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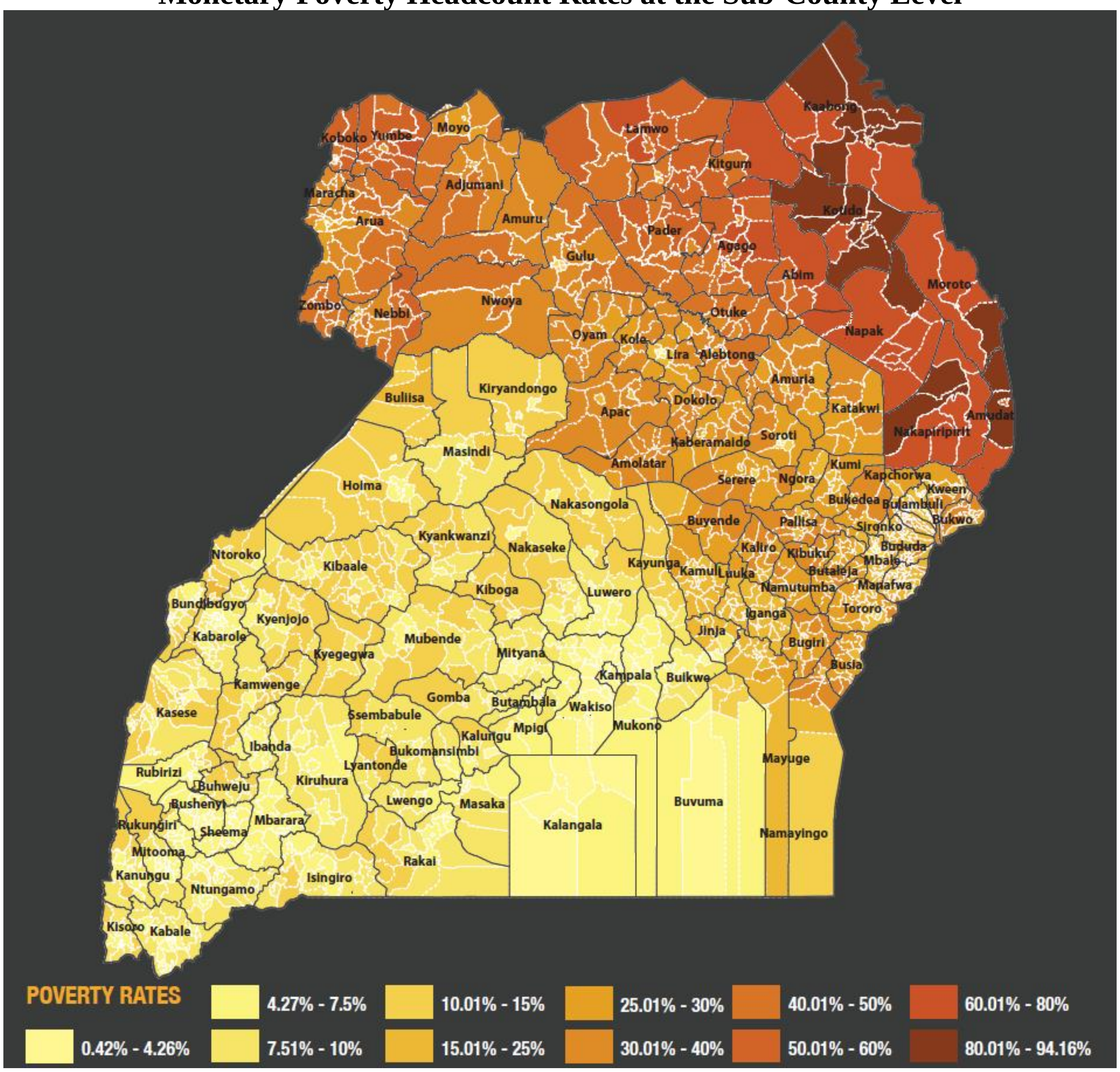
Poverty Maps of Uganda

Mapping the Spatial Distribution of Poor Households Based on Data from the 2012/13 Uganda National Household Survey and the 2014 National Housing and Population Census

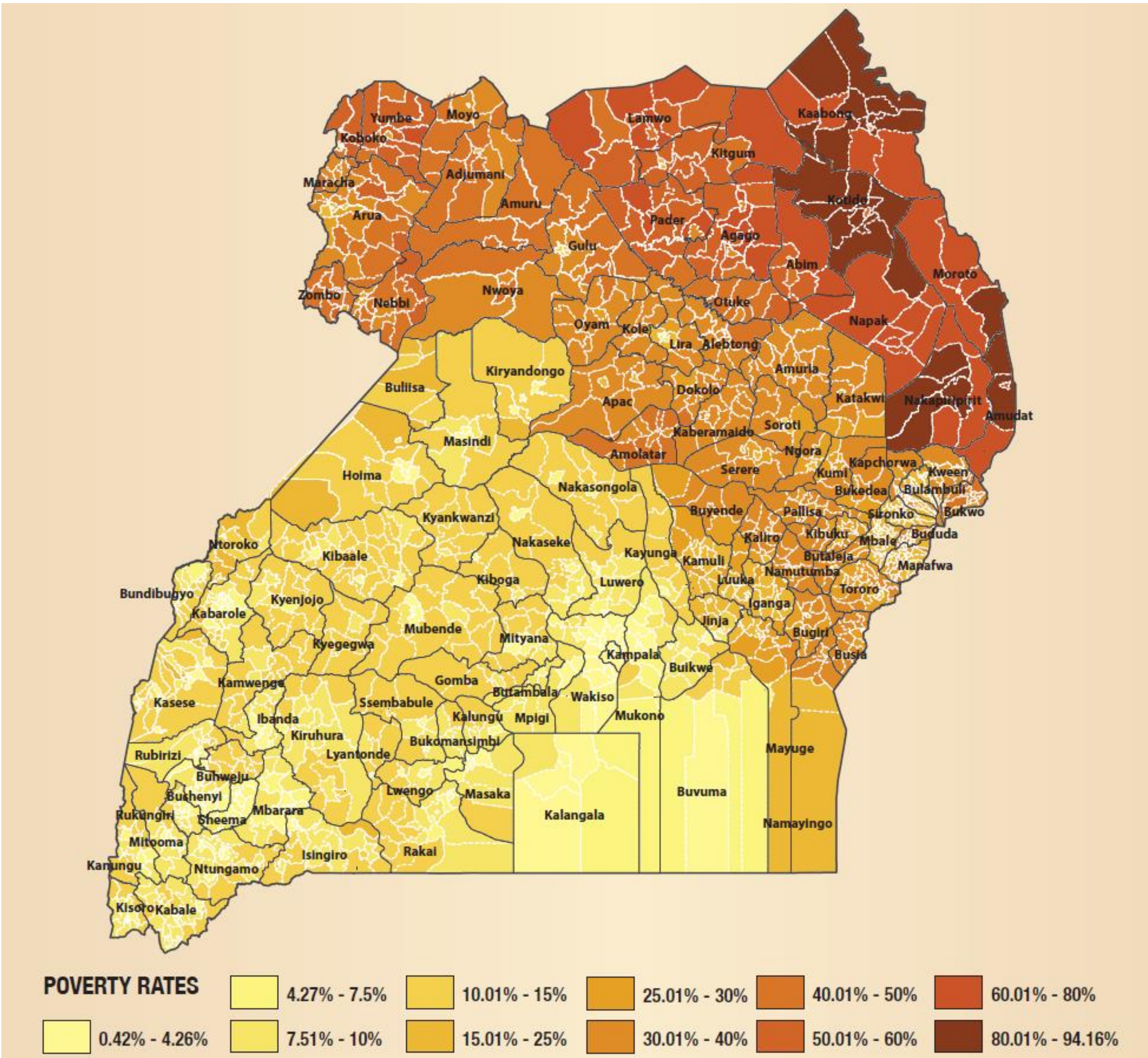
Technical Report

January 2018

Monetary Poverty Headcount Rates at the Sub-County Level



Child Poverty Headcount Rates at the Sub-County Level



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I. Introduction

Over the past two decades, Uganda has achieved remarkable economic growth and substantial poverty reduction. The share of the Ugandan population living below the national poverty line fell from 31.1 percent in 2006 to 19.7 percent in 2013 (UBOS 2013). Meanwhile, the share of the population living on less than US$1.90 per day dropped from 53.2 percent in 2006 to 34.6 percent in 2013, one of the fastest declines in Sub-Saharan Africa (World Bank 2016).

However, income inequality remains high across the country, as evidence by a Gini coefficient of 38.5 in 2013. Economic growth has benefitted the central and western regions more than the relatively isolated northern and eastern regions. Of the total population living below the national poverty line, the share located in the northern and eastern regions increased from 67 percent in 2006 to 84 percent in 2013. Uganda's substantial geographic disparities in patterns of growth and poverty reduction underscore the importance of mapping the distribution of poverty to ensure that policy interventions and external aid effectively target poor households.

Calculating the National Poverty Line

Uganda's national poverty line reflects the estimated cost of meeting basic caloric requirements adjusted for age, gender, and daily activities. The cost of obtaining calories is based on the food basket consumed by the poorest 50 percent of Ugandans in 1993/94. In recognition of changing consumption patterns over the past two decades, the consumption-expenditure module has been expanded to include new types of consumption.

A monetary welfare aggregate based on per capita household consumption expenditure is computed using a detailed consumption-expenditure module included in the household surveys implemented by UBOS every three years. Both food and non-food expenditures are collected over a 12-month period to capture seasonal factors that influence household consumption.

The absolute poverty line was defined by Appleton et al. (1999), following the method developed by Ravallion and Bidani (1994). This method focused on the cost of meeting caloric needs, given the food basket of the poorest half of the population and some allowance for non-food needs. The food poverty line is based on a 3000-calorie food basket, and individual caloric requirements are adjusted according to the methodology used by the WHO (1985).

National poverty rates are expressed in adult-equivalent terms to account for variations in the age and gender of household members. The average monthly consumption expenditure per adult equivalent in 2009/10 prices is UGX 29,100, which is Uganda's current national poverty line. However, statistics based on the national poverty line mask variations in the incidence and severity of poverty across regions and districts. Statistically rigorous, regularly updated poverty maps can greatly enhance the value of national statistics by shedding light on the spatial distribution of both monetary and nonmonetary poverty.

This technical report applies the small-area estimation (SAE) methodology developed by Elbers et al. (2003) to create poverty maps that reflect the findings of the 2012/13 Uganda National Household Survey (UNHS) and the 2014 National Population and Housing Census (NPHS). Ugandan policymakers have long recognized that aggregate national indicators often hide important welfare differences between geographic areas.[1] A similar effort in 2008 generated poverty maps based on UNHS data from 2002/03 and 2005/06. However, these maps are now outdated, and the demand for updated poverty maps is growing among policymakers, donors, and civil society.

