Local Governance Performance Index

2019 LGPI Survey User Guide
Kenya, Zambia, Malawi

Produced by: Governance and Local Development Institute

If you have any questions contact data@gld.gu.se

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About This File

This file was created to assist with research based on data collected from the LGPI Survey 2019.

1 Overview

This document describes how to utilize the LGPI codebook and LGPI data for your research. Specifically you will find:

- Data citation and acknowledgements
- Structure of the data
- Naming scheme of variables
- Coding methods used for different types of data
- How to import the data into both STATA and R
- How to incorporate sample weights

Refer to the table of contents for complete list of all available information.

1.1 Citation and Acknowledgements

When utilizing this dataset, users must use the following citation: Ellen Lust; Kristen Kao; Pierre F. Landry; Adam Harris; Boniface Dulani; Erica Ann Metheney; Sebastian Nickel; Ruth Carlitz; Josephie Gakii Gatua; Prisca Jöst; Valeryia Mechkova; Fison Maxim; John Tengatenga; Marcia Grimes; Cecilia Ahsan Jansson; Witness Alfonso; Dominique

Nyasente; Nesrine Ben Brahim; Jenna Jordan; Monika Bauhr; Frida Boräng; Karen Ferree; Felix Hartmann; Hans Lueders, 2023, "The Local Governance Performance Index (LGPI) Household Survey 2019: Kenya, Malawi, Zambia", https://doi.org/10.7910/DVN/PJKXL1, Harvard Dataverse, V3, UNF:6:BG702JZ8DKUWNWH2nhYDpg== [fileUNF]

We now present some details about the creation and implementation of LGPI 2019.

1.2 Technology

The survey was created in SurveyToGo, a product of Dooblo https://www.dooblo.net/downloads/.

The underlying code of SurveyToGo is JavaScript.

1.3 Data Collection

1.3.1 Location

The LGPI was conducted in 5 regions within 3 countries. Of the five regions, 3 are capital cities and 2 are border areas.

Countries: Kenya, Zambia, Malawi

Regions: Nairobi, Lusaka, Lilongwe, Zambia Border (with Malawi), Malawi Border (with Zambia)

1.3.2 Dates

Kenya: May 2019 – August 2019

Zambia: May 2019 – August 2019

Malawi: September 2019 – November 2019

1.3.3 Survey Implementation

Below is the list of partners who implemented the survey.

Kenya: IPSOS https://www.ipsos.com/en-ke

Zambia: Ubuntu Research and Rural Development Company Ltd (URRDC) rrd-zambia.com

Malawi: Institute of Public Opinion and Research (IPOR) http://www.ipormw.org

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Codebook Contents

The LGPI 2019 survey is structured to include a diverse array of question types. These encompass Multiple Choice questions, where respondents are limited to selecting one option; Multiple Select questions, which allow for the selection of multiple options; and Manual Entry questions, where responses are typed in manually by enumerators.

In terms of data storage, the survey utilizes two primary formats. Numerical data is stored as floats, while categorical data is classified as factors. Notably, within these categorical variables, there are Ordinal categories that are organized in a naturally sequential and meaningful manner.

It is important to recognize that the specific classification of these variables may vary based on the application context. Hence, a thorough examination of the categorical data being handled is essential to determine the most appropriate methods for analysis.

The accompanying codebook for LGPI 2019, provided in PDF format, offers detailed reference and guidance, and contains the following information:

- Variable Name
- Question Text

- Stats/Values
- Freqs (% of Valid)
- Missing

It also contains summary information on the scope, purpose, sampling methods, wording in the consent statement, and citation.

2.1 Details

Variable Name

The variable names are determined by the scheme outlined in Section 3.

Question Text

Question asked in the survey.

Stats/Values

This column represents stats such as mean, median, and minimum for numeric variables, while for categorical variables, it offers value levels and labels.

Frequencies

This column displays the frequencies in each level of a categorical variable.

Missingness

The number and percentage of observations where data points are missing for a variable.

The following snapshot illustrates how the codebook would look like for the aforementioned two types of variables.

