association and population having a positive association. The nonspatial model found only population to be significant, with a positive association.

Figure 8 (A to C) shows minimal variation in the predicted values in Burundi and Uganda. Where there are variations, they do not follow know settlement patterns. In Tanzania, there is a gradual variation in predicted values between the coast, with the highest predicted values, and the shores of Lake Tanganyika, with the lowest values. Like the other two countries, these variations do not track directly with known cities. However, the north western coast (near Dar es Salaam) is in the area with the highest prevalence.

Figure 8 Estimated prevalence of 4+ ANC visits: (A) Burundi, (B) Tanzania, and (C) Uganda

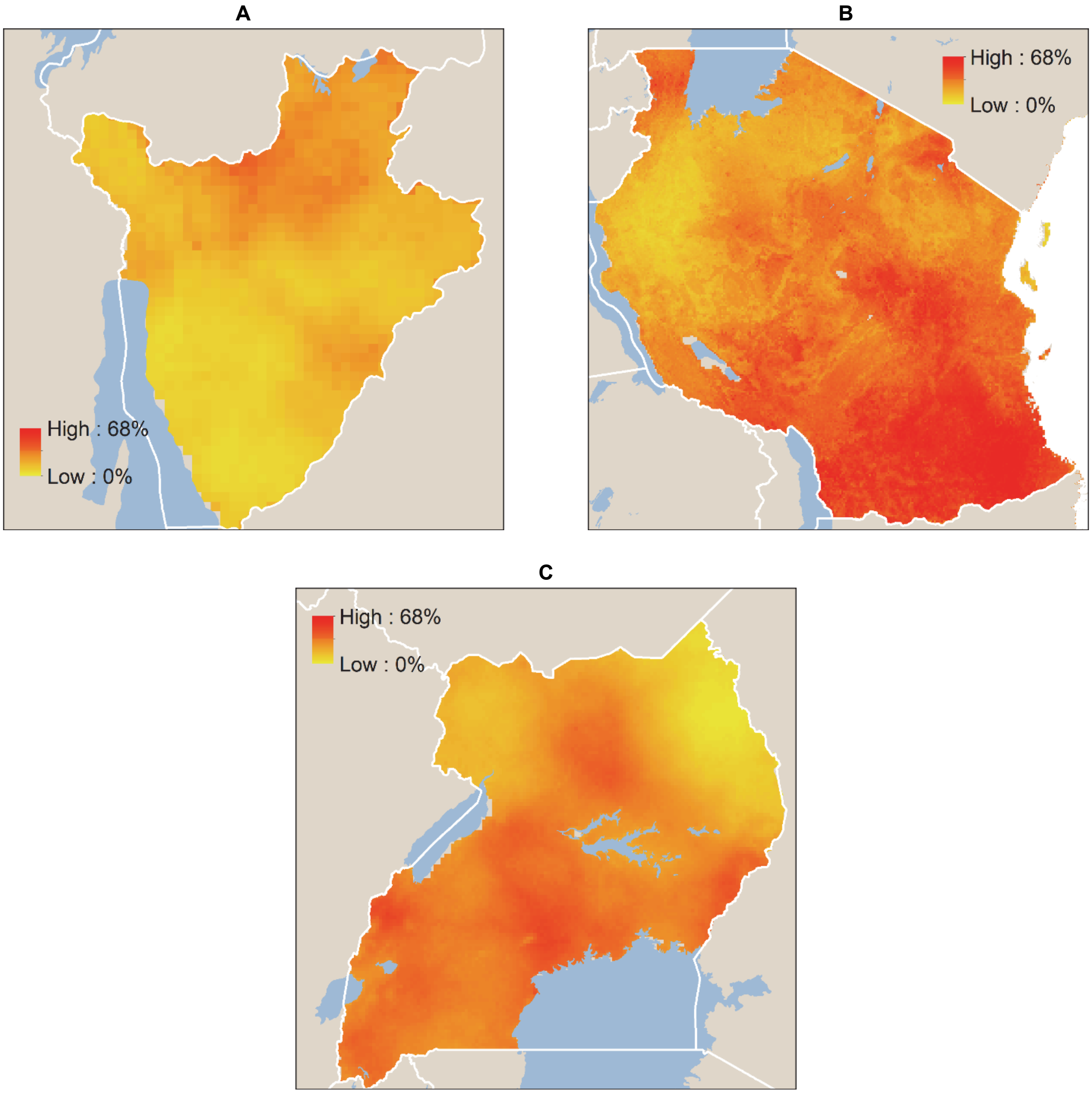


4.2.4 Modern method of FP

Table D4 through Table D6 in Appendix D show the posterior means and their corresponding 95% Bayesian credible intervals for each country model for modern method of FP. Much like 4+ ANC visits, there is no single covariate that is significant in all six models, although several covariates are significant in three more models. Population was significant in all of the models for Tanzania and Uganda and had a positive association in each model. The EVI and BUILT were found to be significant in the nonspatial models for all three countries. However, the associations were not universal. EVI was found to have a positive association in Tanzania and Uganda, but a negative association in Burundi. BUILT was found to have a positive association in Burundi and a negative association in Tanzania and Uganda.

Figure 9 indicates a wide range of patterns shown in the surfaces. Burundi shows the majority of the country having a rather uniform predicted value for modern method of FP. The areas along the border of Rwanda show a higher use of modern methods than the rest of the country. Tanzania shows an area with a high percentage of women using a modern method of FP in the south of the country. That prevalence decreases with movement toward Lake Tanganyika and increases again with movement toward Lake Victoria. In Uganda, the highest areas of use of a modern FP method are near Kampala and Lake Victoria and the lowest levels in West Nile and Karamoja.