To address this demand, the Uganda Bureau of Statistics (UBOS), UNICEF, and the World Bank have launched a joint project to create new poverty maps at the sub-county level. Poverty mapping can be used to estimate poverty incidence for very small spatial areas, for which a typical household income and expenditure survey could not achieve statistically reliable estimates due to high sampling errors. In Uganda, official poverty rates are not produced below the sub-region level—the point at which sampling errors in the UNHS data become non-negligible. Various poverty-mapping methodologies have been devised to overcome the increasing imprecision of more geographically specific poverty estimates. Capitalizing on the extensive socioeconomic data collected by the 2012/13 UNHS and the universal coverage of the 2014 NPHC, the SAE methodology is used to generate four sets of poverty maps capturing regional heterogeneity at the district and sub-county levels, as well as a map of Kampala city uniquely disaggregated at the parish level.

Data-calibration challenges notwithstanding, all area-specific poverty estimations remain faithful to the national and regional poverty profiles issued when the 2012/13 UNHS was released. The creation of new districts and municipalities complicated the process of identifying common administrative areas across the 2012/13 UNHS and 2014 NPHC. The following report describes in detail all methodological elaborations and validation techniques used to safeguard the analytical rigor of the poverty maps.

This report improves upon previous Ugandan poverty maps by including child-poverty estimates across all geographic regions. Close to 60 percent of the Ugandan population is under 18 years of age, and more than 75 percent is under the age of 35. Given this demographic profile, achieving the government's objective of reaching middle-income status by 2040 will hinge on its ability to ensure that today's children reach their full cognitive, socioemotional, and economic potential. In this context, the following report provides strategic guidance designed to improve the targeting of social welfare policies and prioritize distributional equity to reduce poverty and enhance household resilience, especially among vulnerable groups.

Section 2, below, outlines the SAE methodology, explores the dataset, and reviews several key technical challenges. Section 3 explains how the mapping exercise was performed and describes the statistical validation techniques used to verify its accuracy. Section 4 presents the main results of the exercise, including the poverty maps themselves. Section 5 analyses the results and presents a set of policy recommendations designed to accelerate poverty reduction.

[1] See, e.g., UBOS and ILRI (2004).

II. Methodology and Data

II.1. Methodology

The SAE methodology has gained widespread popularity among development practitioners around the world.[2] The SAE approach assigns consumption levels to census households based on a consumption model estimated from the household survey. This consumption model includes explanatory variables (e.g., household and individual characteristics) that are statistically identical in both the census and the household survey. The consumption expenditures of census households are imputed by applying the estimated coefficients to the variables common to both the survey and census data. Poverty and inequality statistics for small areas are then calculated based on the imputed consumption of census households.

In addition to estimating poverty incidence, this approach also produces standard errors of poverty estimates. Poverty estimates are calculated with imputed consumption data and are subject to imputation errors. The authors analyzed the properties of such imputation errors in detail and computed the standard errors of SAE poverty estimates (see Box 1) following Elbers et al. (2003).

II.2. Main Data Sources

The SAE methodology requires data from a household survey and a population census. The NPHC covered roughly 7.3 million households. The census reference night was the night of August 27, 2014 and the enumeration was conducted on a de facto basis. Enumeration began on August 28 and continued to September 7, 2014.[3] The UBOS census team collected a wide range of information on household characteristics, including the age, gender, and education level of household members, their religious affiliation, their livelihood and employment status, the condition of their housing, and the features of their community. Like censuses in other countries, the 2014 NPHC did not include household consumption or income data, but its wide coverage of household characteristics sharpens the precision of imputed household consumption.

[2] For an overview of alternative poverty-mapping techniques, see Bigman and Deichmann (2000).
[3] See UBOS (2014) for more details.

Box 1: The SAE Methodology

The SAE approach developed by Elbers et al. (2003) involves two stages. In the first stage, a model of log per capita consumption expenditure ($\ln y_{ch}$) is estimated based on the 2012/13 UNHS data:

$$\ln y_{ch} = X_{ch}{}' \beta + Z' \gamma + u_{ch}$$

where $X_{ch}{}'$ is the vector of explanatory variables for household *h* in cluster *c*, β is the vector of regression coefficients, Z' is the vector of location-specific variables, γ is the vector of coefficients, and u_{ch} is the regression residuals or errors due to the discrepancy between predicted household consumption and the actual value. This error term is decomposed into two independent components: $u_{ch} = \eta_c + \varepsilon_{ch}$, where η_c is a cluster-specific effect, and ε_{ch} is a household-specific effect. This error structure allows for both a location effect common to all households in the same area and heteroskedasticity in the household-specific errors. The location variables can be any level—district, sub-county, parish, enumeration area, or village—and can be drawn from any data source that includes all locations in the country. All parameters regarding the regression coefficients (β , γ) and distributions of the error terms are estimated by feasible generalized least square.

In the second stage of the analysis, poverty estimates and their standard errors are computed. There are two sources of errors in the estimation process: errors in the estimated regression coefficients ($\hat{\beta}$, $\hat{\gamma}$) and the error terms, both of which affect the accuracy of poverty estimates. To account for these sources of error when calculating poverty estimates and their standard errors, a simulated expenditure value for each census household is calculated with predicted log expenditure $X_{ch}{}' \hat{\beta} + Z' \hat{\gamma}$ and random draws from the estimated distributions of the error terms, η_c and ε_{ch}. These simulations are repeated 100 times. For any given location (e.g., a district or sub-county), the mean across the 100 simulations provides a point estimate of the poverty statistic, and the standard deviation provides an estimate of the standard error.

The 2012/13 UNHS is the fifth in a series of UBOS household surveys that began in 1999. The 2012/13 iteration includes 6,700 households and 10 strata and covers all districts in Uganda. The survey's fieldwork was spread over a 12-month period from June 2012 to June 2013, both to account for seasonality and to enable comparisons with previous surveys. Most variables are representative at the national and sub-regional levels. There were 10 sub-regions in 2012/13.

Like previous household surveys, the 2012/13 UNHS used a population census (conducted in 2002) as its sampling frame. The sample was designed to allow for reliable estimates of key indicators at the national, rural-urban, regional, and sub-regional levels. A two-stage stratified sampling design was used. At the first stage, enumeration areas were grouped by district and rural/urban location, then drawn using the probability proportional to size. At the second stage, households designated "ultimate sampling units" were drawn using systematic random sampling.[4]

[4] See UBOS (2013) for more details.

The UNHS collects detailed data on consumption and income and contains a wealth of information on employment, ownership of assets, housing condition, and access to services such as education and healthcare. This large set of variables helps precisely impute household consumption into the census data. When designing the UNHS 2012/13, deliberate efforts were made to include variables that were also recorded by the NPHC. For example, the questions about housing conditions in the UNHS were almost identical to those in the NPHC. The prior synchronization of variables during the design of UNHS facilitated the matching of variables in the household survey and the census. This synchronization, and the short interval between the 2012/13 UNHS and the 2014 NPHC, present a unique opportunity to precisely estimate poverty indicators at a highly disaggregated level.

II.3. Technical Challenges

II.3.1. Evolving Administrative Boundaries and Classifications

Before a poverty-mapping exercise can be initiated, the geography file must be checked and updated. This file usually includes location codes for different administrative levels and dictates how these codes are organized. The poverty maps produced by the exercise will reflect the location-code system defined by the geography file.

In Uganda, the geography file consists of seven administrative levels: region, sub-region, district, county, sub-county, parish, and enumeration area. Another level, constituency, was added to the geography file for this poverty-mapping exercise. The constituency level is not part of the NPHC location-code system and does not fully align with it. However, a poverty map at the constituency level can be highly useful to policymakers, as it provides detailed poverty information for the communities they represent. UBOS staff conducted a detailed assessment of how constituencies related to the NPHC location-code system and successfully constructed a hierarchical location-code system that includes both constituencies and enumeration areas. The Uganda poverty-mapping update was successfully completed using the NPHC geography file and the constituency location-code system.

However, frequent and unpredictable changes in the boundaries of administrative units posed a serious challenge to the exercise. In addition to the creation of new administrative structures such as districts, municipalities, town councils, sub-counties, and parishes, several rural areas were reclassified as town councils or municipalities. All such changes were meticulously incorporated into the final geography file.

To ensure geographic accuracy, the location-code system for household survey data must be identical to the system for census data. In Uganda, UBOS drew a sample of the 2012/13 UNHS data from a sampling frame based on the 2002 NPHC. UBOS updated the location-code system for the 2012/13 UNHS to be fully consistent with the new geography file. UBOS matched the geography file based on the 2002 NPHC with that of the 2014 NPHC, then matched the latter with the new geography file, incorporating all changes to administrative boundaries and classifications that occurred after the previous census enumeration. The result was a 15-digit hierarchical geocode representing various administrative level (Table 1).

Table 1: The 15-Digit Geocode

1st digit	Region
2nd and 3rd digit	Sub-Region
4th, 5th and 6th digit	District
7th digit	County
8th and 9th digit	Sub County
10th and 11th digit	Parish
12th and 13th digit	Village
14th and 15th digit	Enumeration Area

This geocode incorporates all changes to the geography file since the previous enumeration was completed. These include: (i) the addition of new districts, sub-counties, and other administrative units, (ii) changes in geographic relationships between districts, sub-counties, and smaller administrative areas; (iii) the consolidations of multiple administrative areas; (iv) changes in the status of certain areas as either part of, or independent from, the surrounding administrative area; and (v) changes in the boundaries of administrative units within districts.[5] A separate geocode was used to produce poverty maps for constituencies.

II.3.2. Regional Heterogeneity

Adjusting for regional variations in consumption is critical to the accuracy and statistical validity of the SAE approach.[6] The SAE methodology requires constructing a consumption model that is fixed for all households within a domain. This process assumes that the relationship between household spending and its proxies is the same for all households, implying that all remaining differences are due to errors rather than structural factors.[7] Instead, we introduce multiple models so that regression coefficients and error structures can adjust to the regional variations in consumption.

PovMap2, the World Bank's poverty-mapping software, can incorporate two layers of errors (or residuals), which are typically at the levels of the household and one administrative unit. In addition to household-level errors, the consumption model presented here includes errors at the enumeration-area level. This does not mean, however, that there is no correlation in errors at the district or sub-county levels. Ignoring large district- or sub-county-level correlations in household expenditures after controlling for observables can cause a substantial bias in the standard errors of poverty estimates. An obvious solution to this issue is to introduce multiple layers of errors during the consumption modeling. However, this is not a solution for practitioners, since PovMap2 currently allows for only two layers of errors. Instead, our strategy is to include variables at the

[5] Two enumeration areas covered in the UNHS could not be located in the census data and were not used to produce the poverty maps. The creation of new districts after the 2014 NPHC gave rise to town councils and municipalities, and some nearby communities were annexed into these newly created urban areas, and their names were changed. Consequently, not all merged enumeration areas could be identified.

[6] See more in Tarrozi and Deaton (2008).