Variable Name	Question Text	Stats / Values	Freqs (% of Valid)	Missing
base_q32 [numeric]	Age	Mean (sd) : 35.6 (15) min < med < max: 18 < 32 < 99 IQR (CV) : 19 (0.4)	Not Applicable	176 (0.7%)
base_q33 [factor]	What is your marital status?	1. Single (never married, engaged, not cohabiting) 2. Married 3. Divorced/separated 4. Widowed 5. Cohabitating 6. Don't Know/Refuse to answer	4561 (19.0%) 15452 (64.5%) 2047 (8.5%) 1753 (7.3%) 121 (0.5%) 20 (0.1%)	0 (0.0%)

Due to the survey design, not all questions were posed to every respondent; instead, they were distributed across the sample based on prior Topic classifications. Hence, the percentage of missingness might not reflect actual missing observations.

3 Variable Names

The naming scheme for variables in the LGPI dataset are based on the structure of the LGPI and the question types.

3.1 Sub-Datasets

Due to the size of the LGPI the questions of the survey are categorized into various topics, each creating their own dataset. Each sub-dataset is identified by a 4-letter code. The list of codes is given in Subsection 3.1.1. This structure allows the researcher to select those pieces that meet their research needs without downloading large amounts of unnecessary data.

3.1.1 Sub-dataset Codes

- **BASE**: Demographic , Geographic, and Logistical data
- **AURC**: Authority, Responsibility, and corruption
- **CIAU**: Community Influences and Authorities
- **CONE**: Community Norms and Engagement
- **Land**: Land data

- **MIGR**: Migration
- **EXTR**: Extraction
- **PNPN**: Political Norms and Participation
- **ADMS**: Administrative Services
- **SERV**: Services
- **MUNI**: Municipal `data`[1]
- **FACT**: Factual `data`[2]

3.2 Naming Scheme of Variables

The structure of the variable name depends on the question type. Below we describe the structure of each variable name by variable type.

Multiple Choice	code_q#
Multi Select	code_q#_INDEX
Manual Entry	code_q#
Other Specify*	code_q#_O

*– If a question has an Other (specify) option or any answer choices that request a specified value, there will be variable containing the manually entered information with the naming convention above.

If a single question has multiple answer choices with a specify options the variable name will have the form:

$code_q\#_O$i

where i is the index of the answer choice.

Note that the last character is an upper case "O" for "Other" **not** a zero.

3.2.1 Multiple Choice Example

Question: "Is the house in an urban or rural area?"

Answer Choices: Urban, Rural

[1] data collected from a survey administered to village heads (or their equivalents) or someone who represents the village head.

[2] data collected from individuals in the village who would have extensive information about village characteristics (village secretary, village treasurer, village committee member, etc).

There is 1 column in the dataset that describe the data collected for this question. Suppose this was question 7 in the dataset then the variable name is land_q7 and the variables takes on the values: "Urban", "Rural", or NA

3.2.2 Multi Select

Question: "How do you know this person?"
Answer Choices: Friend, Relative, Neighbor, Work Together

There are 4 columns in the dataset that describe the data collected for this question. Suppose this was question 12 in the dataset, then the variables are

- land_q12_1 : binary variable that is equal to 1 if Friend was chosen, 0 if friend wasn't chosen, or NA if the question wasn't answered
- land_q12_2 : binary variable that is equal to 1 if Relative was chosen, 0 if friend wasn't chosen, or NA if the question wasn't answered
- land_q12_3 : binary variable that is equal to 1 if Neighbor was chosen, 0 if friend wasn't chosen, or NA if the question wasn't answered
- land_q12_4 : binary variable that is equal to 1 if Work Together was chosen, 0 if friend wasn't chosen, or NA if the question wasn't answered

3.2.3 Manual Entry

Question: "What was the name of the person?"
Answer: stated by the respondent and typed in by the enumerator

There is one column in the dataset that describes the data collected for this question. Suppose this was question 5 in the survey, then

- land_q5 : takes on the value of the string typed in by the enumerator or NA if the question was not answered

3.2.4 Questions Asked in Loops

In certain parts of the survey a set of questions is asked repeatedly for a list of individuals (ex. the same questions about school asked for every child in the household).