Figure 9 Estimated prevalence of modern method of FP: (A) Burundi, (B) Tanzania, and (C) Uganda



5 DISCUSSION AND CONCLUSION

The description of urbanicity may lead to an inconsistent classification of EAs as urban or rural, and ultimately may impair comparative analyses of urbanicity's relationship to health outcomes. Between countries, there are many different definitions of urban or rural. Despite the lack of a standard definition, this study suggests that geospatial covariates can be used as a proxy to predict urbanicity-related health outcomes.

In this study, we examined whether urban-related indicators could be predicted by using a slate of covariates, particularly those that measure urbanicity, and we explored which covariates were most useful. We used a spatial, explicitly Bayesian modeling approach to model the relationship between DHS urban-related outcomes and geospatial covariates. A variable selection procedure determined the covariates, uncorrelated and in combination, that could be used to construct the models. For comparison, two models were developed: (1) a model with all covariates and spatial component (the full model), and (2) a model with covariates only and no spatial component (nonspatial). Results of the model comparison indicated that the model with the spatial component had a much lower DIC scores and thus provided a better fit when compared to the nonspatial model. This suggests that the data in the full model support the presence of spatial autocorrelation (Diggle and Giorgi 2019).

All models worked best when predicting women's agricultural employment. The modeled surfaces clearly show that urban centers are locations where there was little agricultural employment. Women's agricultural employment showed a consensus of covariates that were significant in all models: nightlights and travel times to hospitals. Individual countries and model types might have added additional covariates, although every model found that nightlights and travel times to hospitals were significant. In addition, the relationships between the significant covariates and women's agricultural employment were as expected in all but one model.

The other outcomes produced much more mixed results. The models were able to predict 4+ ANC visits and modern FP methods in most every country and to find significant covariates (with the exception of the 4+ ANC visits spatial model for Burundi). The relationships between population, travel times to hospitals, travel times to populated locations, EVI, BUILT, and the outcomes were as expected. For example, as travel time to a populated location fell in Tanzania, the percentage of women who attended 4 or more ANC visits rose. There were some notable exceptions. The spatial model for 4+ ANC visits in Uganda had a negative association with nightlights, and the nonspatial model for modern FP methods had a negative association with BUILT.

A visual inspection of the modeled surfaces for 4+ ANC visits and modern methods of FP produced none of the compelling results seen with women's agricultural employment. This can be attributed to elevated usage of modern methods of FP and attending 4 or more ANC visits in urban areas, although the change is less drastic. For example, the modern method of FP for Uganda shows the highest levels near Kampala.

We conclude that land-use and demographic covariates, the two accepted components that measure urbanicity (Melchiorri et al. 2018), can be used to make predictions about the health and demographics of residents living in different EAs. If women's agricultural employment is the outcome being modeled, nightlights and travel times to hospitals should be included in the model.

5.1 Future Directions

Our models appear to agree that certain urban-related covariates demonstrate potential relationships with selected DHS indicators. These findings help us understand urbanicity in East Africa. However, this study introduced several new questions to be explored in future studies. What would happen if women's agricultural employment was modeled in other parts of Africa, Latin America, or Asia? Would our finding that nightlights and travel times to hospitals are significant be replicated? What happens when you model the inverse indicator, non-agricultural employment, or unemployment? Do the results differ if a larger tranche of covariates is used to model our outcomes?

Larger questions remain. How do the urbanicity-related covariates compare to the urban-rural classifications used in DHS cluster data? Can these classifications better predict DHS indicators related to urbanicity, or are the classifications as arbitrary as they appear? By comparing the urbanicity-related covariates to the traditional urban-rural classifications used by The DHS Program, a future study might reveal a better system for classifying the urbanicity of clusters. If, for example, our covariates more accurately predict urbanicity-related demographic and health outcomes, they could be used to classify DHS clusters instead of the urban-rural designations assigned by countries.