[7] Admittedly, this is a strong assumption. Both Tarrozi and Deaton (2008) and Elbers et al. (2003) acknowledge that this can cause a bias in poverty estimation. Tarrozi and Deaton (2008) also warn that misspecification in error structure can cause a large bias in standard errors of the resulting poverty estimates.

district and sub-county levels in regression models so that correlations in errors at these levels are minimized by explicitly capturing them by observable variables. [8]

However, as there is no technique to fully eradicate these types of potential bias, the original analysis was complemented by a series of validation exercises, which provide empirical evidence to support the reliability of the derived disaggregated poverty estimates.

III. Constructing the 2017 Uganda Poverty Maps

Two key challenges emerged during the process of constructing the Uganda poverty maps: selecting a good consumption model, and choosing an appropriate level of disaggregation. This section details the analytical methodology used to produce Uganda's 2017 poverty maps. The final models are listed in Table A-1 of Annex 1.

III.1. Model Selection

(a) The number of consumption models

As discussed above, to respond to differences in consumption patterns across regions, the 2017 Uganda poverty maps are based on five different consumption models, each of which corresponds to a stratum defined for the 2012/13 UNHS. The strata reflect differences across regions. Uganda's capital city, Kampala, comprises its own stratum due to the unique nature of its consumption dynamics and economic characteristics. As noted above, inadequate adjustment to reflect regional differences in consumption patterns can cause a significant bias in the poverty estimates and corresponding standard errors produced by the SAE approach. For example, the educational attainment of a household head might be a stronger predictor of household wealth in urban Kampala than in the largely agricultural northern region. Applying the same model to the whole country may thus increase the risk of bias in poverty estimates and standard errors.

However, increasing the number of consumption models does not necessarily improve the statistical performance of poverty mapping. As the number of models increases, the sample size of the 2012/13 UNHS data for each model declines, reducing the accuracy and stability of each consumption model.

To balance the necessity of adjusting for regional heterogeneity with the corresponding reduction in sample size, five consumption models were created, one for each 2012/13 UNHS stratum. This approach is reasonable, as the sampling frame used for the 2012/13 UNHS also reflects regional variations across five strata.

(b) The fitness of consumption models by R-square and adjusted R-square

Both R-squared and adjusted R-square provide information on how well a consumption model can predict the actual consumption expenditures of each census household. R-square, or the coefficient of determination, represents the ratio of "explained variance" (i.e., the variance in household consumption expenditures predicted by the model) to the total variance of actual household expenditures. The higher the R-square, the better predicted expenditures fit actual expenditures. Adjusted R-square is modified to reflect the number of variables in the model. R-square always

[8] See, World Bank, 2003; Zhao and Lanjouw, 2008; and Elbers et al., 2008.

increases when a new variable is added to a model, but adjusted R-square increases only if the new variable improves the model more than would be expected by chance. The R-square and adjusted R-square for the models are both high across all regions, with exception of the eastern region, where the adjusted R-square is equal to 35.2 percent (Table 2).

Table 2: The Distribution of R-square (R^2) and Adjusted R-square ($AdjR^2$) by Stratum

Stratum	Name	R^2	$AdjR^2$
1	Kampala	0.567	0.558
2	Central (excluding Kampala)	0.525	0.519
3	Eastern	0.360	0.352
4	Northern	0.506	0.498
5	Western	0.455	0.448

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC

(c) The share of variance of residuals at the enumeration-area level

The consumption model cannot explain all variations in household expenditure. Unexplained variations are commonly associated with residuals, or simply errors, which have two layers in this analysis: enumeration area (EA) and household. EA-level residuals are included because the unexplained part of consumption expenditure can be affected by region-specific factors. Some of these factors are observable, while others may not be. The performance of poverty mapping is considered poor if the variance in EA-level errors constitutes more than 10 percent of the variance of total error. PovMap2 reports the EA-level variance as a proportion of the variance in total error. In this analysis, the proportion of EA-level error is less than 10 percent for all regions (Table 3).

Table 3: The Proportion of EA-level Error to Total Error

Stratum	Proportion
Central (excluding Kampala)	7.1%
Eastern	5.9%
Kampala	5.9%
Northern	4.4%
Western	5.0%

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC

(d) Effects of ignoring errors at levels above enumeration area

As discussed in the previous section, if correlations in household expenditures at levels higher than EAs are large, point estimates of poverty rates and their standard errors can be substantially biased.[9] In principle, this risk can be addressed directly by including error terms at multiple administrative levels, but as noted above, PovMap2 can include error terms for only one administrative unit. An alternative approach is to test for large correlations by carrying out a simple multi-layer random effect model.[10] This estimation procedure allows for more than two layers of errors, but it is more limited than PovMap2 in that it cannot be prevented from introducing heteroskedasticity at the household level. It also differs in terms of optimization because it uses maximum likelihood for estimating coefficients, while the SAE methodology and PovMap2

[9] Deaton and Tarrozzi (2008).
[10] The model used here is based on Elbers et al. (2008).

software apply generalized least squares. Despite these differences, this approach is still useful to examine the relevance of accounting for errors at different administrative levels, which are measured by the ratio of the variance of these errors to the total error variance.

Table 4: The Contribution of Errors at Different Administrative Levels

	Kampala	Eastern	Western	Northern	Central
EA	6.8%	0.0%	0.0%	4.8%	1.1%
Parish	0.0%	1.6%	3.8%	1.4%	5.1%
Sub-county	0.0%	3.7%	0.0%	1.4%	0.0%
County	0.0%	0.0%	0.7%	4.0%	1.6%
Household	93.2%	94.7%	95.5%	88.5%	92.2%

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.
Note: These calculations were performed using a STATA's command.

In most strata, the contribution of errors at administrative levels higher than the EA is limited to no more than 5.1 percent. Most errors are concentrated at the EA level and the household level, and can be accounted for explicitly by PovMap2.

(e) Incidence of trimming

A low incidence of outliers in the simulated household expenditures of census households is another important selection criterion for consumption models. The SAE method simulates household expenditures for all census households, randomly drawing parameters (including both regression coefficients and residuals) from the distributions estimated from a consumption model. While the probability of drawing outliers is low, the simulated household expenditures do tend to have a few of them, which can have a nonnegligible bias on estimates of inequality. PovMap2 controls for outliers by dropping them before estimating poverty and inequality indicators. Trimming is a pragmatic solution, rather than one derived from statistical theory, and estimating poverty and inequality indicators from consumption models with less incidence of trimming are more statistically rigorous. Therefore, at the stage of modeling, we tried to select models that have a low incidence of trimming. An analysis across administrative levels confirms that the incidence of trimming remains low even at the sub-county and parish levels (Table 5).

Table 5: The Incidence of Trimming at Various Administrative Levels[11]

Percentile	**Share of trimmed simulated expenditures (%)**		
	District	Sub-county	Parish*
Median	0.07	0.04	0.07
95%	0.26	0.18	0.36
Max	0.6	1.84	4.71

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.
Note: * Kampala only

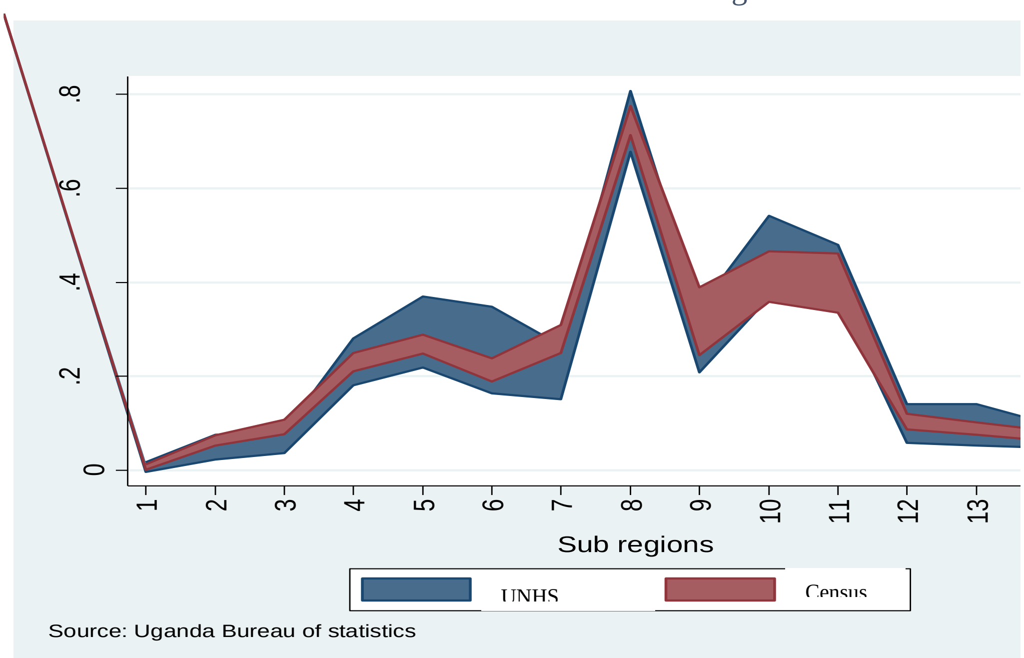
(f) Consistency in sub-regional poverty estimates between direct estimation based on 2012/13 UNHS data and the SAE method

[11] This table summarizes the incidence of trimming at different administrative levels if the final consumption models were adopted. Each administrative level is ranked by incidence of trimming (the share of trimmed simulated expenditures) at the median, the 95th percentile, and the maximum number. This analysis confirms that all strata and districts require a very low incidence of trimming.

Although the 2012/13 UNHS is not representative at the level of the 15 sub-regions, a reasonable sample size is available for each stratum. Sub-regional poverty estimates based on household expenditure data from the 2012/13 UNHS are thus good predictors of true poverty incidence. The SAE method can also estimate poverty rates at the sub-region level, which should, in principle, predict the true level of poverty incidence. Consequently, the SAE estimates should be consistent with those derived from the household expenditure data in the 2012/13 UNHS.

This consistency check is conducted using the 95 percent confidence intervals of both estimates. Since the 2012/13 UNHS and the SAE method both produce poverty estimates, rather than true numbers, their 95 confidence intervals were constructed to illustrate margins of error—i.e., the extent to which their poverty estimates may be inaccurate. The two estimates are considered to be consistent if their 95 percent confidence intervals overlap. This consistency check shows that both estimates are consistent across all strata (Figure 1). Moreover, the poverty estimates produced by the SAE method for most sub-regions have substantially smaller 95 percent confidence intervals than the estimates based on the 2012/13 UNHS data. This indicates that the SAE method can yield more accurate poverty rates than direct estimates from the 2012/13 UNHS.

Figure 1: A Comparison between Sub-Regional Poverty Incidence Directly Estimated from the 2012/13 UNHS and Obtained through the SAE Method



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Note: red area illustrates the 95 percent confidence interval of SAE, while the blue that of the UNHS 12/13.