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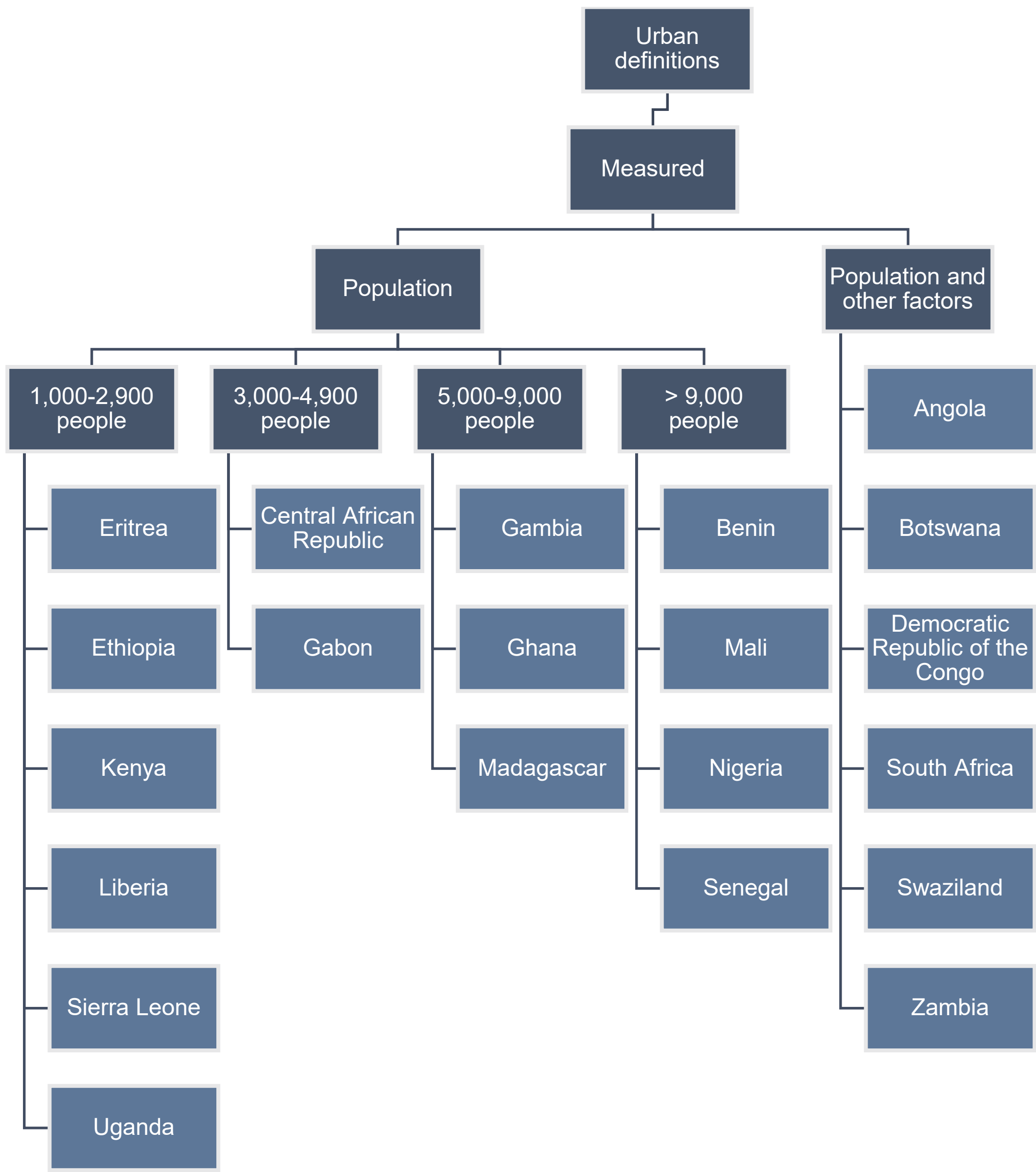
APPENDICES

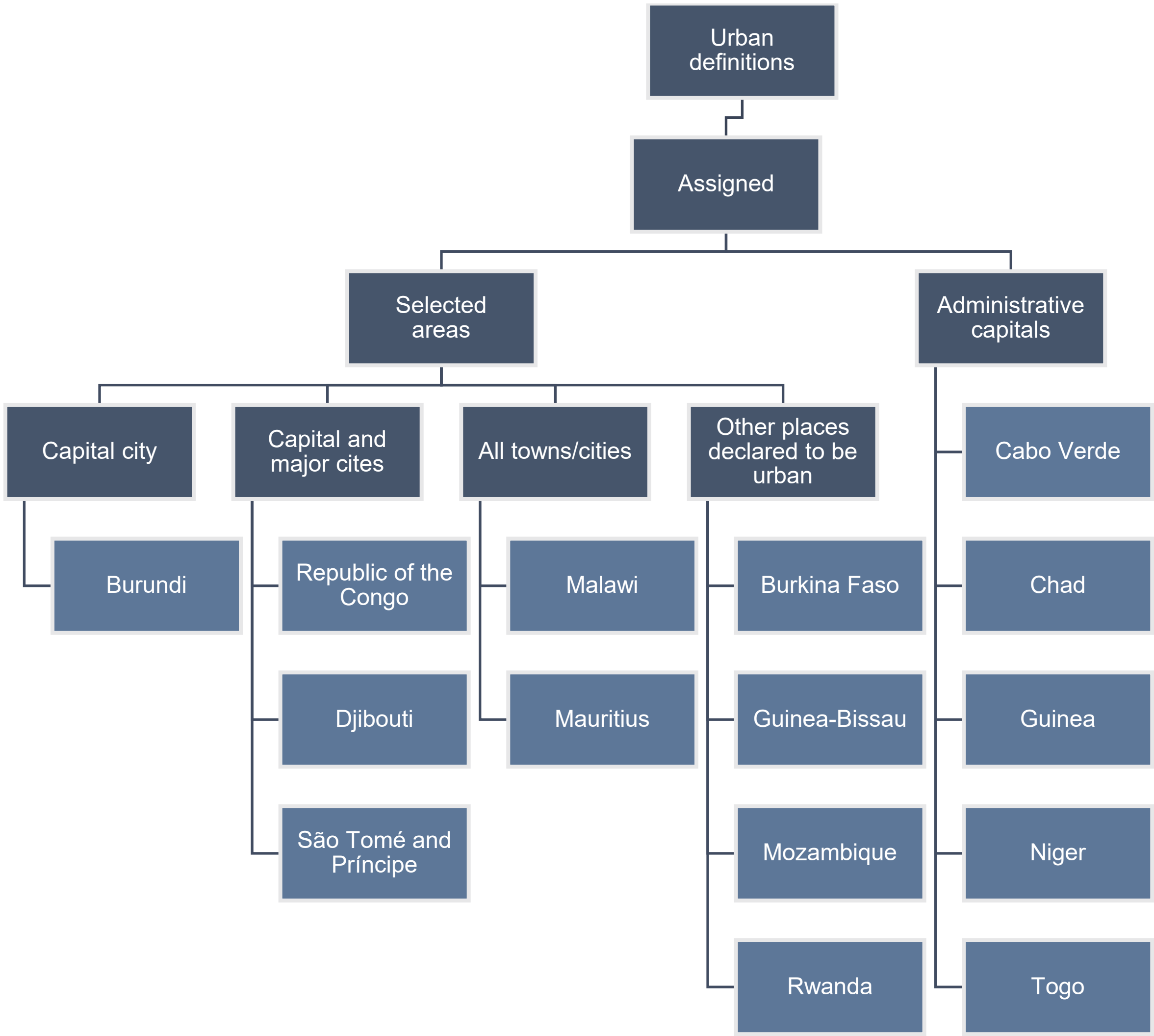
APPENDIX A URBAN AND RURAL TAXONOMY

Figures A1, A2, and A3 were derived from the urban definitions from the United Nations by country and published in the 2018 United Nations World Urbanization Prospectus. The population count found in Figure A1 refers to the cutoff for a small administrative unit such as a town, ward, or village to be considered urban. The population counts in Figure A3 are similar to those in Figure A 1, but may be used with other factors such as employment and infrastructure. See Tables A1 and A2 for the exact definitions.

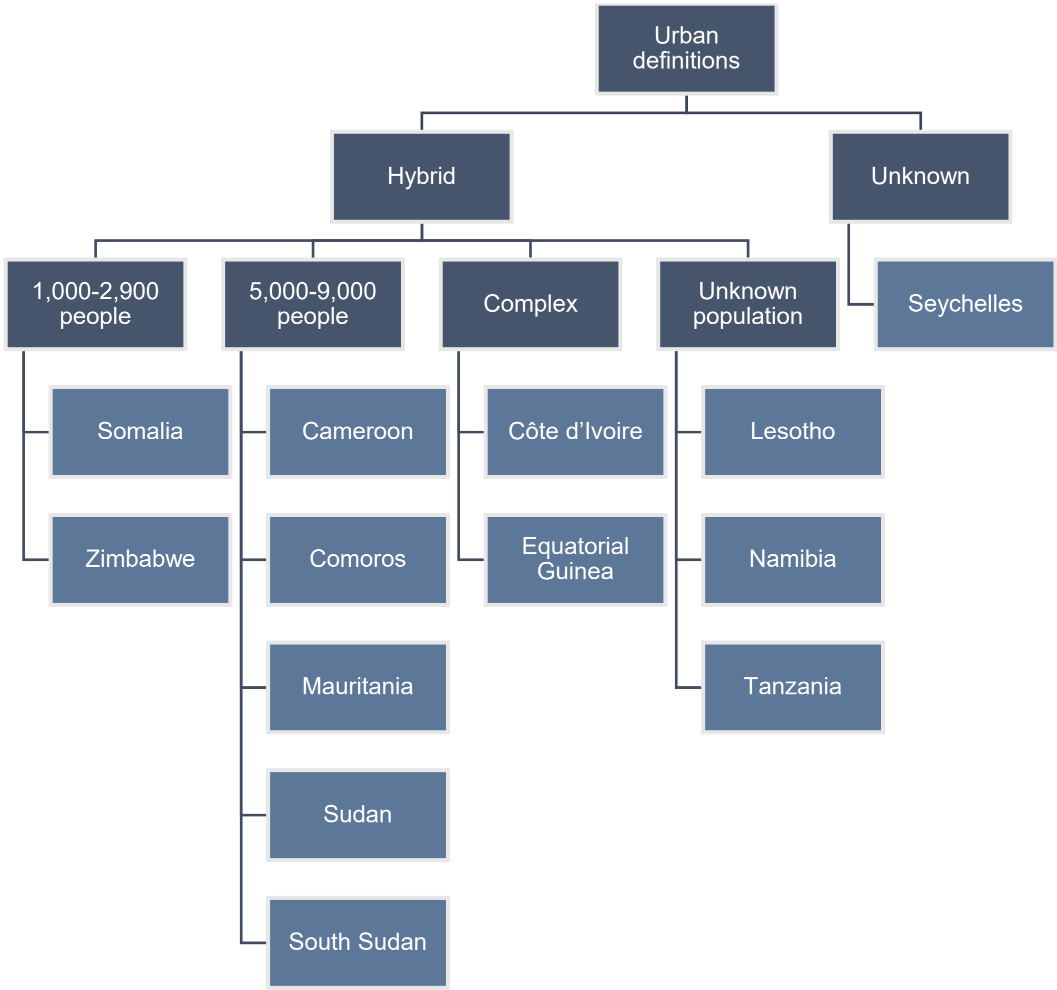
Appendix Figure A1 Measure-derived urban definitions in sub-Saharan Africa



Appendix Figure A2 Assigned urban definitions in sub-Saharan Africa



Appendix Figure A3 Hybrid and unknown urban definitions in sub-Saharan Africa



Appendix Table A1 Urban definitions of sub-Saharan African nations (A–M)