III.2. The Level of Disaggregation

The SAE method's margin of error tends to increase at lower administrative levels. Examining standard errors can identify the level of disaggregation where the level of precision of poverty estimates is acceptable. The analysis shows that the standard errors of poverty estimates at the sub-region, district, and even sub-county levels are relatively small (Table 6). For example, the largest standard error among all district estimates is just 5.7 percentage points. At the sub-county level, the standard errors are significantly higher than those at the district level, but except for the top 5 percent, the standard errors are less than 10 percent or so.

Table 6: Standard Errors at Various Administrative Levels

Percentile	**Standard Errors of Poverty Estimates (%)**		
	Sub region	District	Sub-county
Median	1.5	2.4	5.6
95%	3.7	5.0	10.8
Max	3.7	5.7	13.7

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

IV. Key Features of the 2017 Uganda Poverty Maps

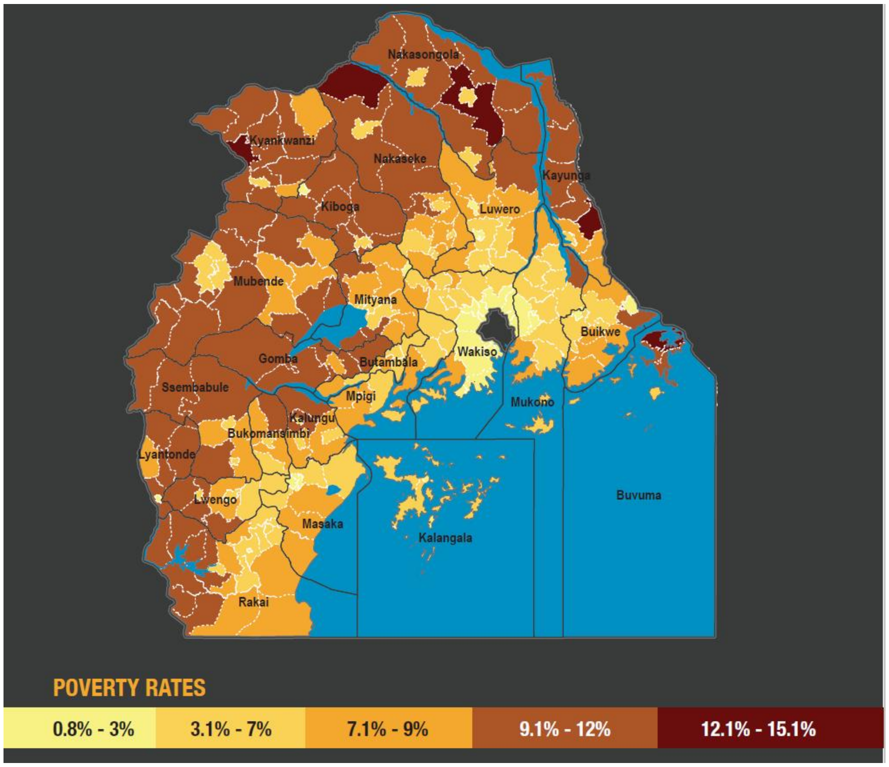
IV.1. The Value of Poverty Mapping

This section presents a new round of poverty analysis and mapping in Uganda. The methodology described above yields reliable indicators at multiple administrative levels. Poverty maps offer the authorities a clear view of the evolving distribution of poverty across regions and localities. They also provide an opportunity for officials at multiple government levels to evaluate the effectiveness of the poverty-reduction policies implemented in their respective areas.

IV.2. The Incidence and Distribution of Poverty in the Central Region

Uganda's national poverty estimates mask wide variations across regions. According to the 2012/13 UNHS, 19.7 percent of the population is below the national poverty line, but the poverty rate for the central region is just 7.8 percent. The districts of Gomba, Kayunga, Kyankwanzi, and Nakasongola have the highest poverty incidence in the central region, though at about 10.3 percent each, even these rates are still well below the national average. Wakiso district, which includes Entebbe and much of suburban Kampala, has the region's lowest poverty rate at about 2 percent (Figure 2).

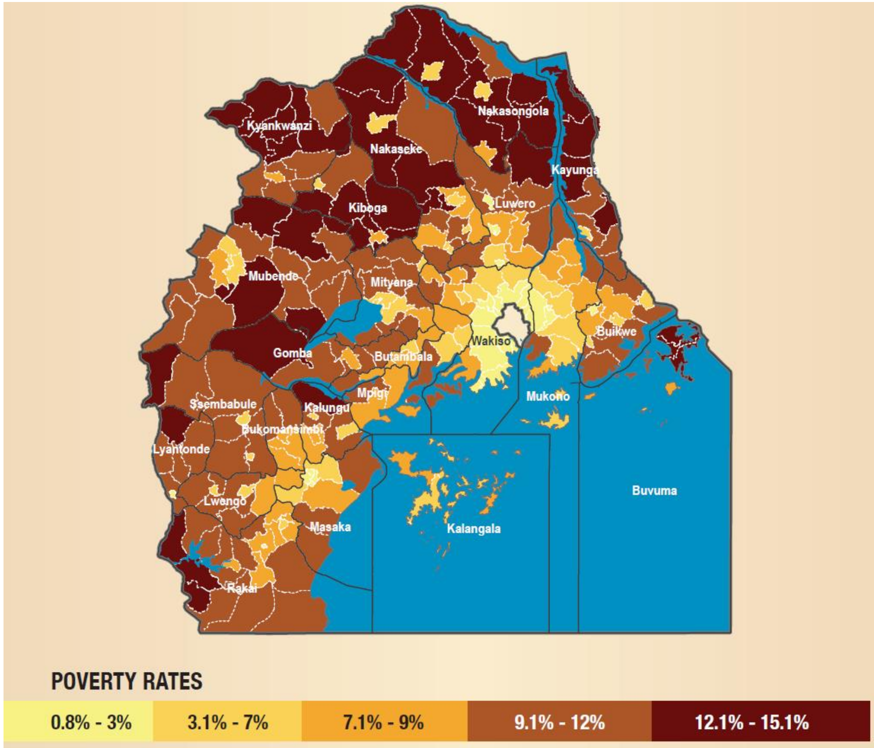
Figure 2: Poverty Incidence by Sub-County, Central Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Poverty impacts demographic groups differently. Children are particularly vulnerable to the negative effects of poverty and related forms of deprivation associated with the welfare status of the households in which they reside. Within the central region, the incidence of child poverty is highest in the districts of Kyankwanzi, Nakasongola, and the Buvuma Islands, where over 12 percent of children are below the poverty line. Child poverty rates in the districts of Kalungu, Lyantonde, Mubende, Kiboga, and Gomba also exceed 10 percent. Wakiso district has the lowest rate of child poverty at 2.4 percent (Figure 3).

Figure 3: Child Poverty Incidence by Sub-County, Central Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

While poverty rates differ substantially by district, inequality is prevalent across all districts in the central region. The Gini coefficient is lowest in Buvuma and Kyankwanzi districts at about 0.33 and highest in Masaka and Mukono districts at 0.38. Relatively low levels of income inequality are observed in districts with relatively high levels of income poverty, indicating that the low income levels of these two districts are relatively uniform. Overall, the ranking of districts by inequality level is the same for children and for the overall population. The districts of Masaka and Mukono have high levels of inequality among children and among the population as a whole.

While the central region has Uganda's lowest regional poverty rate, the incidence of poverty varies substantially at the district and sub-county levels. Kinoni sub-county in Nakaseke district and Byerima sub-county in Kyankwanzi district have the highest poverty rates at about 13 percent, while poverty rates are extremely low in virtually all sub-counties in Wakiso district. Child poverty rates are highest in Buwooya and Busamuizi sub-counties in Buvuma district, Byerima in Kyankwanzi district, and Kinoni in Nakaseke district, where about 15 percent of children live in poverty. Again, Wakiso district has the lowest rates at about 1 percent in almost all sub-counties. Child poverty rates are especially low in Nyendo/Ssenyange in Masaka municipality and Lyantonde town council.

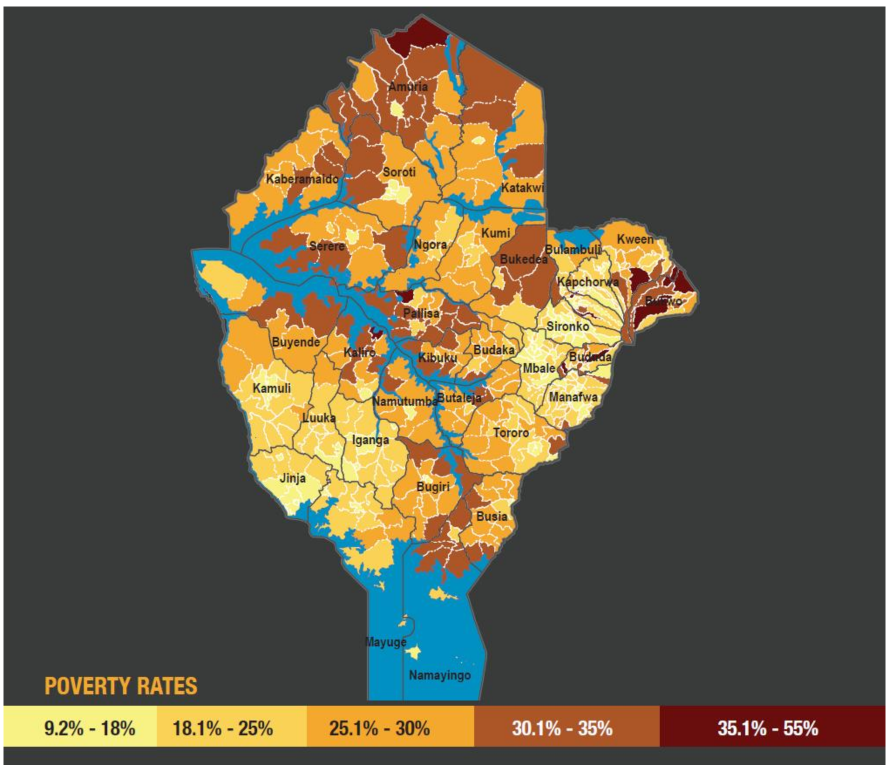
The greatest levels of inequality in the central region are found in urban areas. The Gini coefficient is highest in the Western Division municipality of Mubende (0.39) and the lowest in Butoloogo sub-county in Mubende district and Kiziba sub-county in Rakai district (0.30), indicating substantial variations in inequality across districts.

IV.3. The Incidence and Distribution of Poverty in the Eastern Region

At 24.5 percent, the overall poverty rate in the eastern region is significantly higher than the national rate (19.7 percent), and 27.6 percent of children in the eastern region live below the national poverty line. Poverty rates vary between sub-regions, ranging from 21 percent in Bugisu/Sebei to 28 percent in Teso. The gap between the poor and non-poor is narrow in the eastern region, and inequality is low and relatively uniform: Gini coefficients range from 0.29 in Teso to 0.30 in Busoga. At the district level, Bukwo district has the highest poverty rates both for children (34 percent) and the population as a whole (31 percent).