Country	Definition
Angola	Geographic areas with a high population density and concentrated population groups with a high level of infrastructure
Benin	Localities with 10,000 inhabitants or more
Botswana	Agglomerations of 5,000 inhabitants or more where at least 75% of the economic activity is non-agricultural
Burkina Faso	Cities and urban-type communes, officially designated as such, according to socioeconomic characteristics such as a non-agricultural economy
Burundi	Commune of Bujumbura
Cameroon	Administrative centers of territorial units (district, subdivision, division, or province) or any locality with 5,000 inhabitants or more and with sufficient socioeconomic and administrative infrastructures
Cabo Verde	Cities and towns as defined in the administrative division
Central African Republic	Principal centers with 3,000 inhabitants or more
Chad	Administrative centers of prefectures, sous-prefectures, and administrative posts
Comoros	Administrative centers of prefectures and localities with 5,000 inhabitants or more
Côte d'Ivoire	Agglomerations with 10,000 inhabitants or more; agglomerations with between 4,000 and 10,000 inhabitants and with more than 50% of households engaged in non-agricultural activities; and the administrative centers of Grand Lahoun and Dabakala
Democratic Republic of the Congo	Places with 2,000 inhabitants or more where the predominant economic activity is non-agricultural; and places with fewer than 2,000 inhabitants that are considered urban because of their type of economic activity (predominantly non-agricultural)
Djibouti	Djibouti ville, and urban and rural sedentary populations of the regions of Ali Sabieh, Dikhil, Tadjourah, Obock and Arta
Equatorial Guinea	District centers and localities with 300 dwellings or more or with 1,500 inhabitants or more
Eritrea	Localities with 2,000 inhabitants or more
Ethiopia	Localities with 2,000 inhabitants or more
Gabon	Towns with 3,000 inhabitants or more
Gambia	Settlements with 5,000 inhabitants or more
Ghana	Localities with 5,000 inhabitants or more
Guinea	Administrative centers of prefectures
Guinea-Bissau	Cities and towns, officially designated as such, according to the administrative division of the country
Kenya	Municipalities, town councils, and other urban centers with 2,000 inhabitants or more
Lesotho	District headquarters and other settlements with rapid population growth and with facilities that tend to encourage people to engage in non-agricultural economic activities
Liberia	Localities with 2,000 inhabitants or more
Madagascar	Centers with 5,000 inhabitants or more
Malawi	Townships, town planning areas and district centers
Mali	Localities with 30,000 inhabitants or more
Mauritania	Localities with 5,000 inhabitants or more and the administrative centers of departments (moughataa)
Mauritius	Towns with proclaimed legal limits
Mozambique	23 cities and 68 towns/vilas

Appendix Table A2 Urban definitions of sub-Saharan African nations (N–Z)

Country	Definition
Namibia	The district headquarters and other settlements of rapid population growth with facilities that encourage people to engage in non-agricultural activities
Niger	Localities serving as administrative centers, namely, the capital city and the administrative centers of regions and departments
Nigeria	Towns with 20,000 inhabitants or more
Democratic Republic of the Congo	Six communes: Brazzaville, Pointe-Noire, Dolisie/Loubomo, Nkayi, Ouesso, and Mossendjo
Rwanda	Kigali, administrative centers of prefectures and important agglomerations with their surroundings
São Tomé and Príncipe	The district of Água Grande (São Tomé and Pantufo) and 6 other small settlements
Senegal	Agglomerations of 10,000 inhabitants or more
Seychelles	No official definition available
Sierra Leone	Towns with 2,000 inhabitants or more
Somalia	District capitals and towns or villages with 1,500 inhabitants or more
South Africa	A classification based on dominant settlement type and land use. Cities, towns, townships, suburbs, etc., are typical urban settlements. Enumeration areas comprising informal settlements, hostels, institutions, industrial and recreational areas, and smallholdings within or adjacent to any formal urban settlement are classified as urban.
South Sudan	Localities of administrative and/or commercial importance or with 5,000 inhabitants or more
Sudan	Localities of administrative and/or commercial importance or with 5,000 inhabitants or more
eSwatini	Localities officially designated as urban
Tanzania	All regional and district headquarters, as well as all wards with urban characteristics (i.e., exceeding certain minimal level of size-density criteria and/or with many of their inhabitants in non-agricultural occupations). No specific numerical values of size and density are identified, and wards are defined as urban based on the decision of the District/Regional Census Committees.
Togo	21 administrative centers of prefectures
Uganda	Gazetted cities, municipalities and towns with 2,000 inhabitants or more
Zambia	Localities with 5,000 inhabitants or more and with a majority of the labor force not in agricultural activities
Zimbabwe	Places officially designated as urban, as well as places with 2,500 inhabitants or more whose population resides in a compact settlement pattern and where more than 50% of the employed persons are engaged in non-agricultural occupations

Appendix Table A3 Urban definitions of other selected DHS countries (A–N)

Country	Definition
Afghanistan	Sixty-six localities and provincial centers
Albania	Towns and other industrial centers with 400 inhabitants or more
Bangladesh	Localities having a municipality, town committee or cantonment board. In general, urban areas are a concentration of 5,000 inhabitants or more in a continuous collection of houses where the community sense is well developed and the community maintains public utilities, such as roads, street lighting, water supply, sanitary arrangements, etc. These places are generally centers of trade and commerce where the labor force is mostly non-agricultural and literacy levels are high. An area that has urban characteristics but has fewer than 5,000 inhabitants may, in special cases, be considered urban.
Cambodia	Communes that meet at least one of the following criteria: (1) population density exceeding 200 persons per square kilometer, (2) percentage of male employment in agriculture below 50%, or (3) 2,000 inhabitants or more. For 1962 and 1980, municipalities of Phnom Penh, Bokor and Kep, as well as 13 additional urban centers.
Colombia	Administrative headquarters with 2,000 inhabitants or more
Dominican Republic	Administrative centers of communes and municipal districts
Egypt	Governorates of Al-Qahirah (Cairo), Al-Iskandariyah (Alexandria), Bur Sa'id (Port Said), Al-Isma'iliyah (Ismailia) and As-Suways (Suez); frontier governorates; and capitals of other governorates as well as district capitals (markaz)
Guatemala	The municipio of Guatemala Department and officially recognized centers of other departments and municipalities
Haiti	Administrative centers of communes
Honduras	Populated centers with 2,000 inhabitants or more that also meet the following criteria: piped water service; communication by land (road or train) or regular air or maritime service; complete primary school (six grades); postal service or telegraph; and at least one of the following: electrical light, sewer system, or a health center
India	Statutory places with a municipality, corporation, cantonment board or notified town area committee and places satisfying all of the following three criteria: (1) 5,000 inhabitants or more; (2) at least 75% of male working population engaged in non-agricultural pursuits; and (3) at least 400 inhabitants per square kilometer
Indonesia	Municipalities, regency capitals and other places with urban characteristics
Jordan	Localities with 5,000 inhabitants or more as well as the district and sub-district centers of each governorate irrespective of population size
Kazakhstan	Cities and urban-type localities, officially designated as such, usually according to criteria based on the number of inhabitants and the predominance of non-agricultural workers and their families
Kyrgyzstan	Cities and urban-type localities, officially designated as such, usually according to criteria based on the number of inhabitants and predominance of non-agricultural workers and their families
Laos	Areas within municipal vicinity with the center of that municipality having 600 inhabitants or more, or at least 100 households. Further, the areas must have certain urban characteristics (roads, electricity, market function, tap water supply).
Maldives	Male (capital) and other small settlements
Myanmar	No official definition available
Nepal	A complex set of rules varying by ecological zones and based on annual revenue, population size and infrastructure is used

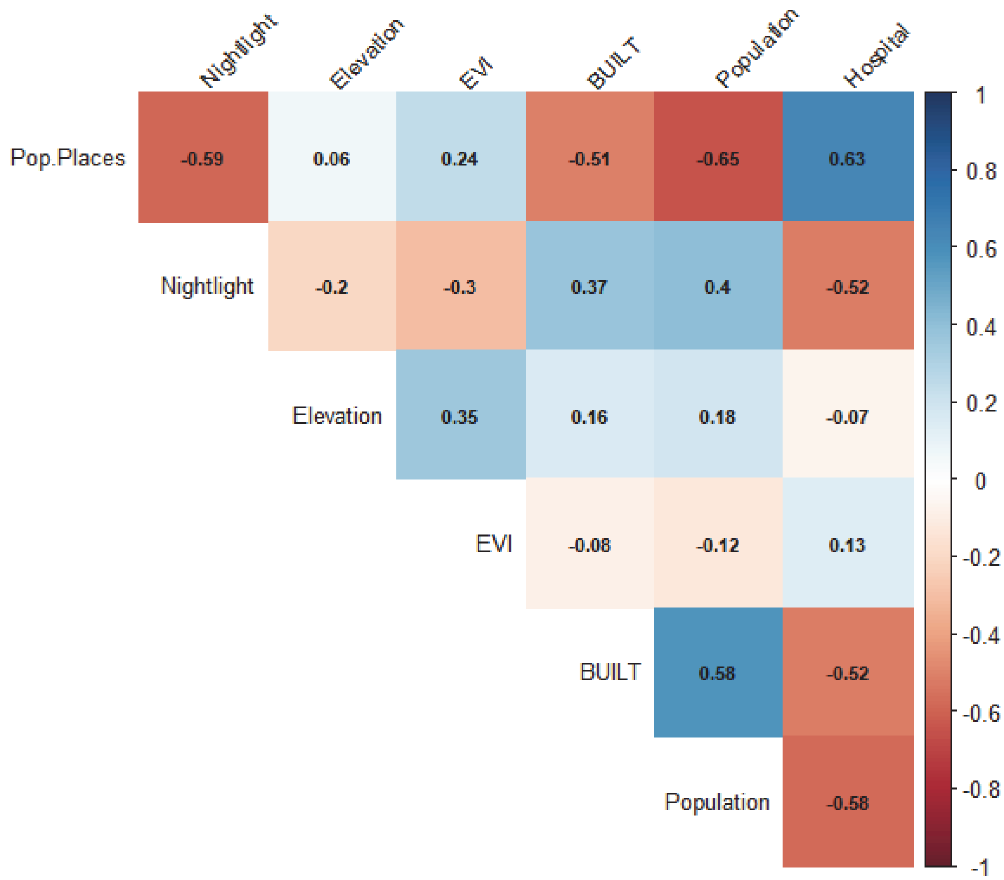
Appendix Table A4 Urban definitions of other selected DHS countries (P–Y)

Country	Definition
Pakistan	Places with municipal corporation, town committee, or cantonment
Papua New Guinea	Centers with 500 inhabitants or more, excluding separately located schools, hospitals, missions, plantations, rural settlements and rural villages regardless of population size
Peru	Populated centers with 100 dwellings or more grouped contiguously and administrative centers of districts
Philippines	Cities and municipalities with at least 1,000 inhabitants per square kilometer; administrative centers, barrios with 2,000 inhabitants or more, and barrios with 1,000 inhabitants or more which are contiguous to the administrative center, in all cities and municipalities with at least 500 inhabitants per square kilometer; and all other administrative centers with 2,500 inhabitants or more
Tajikistan	Cities and urban-type localities, officially designated as such, usually according to criteria based on the number of inhabitants and the predominance of non-agricultural workers and their families
Timor-Leste	Dili and other small settlements designated as urban
Turkey	Localities within the municipality limits of administrative centers of provinces and districts
Ukraine	Cities and urban-type localities, officially designated as such, usually according to criteria based on the number of inhabitants and predominance of non-agricultural workers and their families
Yemen	Capitals of 17 governorates and other towns