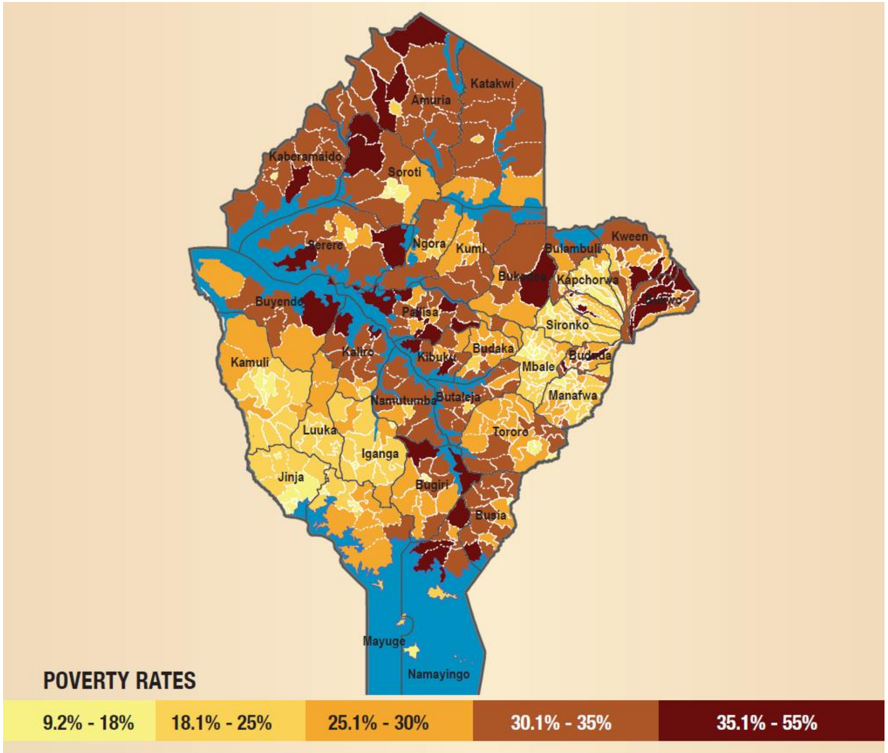
At the sub-county level, poverty rates vary widely. Bulegeni town council in Bulambuli district was the poorest sub-county, with a poverty rate of 51 percent, while Kwosir sub-county in Kween District was the second-poorest at 35 percent (Figure 4). Of the region's 13 poorest sub-counties, ten are located in the Bugisu/Sebei sub-region. Overall poverty and child poverty are closely correlated in the sub-counties of the eastern region (Figure 5).

Figure 4: Poverty Incidence by Sub-County, Eastern Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Figure 5: Child Poverty Incidence by Sub-County, Eastern Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

IV.4. The Incidence and Distribution of Poverty in the Northern Region

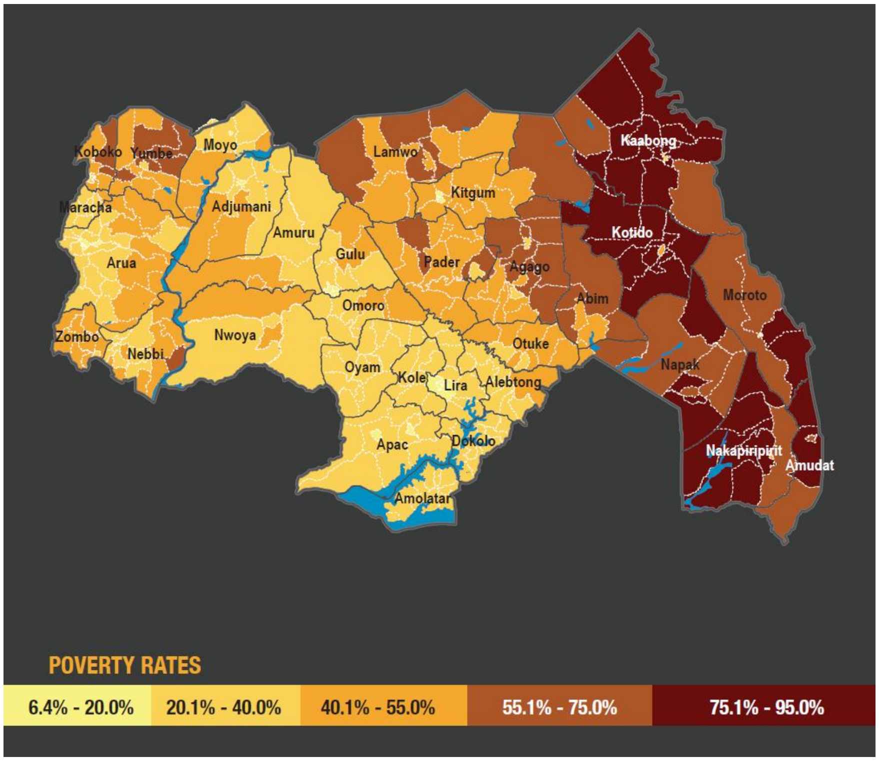
The incidence of poverty in northern Uganda is the highest in the country at 42 percent, far above the national average of 19.7 percent. An estimated 45 percent of children in the northern region live in households below the national poverty line. Inequality indicators are also very high. The Gini coefficient is 0.38 for the entire population and 0.37 for children. Inequality indicators are also high in each of the four sub-regions; Gini coefficients range from 0.34 in the Lango sub-region to 0.38 in the Karamoja sub-region.

There are vast disparities in poverty incidence between sub-regions. The poverty rate in the Lango sub-region is 32 percent, the lowest rate in northern Uganda, but still well above the national average. The Karamoja sub-region has the highest poverty rate in northern Uganda at 74 percent. Moreover, poverty is extremely prevalent across Karamoja: in five of the sub-region's seven districts, more than 7 of every 10 people live below the poverty line. The same ratio applies to children in all districts except Abim. Kotido district has the highest rates of both poverty and child poverty at 82 percent and 83 percent, respectively.

The Acholi sub-region has northern Uganda's second-highest poverty incidence, followed by the West Nile sub-region. Outside of Karamoja, the districts with the highest poverty rates are Lamwo (53.8 percent), Agago (52.9 percent), and Yumbe (51.7 percent). These are the only districts outside of Karamoja where more than half of the population lives in poverty.

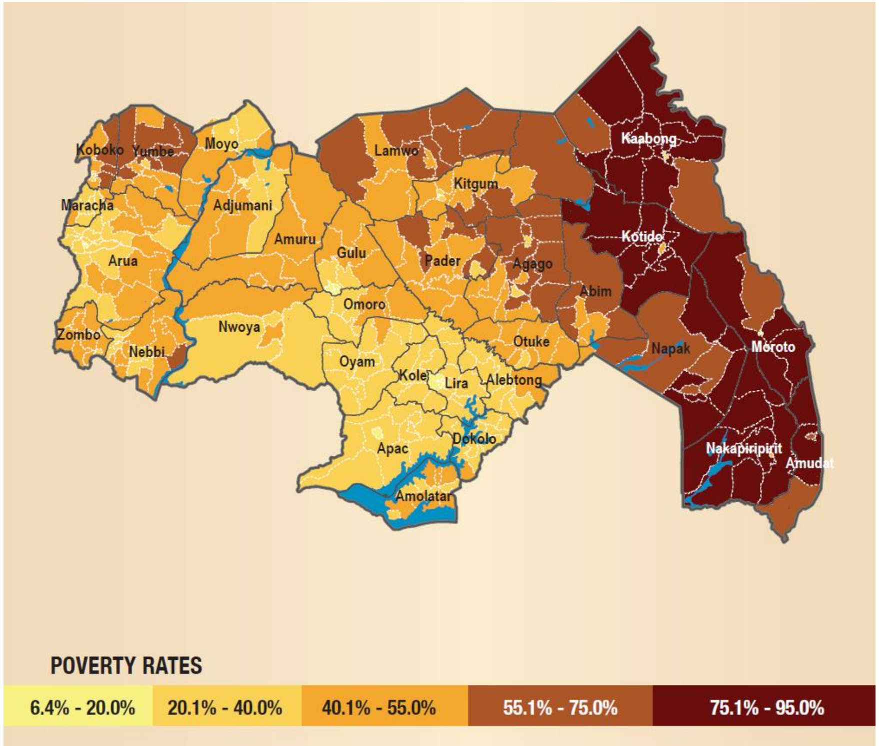
All of the sub-counties with the highest poverty rates—ranging from 65 percent to 95 percent—are located in Karamoja (Figure 6). The Karamoja sub-region also includes 44 of the 47 districts where poverty rates exceed 65 percent. Kawalakol sub-county in Kaabong district has the highest poverty incidence in the entire northern region: its poverty rate is 94 percent for the whole population and 95 percent among children (Figure 7).

Figure 6: Poverty Incidence by Sub-County, Northern Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Figure 7: Child Poverty Incidence by Sub-County, Northern Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Generally, towns and municipalities tend to have a lower incidence of poverty in the northern region. Even in Moroto district, part of the Karamoja sub-region, the Northern Division has relatively low poverty rates. The region's lowest poverty rate is in Lira district's Adyel Division at just 5 percent. Kitgum district's Central Division has the highest poverty rate among towns and municipalities at 13 percent. Child poverty rates in towns and municipalities range from 6.4 percent in Aydel Division to 15.1 percent in Kitgum's Central Division.

IV.5. The Incidence and Distribution of Poverty in the Western Region

At just 8.7 percent, the incidence of monetary poverty in western Uganda is less than half the national average. The poverty rate among children is 10.1 percent. Inequality is substantial; the region's Gini coefficient is 0.35 for the general population and 0.33 for children.