APPENDIX B COVARIATE CORRELATION PLOTS

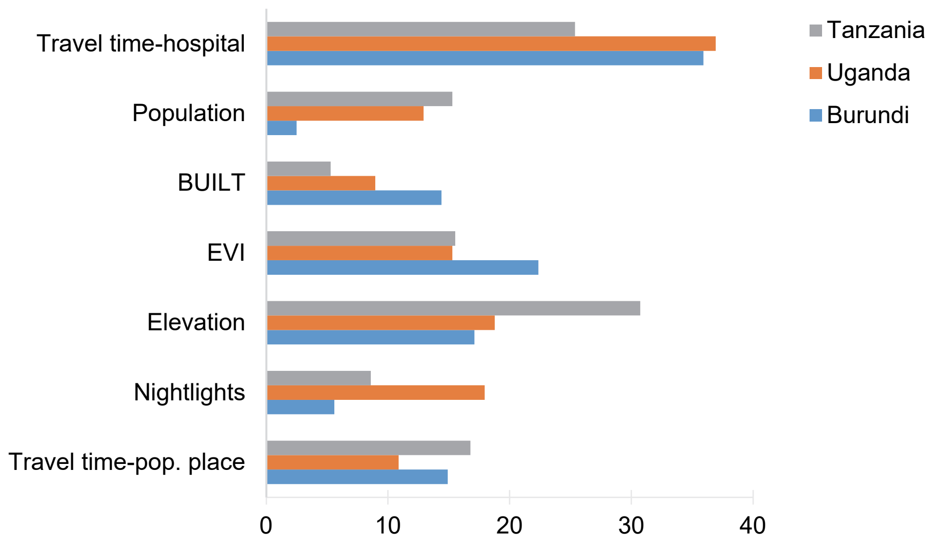
Appendix Figure B1 Correlation matrix for covariates in Tanzania

Appendix Figure B2 Correlation matrix for covariates in Uganda

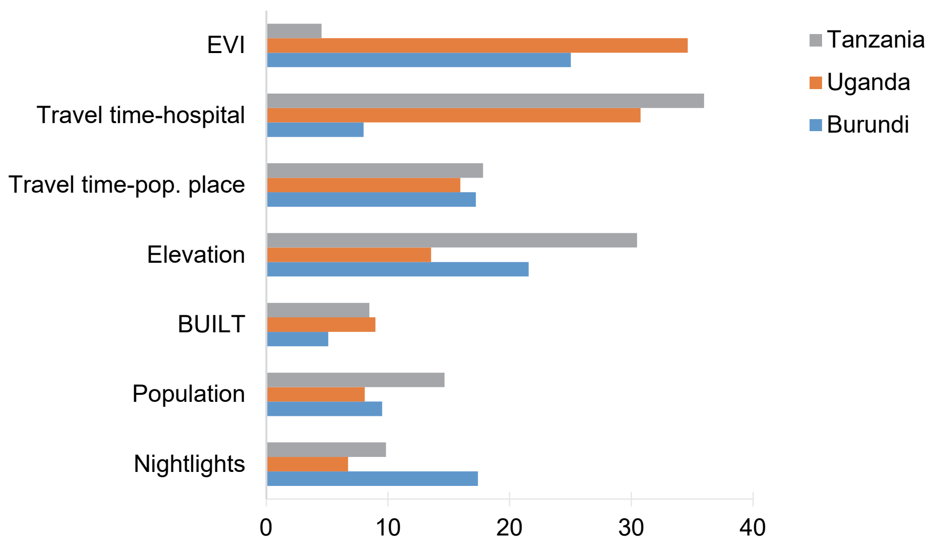


APPENDIX C PERCENT CONTRIBUTION OF THE COVARIATES

Appendix Figure C1 Percent contribution of the covariates for 4+ ANC visits



Appendix Figure C2 Percent contribution of the covariates for modern method of FP



APPENDIX D RESULTS OF THE MODELS BY COUNTRY AND OUTCOME

Appendix Table D1 Posterior estimates (mean and 95% CI) of the 4+ ANC visits models, Burundi

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	0.0279	(-0.0699, 0.1257)	-0.0010	(-0.0452, 0.0432)
Travel time to a populated place	-0.0749	(-0.1642, 0.0141)	-0.0372	(-0.0902, 0.0155)
Nightlights	0.0191	(-0.1104, 0.1489)	-0.0083	(-0.0852, 0.0691)
Elevation	0.0106	(-0.097, 0.1181)	0.0495	(-0.0075, 0.1066)
EVI	-0.0805	(-0.1855, 0.0244)	**-0.1034**	**(-0.1623, -0.0447)**
BUILT	-0.0017	(-0.0898, 0.0863)	0.0296	(-0.0297, 0.0892)
Population	0.074	(-0.0319, 0.1802)	0.0639	(-0.0046, 0.133)
Travel time to a hospital	0.0502	(-0.0343, 0.1348)	**0.0548**	**(0.0043, 0.1053)**
Spatial parameter variance	0.3127	(0.2070, 0.4651)		
Range	0.1789	(0.1014, 0.2767)		

Appendix Table D2 Posterior estimates (mean and 95% CI) of the 4+ ANC visits models, Tanzania

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-0.0016	(-0.2693, -0.0433)	0.0115	(-0.0389, 0.0620)
Travel time to a populated place	**-0.1562**	**(-0.2693, -0.0433)**	**-0.1646**	**(-0.2241, -0.1055)**
Nightlights	0.1094	(-0.0509, 0.2727)	**0.2242**	**(0.0875, 0.3648)**
Elevation	-0.0247	(-0.1738, 0.1243)	**-0.0932**	**(-0.1622, -0.0243)**
EVI	0.0971	(-0.0063, 0.2007)	**0.1305**	**(0.0659, 0.1951)**
BUILT	0.052	(-0.0545, 0.1593)	0.072	(-0.0161, 0.161)
Population	-0.0618	(-0.207, 0.0823)	-0.0661	(-0.2051, 0.072)
Travel time to a hospital	0.0073	(-0.0683, 0.0829)	0.037	(-0.0171, 0.0911)
Spatial parameter variance	0.3628	(0.2262, 0.5586)		
Range	0.5870	(0.3242, 0.9827)		

Appendix Table D3 **Posterior estimates (mean and 95% CI) of the 4+ ANC visits models, Uganda**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	0.4373	(0.3159, 0.5587)	0.4124	(0.3706, 0.4543)
Travel time to a populated place	0.0223	(-0.0784, 0.1229)	0.0424	(-0.0151, 0.1)
Nightlights	**-0.2908**	**(-0.49, -0.0957)**	-0.1274	(-0.2968, 0.0395)
Elevation	0.0082	(-0.0779, 0.0943)	-0.0044	(-0.0479, 0.0392)
EVI	0.0102	(-0.0933, 0.1135)	0.0372	(-0.016, 0.0905)
BUILT	0.0513	(-0.0865, 0.1898)	0.0628	(-0.0484, 0.1749)
Population	**0.2116**	**(0.0401, 0.3844)**	**0.1684**	**(0.0152, 0.3229)**
Travel time to a hospital	-0.0649	(-0.1404, 0.0106)	-0.0224	(-0.0688, 0.024)
Spatial parameter variance	0.2158	(0.1516, 0.2982)		
Range	0.2862	(0.1728, 0.4342)		

Appendix Table D4 **Posterior estimates (mean and 95% CI) of the modern method of FP models, Burundi**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-0.8320	(-0.9617, -0.7026)	**-0.7295**	**(-0.7743, -0.6850)**
Travel time to a populated place	-0.1094	(-0.2271, 0.0065)	**-0.2845**	**(-0.3493, -0.2212)**
Nightlights	0.0087	(-0.1153, 0.1317)	-0.0188	(-0.0924, 0.0523)
Elevation	-0.0927	(-0.2629, 0.0772)	-0.0289	(-0.0881, 0.0306)
EVI	-0.0564	(-0.1929, 0.0808)	**-0.0882**	**(-0.1497, -0.0267)**
BUILT	-0.0372	(-0.1425, 0.0638)	**-0.1769**	**(-0.2546, -0.1046)**
Population	**0.108**	**(0.0185, 0.1981)**	**0.1115**	**(0.0591, 0.1637)**
Travel time to a hospital	0.0586	(-0.0422, 0.1592)	**0.1895**	**(0.1387, 0.24)**
Spatial parameter variance	0.3111	(0.2223, 0.4240)		
Range	0.2522	(0.1433, 0.4056)		

Appendix Table D5 **Posterior estimates (mean and 95% CI) of the modern method of FP models, Tanzania**

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-0.9935	(-1.3622, -0.6250)	-0.9359	(-0.9765, -0.8955)
Travel time to a populated place	**-0.2236**	**(-0.3555, -0.0923)**	0.0291	(-0.0205, 0.0782)
Nightlights	0.0002	(-0.1062, 0.1056)	0.0504	(-0.0276, 0.1274)
Elevation	0.1435	(-0.0127, 0.2993)	-0.03	(-0.0838, 0.0237)
EVI	0.0902	(-0.0036, 0.1842)	**0.1574**	**(0.1075, 0.2073)**
BUILT	-0.0528	(-0.1302, 0.0242)	**-0.1016**	**(-0.1595, -0.0444)**
Population	**0.0828**	**(0.0055, 0.1602)**	**0.0765**	**(0.0045, 0.1485)**
Travel time to a hospital	0.0521	(-0.0276, 0.1316)	-0.0191	(-0.0674, 0.0288)
Spatial parameter variance	0.7733	(0.4796, 1.1897)		
Range	0.6457	(0.4385, 0.9172)		

Appendix Table D6 Posterior estimates (mean and 95% CI) of the modern method of FP models, Uganda

	Spatial		Nonspatial	
	Mean	**95% CI**	**Mean**	**95% CI**
Intercept	-1.9628	(-2.1940, -1.7320)	-1.7885	(-1.8342, -1.7434)
Travel time to a populated place	**-0.1722**	**(-0.2873, -0.0574)**	**-0.1851**	**(-0.2477, -0.1229)**
Nightlights	-0.0864	(-0.2628, 0.09)	-0.0803	(-0.2305, 0.07)
Elevation	0.0203	(-0.0735, 0.1138)	**0.0682**	**(0.0234, 0.1128)**
EVI	**0.289**	**(0.1648, 0.4136)**	**0.2773**	**(0.2185, 0.3364)**
BUILT	0.1176	(-0.0219, 0.2571)	**0.1181**	**(0.0194, 0.2168)**
Population	0.0924	(-0.0678, 0.2521)	0.0874	(-0.0526, 0.2268)
Travel time to a hospital	-0.0637	(-0.1528, 0.0251)	-0.0364	(-0.0894, 0.0163)
Spatial parameter variance	0.4180	(0.2865, 0.5938)		
Range	0.5651	(0.4006, 0.7801)		

Appendix Table D7 DIC values for each model

	Burundi		Tanzania		Uganda	
	Spatial	**Nonspatial**	**Spatial**	**Nonspatial**	**Spatial**	**Nonspatial**
Women's agricultural employment	2613.511	4607.221	2835.206	4992.007	3567.014	5732.424
4+ ANC Visits	2417.721	2676.201	2343.678	2643.768	2900.348	3134.542
Modern Method of FP	2216.868	2752.401	2429.844	3186.614	2792.854	3115.436