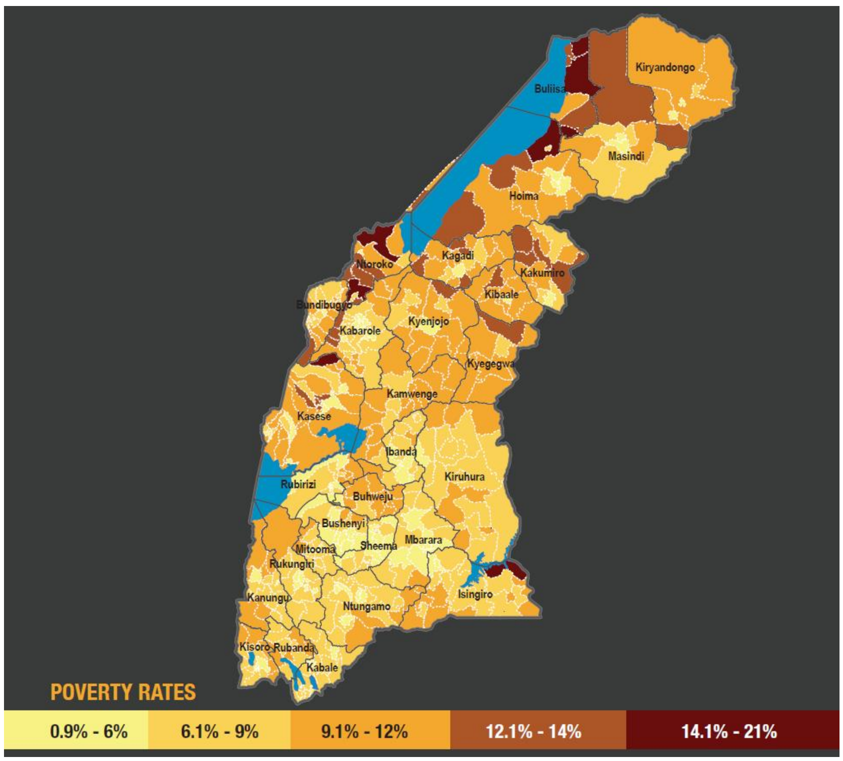
Bunyoro sub-region has western Uganda's highest poverty rate at 10.4 percent. Other sub-regions have poverty rates ranging from 7.4 percent in Ankole to 8.9 percent in Tooro. Among the population as a whole, Gini coefficients range from 0.34 in Kigezi to 0.36 in Ankole; among children, they range from 0.32 in Kigezi to 0.33 in Bunyoro and Ankole.

Thirteen districts have poverty rates over 10 percent, either for the general population, the child population, or both. These include all seven districts of Bunyoro sub-region. The other 6 districts are Ntoroko, Kyegegwa, Kamwenge, and Kyenjojo in the Tooro sub-region and Isingiro and Buhweju in the Ankole sub-region. Buliisa district has the region's highest poverty rates: 14 percent for the total population and 16 percent among children. Gini coefficients are high at over

0.3 in all 13 districts, both for the total population and the child population, revealing large disparities in household consumption within each district.

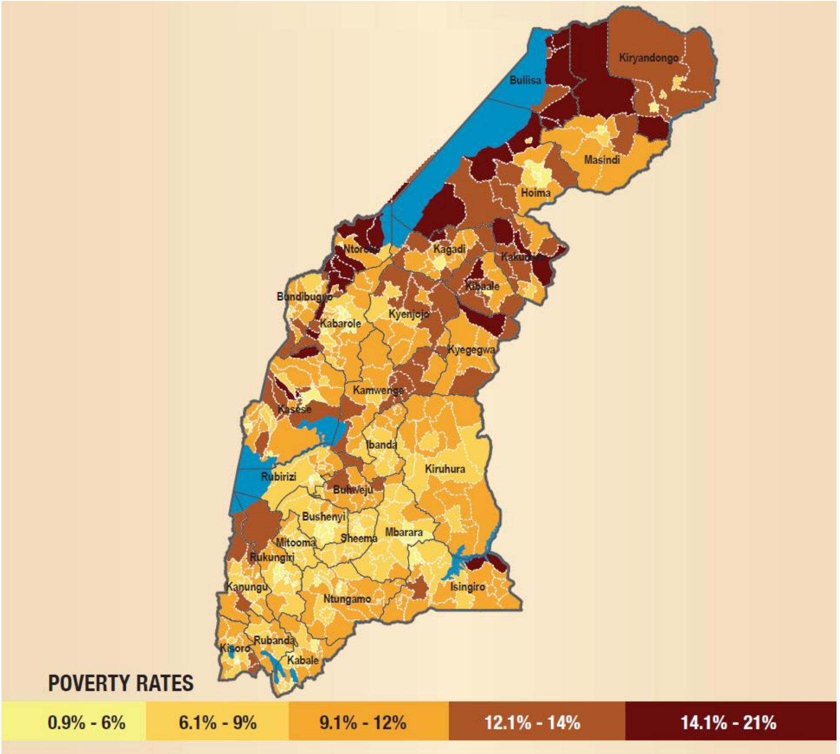
Buliisa sub-county has the highest poverty rate in the Western region, which reaches 18.5 percent for the general population and 20.7 percent for the child population. Moreover, Buliisa district includes four of the region's poorest sub-counties (Figure 8). Eleven of the poorest sub-counties are in the Bunyoro sub-region, eight are in Tooro, and one is in Ankole. Poverty rates among children are higher than the rates for the general population. While 126 sub-counties have total poverty rates over 10 percent, 205 sub-counties have child poverty rates over 10 percent (Figure 9).

Figure 8: Poverty Rates by Sub-County, Western Region



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Figure 9: Child Poverty Rates by Sub-County, Western Region

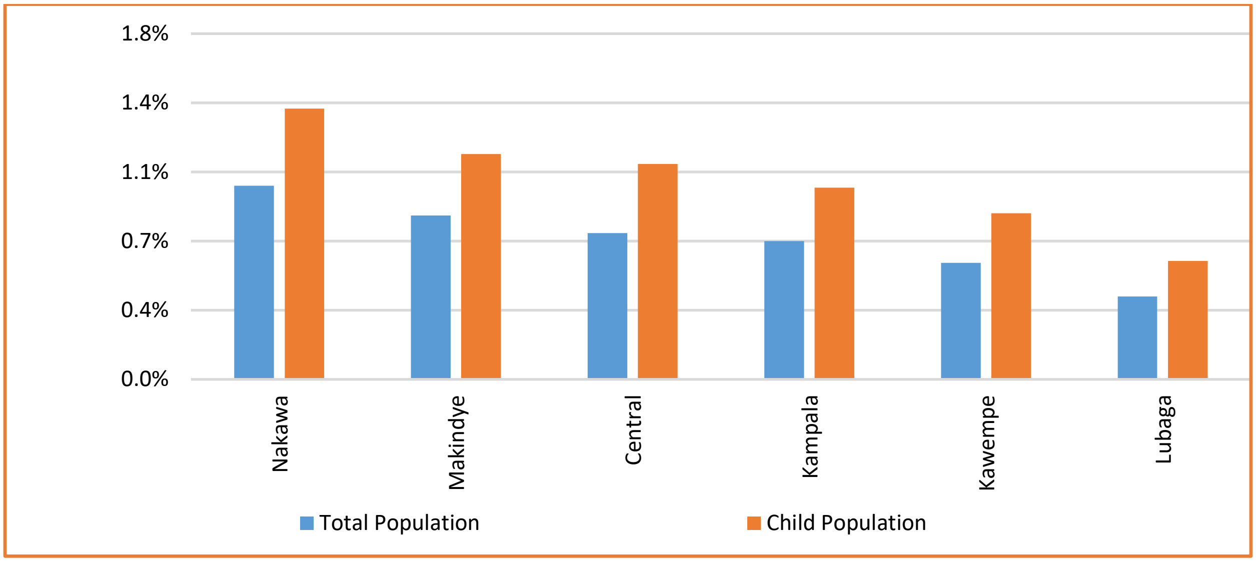


Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

IV.6. The Incidence and Distribution of Poverty in Kampala District

Kampala has the lowest poverty rates in the country. Just 0.7 percent of the total population and 1.0 percent of the child population live below the national poverty line. Poverty rates differ substantially between divisions, but are consistently higher among children than among the population as a whole (Figure 10). Nakawa Division has the highest poverty rates for both the total population (1.0 percent) and among children (1.4 percent). Rubaga Division has the lowest poverty rates for both the total population (0.4 percent) and the child population (0.6 percent). Kampala's high Gini coefficients also reveal significant disparities in household consumption. Inequality within each division is high, with Gini coefficients ranging from 0.38 to 0.41. Differences in child poverty and inequality indicators between districts are similar to those for the total population (Table 7).

Figure 10: Poverty Rates by Division, Kampala



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

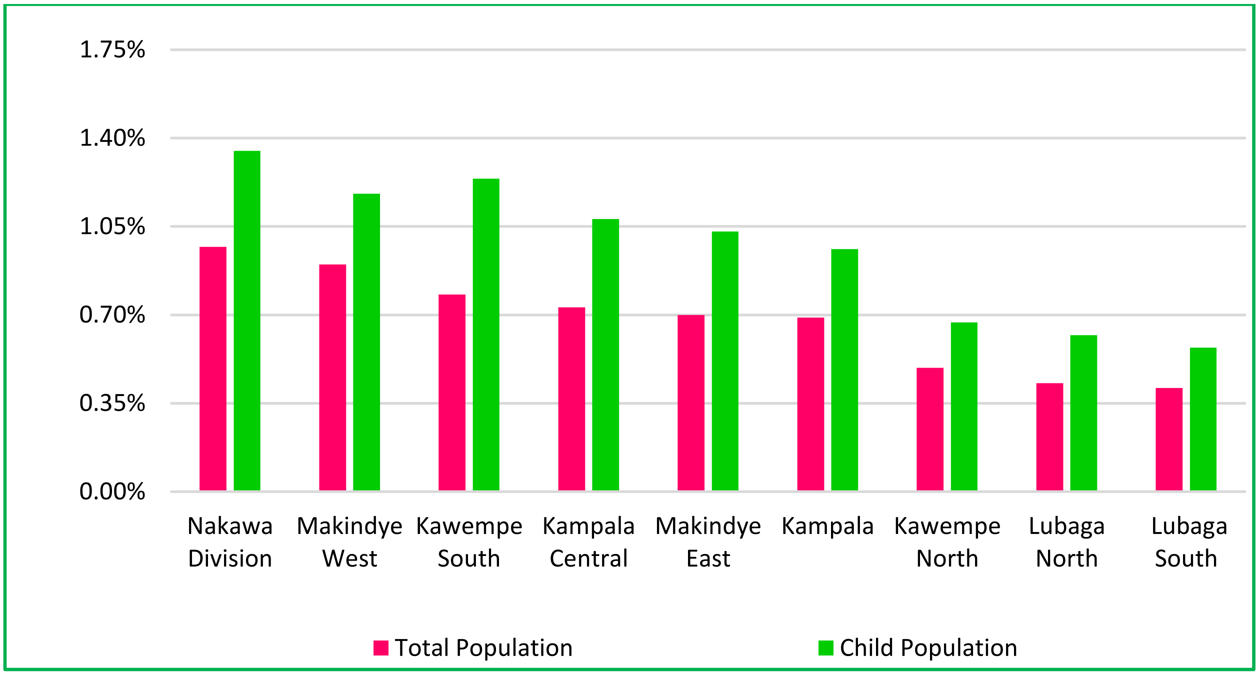
Table 7: Poverty and Inequality Indicators by Division, Kampala

Division	Total Population (WP)	Child Population (CP)	Gini Coefficient (WP)	Gini Coefficient (CP)
Nakawa	0.98%	1.37%	0.413	0.417
Makindye	0.83%	1.14%	0.404	0.410
Central	0.74%	1.09%	0.388	0.386
Kampala	0.70%	0.97%	0.397	0.400
Kawempe	0.59%	0.84%	0.391	0.393
Rubaga	0.42%	0.60%	0.379	0.381

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

The overall poverty rate is below 1 percent in all of Kampala's constituencies, but the child poverty rate exceeds 1 percent in five constituencies (Figure 11). Nakawa Division has the highest poverty rates, both overall (1.0 percent) and among children (1.4 percent). Lubaga South has the lowest total poverty rate (0.4 percent) and the lowest child poverty rate (0.6 percent). While poverty rates are low across all constituencies, Nakawa's rates are more than double those of Lubaga South (Table 8).

Figure 11: Poverty Rates by Constituency, Kampala



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

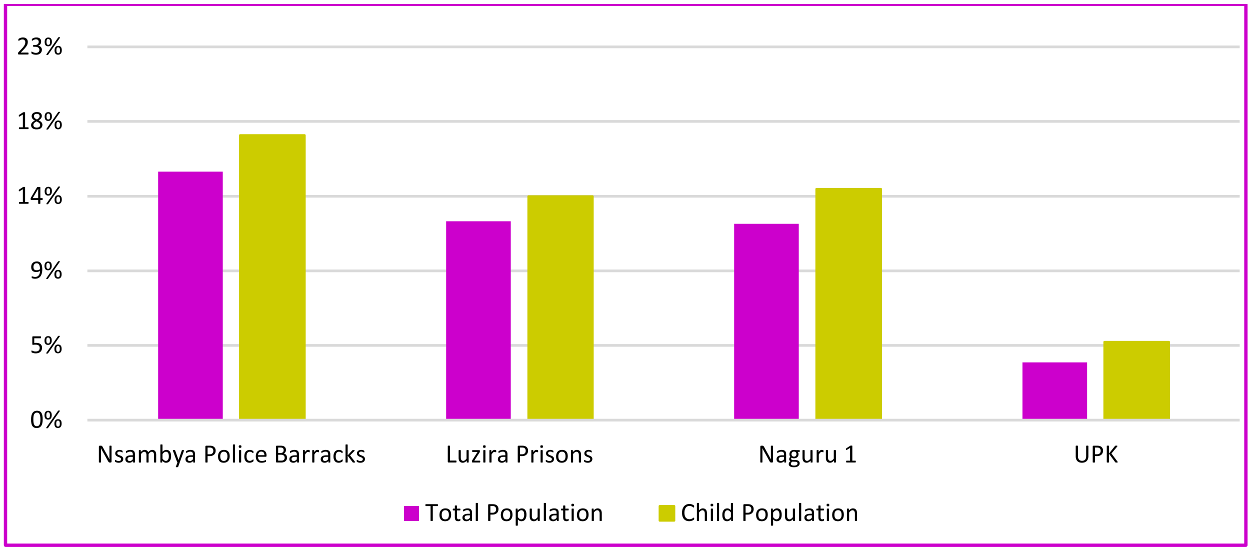
Table 8: Poverty Rates by Constituency, Kampala

Constituency	Total Population	Child Population
Nakawa Division	0.97%	1.35%
Makindye West	0.90%	1.18%
Kawempe South	0.78%	1.24%
Kampala Central	0.73%	1.08%
Makindye East	0.70%	1.03%
Kampala	0.69%	0.96%
Kawempe North	0.49%	0.67%
Lubaga North	0.43%	0.62%
Lubaga South	0.41%	0.57%

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

At the parish level, Nsambya Police Barracks, Luzira Prisons, and Naguru 1 have the highest poverty rates in Kampala (Figure 12). The total poverty rate in Nsambya Police Barracks is almost 15 percent, above the national average and far above the average for Kampala. Luzira Prisons and Naguru 1 both have overall poverty rates of about 12 percent, while the fourth-poorest parish, UPK, has a rate of just 3.5 percent. Inequality indicators are high in all four parishes, but highest in UPK, which has an overall Gini coefficient of 0.43 (Table 9).

Figure 12: Poverty Rates in Kampala's Four Poorest Parishes



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

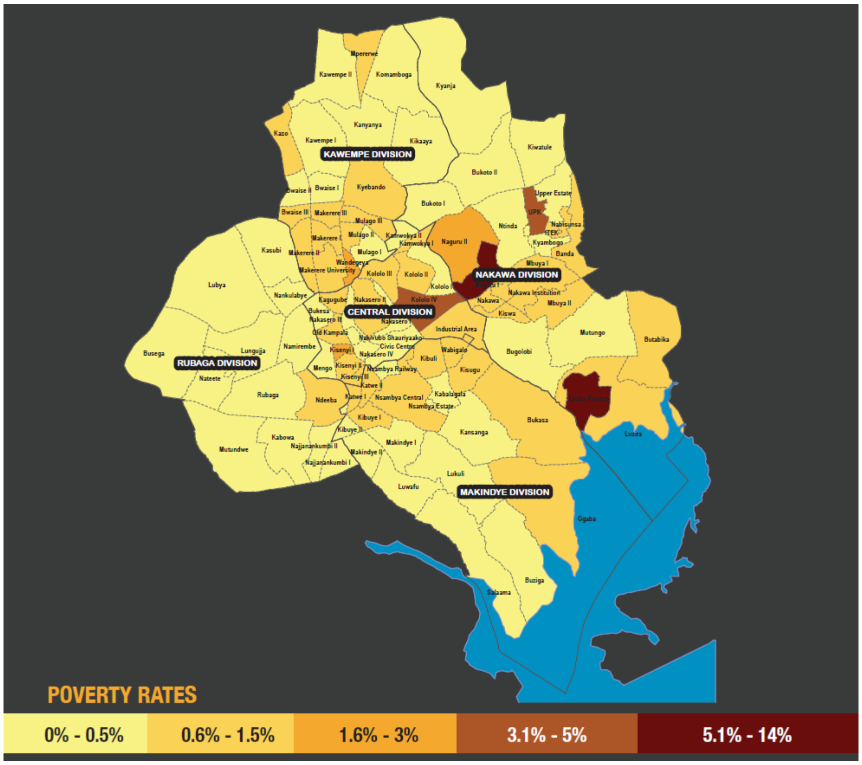
Table 9: Poverty and Inequality Indicators in Kampala's Four Poorest Parishes

Parish	**Total Poverty Rate**	**Child Poverty Rate**	**Overall Gini Coefficient**	**Gini Coefficient among Children**
Nsambya Police Barracks	14.97%	17.18%	0.3385	0.334
Luzira Prisons	11.98%	13.50%	0.3296	0.319
Naguru 1	11.83%	13.94%	0.3331	0.329
UPK	3.48%	4.71%	0.4405	0.431

Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

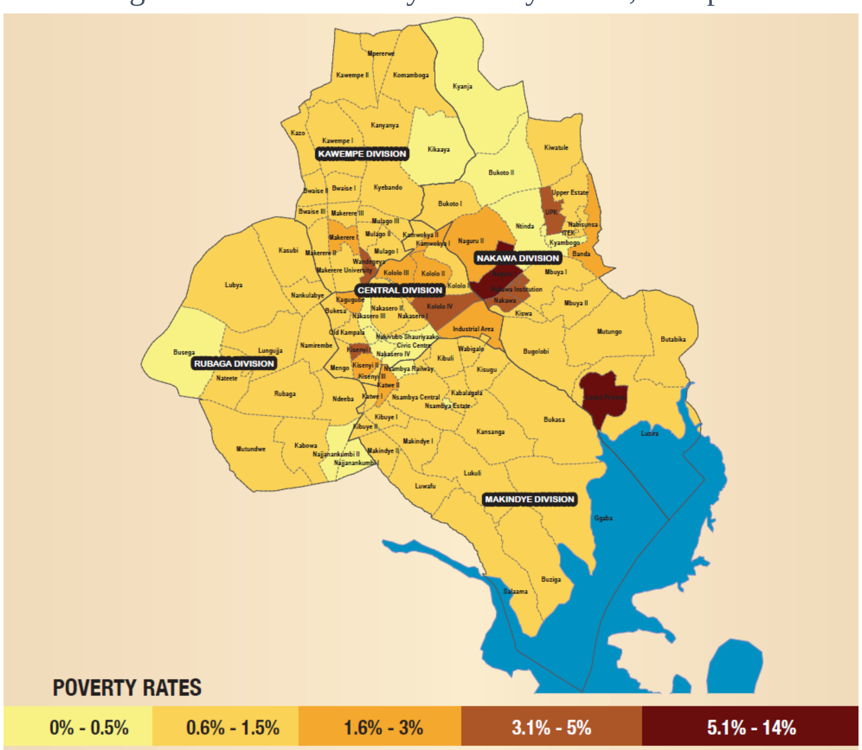
As in the other regions of Uganda, child poverty levels in Kampala are significantly higher than those of the general population across all administrative levels. While 22 parishes have total poverty rates over 1 percent, child poverty exceeds 1 percent in more than 30 parishes (Figure 13 and Figure 14). Kampala's three poorest parishes all have child poverty rates over 13 percent, and the child poverty rate in Nsambya Policy Barracks is over 17 percent.

Figure 13: Poverty Rates by Parish, Kampala



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

Figure 14: Child Poverty Rates by Parish, Kampala



Source: Authors' calculations based on the 2012/13 UNHS and the 2014 NPHC.

V. Conclusion and Next Steps

This report has presented the results of the 2017 Uganda poverty-mapping exercise conducted by UBOS, UNICEF, and the World Bank. The updated poverty maps shown above are based on data from the 2014 NPHC and the 2012/13 UNHS. They incorporate many methodological improvements over the previous poverty maps, which were created in 2002, and a wide range of validation techniques were used to ensure the quality of results. While frequent and unpredictable changes in the boundaries of administrative units, the creation of new administrative levels, and the reclassification of individual areas all posed significant methodological challenges, the results are robust.

These challenges underscore the importance of capacity building at the national level, which will be critical to future poverty-map updates. The World Bank and UNICEF worked closely with UBOS counterparts to facilitate the transfer of knowledge and skills. Several training workshops were held for UBOS staff, as well as an educational visit to Washington DC, to ensure that UBOS has access to the technical proficiency necessary to update Uganda's poverty maps in the future.

Validation exercises show that the statistics predicted by the SAE poverty-mapping technique are robust, and that poverty and inequality estimates remain reasonably precise to the sub-county level. Both R-square and adjusted R-square are high for all models. Error variances at administrative levels higher than the EA amount to no more than 5.1 percent of the total error variance. This means most errors are concentrated at the EA and household levels for which PovMap2, the poverty mapping tool, can explicitly account for. For most sub-regions, the 95 percent confidence intervals for poverty estimates produced by the SAE method are substantially smaller than those of estimates based on the 2012/13 UNHS data. This indicates that the SAE method can produce more precise poverty statistics than direct estimation from household surveys.

Poverty mapping offers policymakers and other stakeholders a tool to observe the spatial distribution of poverty and inequality with a high degree of accuracy and detail. The results of this exercise yield important conclusions about the general characteristics of poverty in Uganda. The northern region is by far the poorest part of the country, Karamoja is the poorest part of the north, and Kotido district is the poorest part of Karamoja. The highest rates are more than 90 percent, which means almost everyone in these areas are living below the national poverty line. Poverty rates are also extremely high in the Acholi and West Nile sub-regions.

However, the poverty maps also reveal concentrated pockets of poverty within regions that are otherwise relatively wealthy. For instance, while Kampala has the lowest poverty rates in the country, three of its parishes—Nsambya Police Barracks, Luzira Prisons, and Naguru 1—have poverty rates that are an order of magnitude higher significantly than the city's average. After Kampala, central Uganda has the country's lowest poverty rates, especially Wakiso district, which includes a number of wealthy Kampala suburbs. Even the region's poorest districts—Gomba, Kayunga, Kyankwanzi, and Nakasongola—have poverty rates that are about half the national average. Poverty rates are also low in the western region, though Buliisa district includes several sub-counties with rates close to the national average. Poverty rates in the eastern region are elevated but not extreme, and they tend to be relatively uniform across districts. The poverty rate in the poorest district, Teso, is only 7 percentage points higher than the rate in the least-poor district, Bugisu/Sebei. Nationwide, towns and municipalities tend to have significantly lower poverty rates than rural rates.

This poverty mapping exercise also shows that poverty rates for children tend to be higher than those for the whole populations at any level of disaggregation. This is likely because poorer households tend to have more children, but it requires further analysis to fully understand this.

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Table A-1: Final Models with the OLS coefficients

Kampala				
	Coefficient	Std. Err.	t	|Prob|>t
Intercept	11.8784	0.0872	136.1907	0.00000
BATHROOM_1	0.4599	0.0591	7.7832	0.00000
BATHROOM_3	0.1888	0.0387	4.8817	0.00000
ENERGYCOOKING_1_1	0.2782	0.1352	2.0575	0.04010
ENERGYCOOKING_1_MEAN_	-0.9948	0.603	-1.6498	0.05950
ENERGYSOURCE_01	0.1442	0.0497	2.9026	0.00380
HEAD_ATTENDING_2_1	-0.2549	0.0565	-4.5128	0.00000
HEAD_SCHOOLYEAR	0.0326	0.0043	7.5972	0.00000
HSIZE	-0.3260	0.029	-11.257	0.00000
HSIZE_SQ	0.0184	0.0035	5.283	0.00000
ROOMS	0.2120	0.0302	7.0214	0.00000
TELEVISION_1	0.2435	0.0437	5.5702	0.00000
TENURE_1_1	0.1421	0.0476	2.9859	0.00290
Central Region (Excluding Kampala)				
	Coefficient	Std. Err.	t	|Prob|>t
Intercept	10.6539	0.0626	170.2368	0.0000
AGE_SQ	0	0	-3.9667	0.0001
BATHROOM_1	0.474	0.0787	6.0202	0.0000
BATHROOM_2	0.2041	0.0886	2.303	0.0214
BATHROOM_3	0.1886	0.0436	4.3249	0.0000
BATHROOM_4	0.0839	0.0402	2.0883	0.0370
ENERGYCOOKING_7_1	0.1636	0.0337	4.8504	0.0000
ENERGYSOURCE_01	0.3983	0.0491	8.1122	0.0000
ENERGYSOURCE_07	0.3617	0.1261	2.8678	0.0042
FLOOR_3_1	0.1436	0.0345	4.1618	0.0000
HEAD_ECONACTV_2_1	0.1672	0.0806	2.0751	0.0382
HEAD_MARSTAT_1_1	-0.0921	0.0269	-3.418	0.0007
HEAD_SCHOOLYEAR	0.0203	0.0038	5.3236	0.0000
HSIZE	-0.0447	0.0065	-6.8665	0.0000
MOTORCYCLE_1	0.2879	0.0444	6.4896	0.0000
PADULT	0.6031	0.0619	9.7395	0.0000
TENURE_1_1	0.2568	0.0326	7.8785	0.0000
Eastern Region				
	Coefficient	Std. Err.	t	|Prob|>t
Intercept	11.1194	0.133	83.6289	0.00000
ENERGYSOURCE_11_EA	0.225	0.0981	2.2951	0.02190

HEAD_AGE	-0.0027	0.0009	-3.1157	0.00190
HEAD_GRADE_5_1	-0.0916	0.0434	-2.1087	0.03520
HEAD_GRADE_6_1	-0.0873	0.0401	-2.1755	0.02980
HEAD_GRADE_7_1	-0.0868	0.035	-2.4794	0.01330
HEAD_LITERACY_1_1	0.197	0.0273	7.2195	0.00000
HEAD_MARSTAT_2_1	0.0914	0.0339	2.6933	0.00720
HEAD_MARSTAT_3_1	-0.1438	0.0463	-3.105	0.00190
HEAD_SEX_1	-0.0885	0.0322	-2.7493	0.00610
HSIZE	-0.0412	0.0069	-5.9676	0.00000
HSIZE_MEAN_EA	-0.0638	0.0196	-3.2608	0.00110
PADULT	0.6492	0.0748	8.6773	0.00000
POP_EA	0.0002	0.0001	2.1096	0.03510
ROOF_6_1	-0.1848	0.0321	-5.7478	0.00000
ROOMS_1_1	-0.1782	0.041	-4.345	0.00000
ROOMS_2_1	-0.1098	0.0362	-3.0345	0.00250
WATERDRINKING_2_1	0.4143	0.0986	4.2012	0.00000
Northern Region				
	Coefficient	Std. Err.	t	|Prob|>t
Intercept	11.1094	0.1766	62.9164	0.0000
AGE_SQ	0	0	-3.1031	0.0020
DWELLING_02	0.2134	0.1241	1.7194	0.0858
ENERGYCOOKING_7_1	0.237	0.1234	1.9204	0.0550
ENERGYCOOKING_8_1	-0.2493	0.1053	-2.3676	0.0181
ENERGYSOURCE_6_1	0.1258	0.0341	3.6855	0.0002
HEAD_ATTENDING_1_1	-0.1016	0.0398	-2.5514	0.0108
HEAD_GRADE_6_1	0.116	0.0572	2.0278	0.0428
HEAD_LITERACY_1_1	0.0958	0.0389	2.4617	0.0140
HSIZE	-0.0827	0.0075	-11.0866	0.0000
KITCHEN_3_1	0.0968	0.0334	2.9003	0.0038
NRADIO_0	-0.3317	0.1093	-3.0342	0.0025
PADULT	0.3584	0.0741	4.8387	0.0000
POP_EA	0.0002	0.0001	2.9737	0.0030
ROOF_6_1	-0.2213	0.0652	-3.3937	0.0007
SHARETOILET_0_1	-0.2285	0.0347	-6.585	0.0000
TENURE_1_1	0.1416	0.0703	2.0146	0.0442
TOILET_6_1	-0.1135	0.0415	-2.7381	0.0063
WALLS_7_1	-0.1463	0.0378	-3.8688	0.0001
Western Region				
	Coefficient	Std. Err.	t	|Prob|>t

Intercept	11.1427	0.1	111.3776	0.00000
BATHROOM_1	0.3492	0.0994	3.5137	0.00050
BATHROOM_5	-0.1599	0.0413	-3.8749	0.00010
BATHROOM_6	-0.3165	0.0457	-6.9302	0.00000
DWELLING_2_1	-0.103	0.0363	-2.8352	0.00460
ENERGYCOOKING_7_1	0.1599	0.05	3.1996	0.00140
ENERGYSOURCE_01	0.2972	0.0733	4.0548	0.00010
ENERGYSOURCE_02	0.2892	0.0833	3.4744	0.00050
ENERGYSOURCE_03	0.9139	0.2481	3.6841	0.00020
HSIZE	-0.1344	0.0194	-6.9398	0.00000
HSIZE_SQ	0.0056	0.0014	4.0586	0.00010
PADULT	0.4205	0.0712	5.9023	0.00000
PHONE_1	0.2633	0.0267	9.8438	0.00000
ROOF_1_1	0.1295	0.0381	3.3955	0.00070
ROOMS_4	0.1271	0.046	2.7615	0.00580
ROOMS_5	0.2349	0.0997	2.3564	0.01860
ROOMS_6	0.3514	0.1453	2.4184	0.01570
ROOMS_8	1.2819	0.1724	7.4352	0.00000
TENURE_1_1	0.1125	0.041	2.7412	0.00620
WALLS_7_1	-0.1017	0.0323	-3.1451	0.00170

Table A-2: Definition of Variables

tenure	
	1= owner-occupied 2= free public 3= free prive 4= subsidized public
	5= subsidized private 6= rented public 7= rented private 8= other
dwelling	
	1= detached 2= semi-detached 3= flat 4= room 5= servant quarter
	6= tenement 7= garage 8= go down/basement 9= store 10= other
roof	
	1= iron sheets 2= tiles 3= asbestos 4= concrete 5= tins
	6= thatch 7= other
walls	
	1= concrete/stones 2= cement blocks 3= burnt bricks
	4= unburnt bricks w/ cement 5= unburnt bricks w/ mud
	6= wood 7= mud and pole 8= tin or iron sheets 9= others
room	
	1= 1= room 2= 2= rooms 3= 3= rooms 4= 4= rooms 5= 5= rooms
	6= 6= rooms 7= 7= rooms 8= 8= rooms 9= 9= or more rooms
attending	

	1= Never attended 2= attended in the past 3= currently attending
birth certificate	
	1= yes, long 2= yes, short 3= no/I don't know
marstat	
	1= married (monogamous) 2= married (polygamous) 3= divorced/separated
	4= widowed 5= never married
energysource	
	1= electricity-national grid 2= electricity-solar 3= electricity-personal generator
	4= electricity-community plant 5= gas/biogas/LPG 6= paraffin-lantern/tadooba
	7= candles 8= firewood 9= cow drug
	10= grass/reeds) 11= other
energycooking	
	1= electricity-national grid 2= electricity-solar 3= electricity-personal generator
	4= electricity-community plant 5= gas/biogas/LPG 6= paraffin-lantern
	7= charcoal 8= firewood 9= cow drug 10 =grass/reeds) 11= other
waterdrinking	
	1= piped water into dwelling 2= piped water to the yeard 3= public taps
	4= borehole in yard/plot 5= public borehole 6= protected well/spring
	7= unprotected well/spring 8= river/stream/lake 9= vendor
	10 =tanker truck 11= gravity flow scheme 12= rain water
	13= bottled water 14= other
toilet	
	1= flush toilet 2= VIP latrine 3= covered pit latrine w/ slab
	4= covered pit latrine w/o slab
	5= uncovered pit latrine w/ slab 6= uncovered pit latrine w/o slab
	7= ecosan 8= no facility 9= other
sharetoilet	
	1= shared 2= not shared 0 N/A or no toilet
bathroom	
	1= inside w/ drainage provided 2= inside w/o drainage 3= outside w/ drainage
	4= outside w/o drainage 5= make shift 6= none 7= other
kitchen	
	1= inside, specific room 2= inside, no specific room 3= outside, built
	4= makeshift 5= open space