In these types of cases the variable names will follow the same convention as outlined above with an additional component to identify the individual.

Multiple Choice	code_q#_Ii
Multi Select	code_q#_Ii_INDEX
Manual Entry	code_q#_Ii
Other Specify*	code_q#_Ii_O

where the capital "I" stands for "Individual" and i represents the ith person in the loop.

3.2.5 Questions Asked in Double Loops

In the SERV(services) sub-dataset, there are a number of questions that were asked inside a *double* loop.

For example, we asked the respondent to choose what disputes/crimes they had experienced in the past year, and then for each dispute/crime asked them who they turned to for help. For each person they turned to for help we asked a standard set of questions. This standard set of questions exists in a double loop indexed by the dispute/crime and the person turned to for help.

In these types of cases the variable names will follow the same convention as outlined above with an additional component to identify the individual and the dispute/crime.

Multiple Choice	code_q#_Dd_Ii
Multi Select	code_q#_Dd_Ii_INDEX
Manual Entry	code_q#_Dd_Ii
Other Specify*	code_q#_Dd_Ii_O

where the capital "D"("C") stands for "Dispute"("Crime"), d represents the d (c)th dispute (crime), the capital "I" stands for "Individual", and i represents the ith person in the loop.

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Coding of Variables

4.1 Missing Data

All missing data is coded as NA. Note that many questions were only asked to subset of individuals so NA may represent data that is "missing" because it was not collected. Therefore when analyzing data it is imperative to consider the conditions under which the question was asked (this can be found in the codebook).

4.2 Don’t Know/Refuse to Answer

Within the survey, the options Don’t Know, Refuse to Answer, and Don’t Know/Refuse to Answer occur frequently. The coding of these options depends on the type of variable they occur in.

Categorical Variables If there is a Don’t Know, Refuse to Answer, or Don’t Know/Refuse to Answer option in a categorical variable, the string "Don’t Know", "Refuse to Answer", or "Don’t Know/Refuse to Answer" will be used.

It is important to note that when a numerical code is assigned to "Don’t Know", "Refuse to Answer", or "Don’t Know/Refuse to Answer" in either STATA or R, the coding number will

be equal to the place of the phrase in the answer choice list.

For instance, if "Don't Know/Refuse to Answer" is the 14th option in the answer choices, then the coding of "Don't Know/Refuse to Answer" will be 14. We emphasize this point since in many datasets this type of value would be coded as some other value such as 98 or 97. Therefore we urge the researcher to take great care in the handling of these types of values.

Numerical Variables In order to keep numerical variables coded as float data types we code these options in the following way:

- -1 = Don't Know
- -2 = Refuse to Answer
- -3 = Don't Know/Refuse to Answer

4.3 Numerical and Categorical Variables

4.3.1 Numerical

All numerical variables are coded as floats regardless of being discrete or continuous.

4.3.2 Categorical

Categorical variables are always coded as strings, not by their code value. For example if the question was "Was the person who helped you a man or a woman?" and the answer choices where Man, Woman, Don't Know/Refuse to Answer, the answer in the dataset is recorded at "Man" or "Woman" as opposed to 1 or 0. This guarantees consistent recording of data throughout the survey.

If you need assistance with encoding the string data in STATA or R please see Chapter 5.

5

Importing, Encoding, and Merging Data

This chapter provides instructions for importing datasets, checking the encodings of variables, subsetting, and/or merging datasets in both STATA (.dta file) and R (.rds file).

IMPORTANT: Only use the STATA file in STATA and the R file in R. Importing the data into the wrong software might result in a loss of information regarding the levels of the categorical variables.

5.1 STATA

5.1.1 Importing

- Save the STATA file (.dta) to your directory of choice.
- Click the *Open File* button in STATA and search for the file.

5.1.2 Encoding of Variables

If you would like to see all the levels of a particular variable use the command *label list VARIABLE-NAME*. See the example below.

```
. label list LAND_Q8
LAND_Q8:
           1 Village/Town Council
           2 Spouse's parents
           3 Spouse's other relatives
           4 Chief
           5 Village Head/Neighborhood Block Leader
           6 Assistant chief/Group Village Head
           7 Local elder
           8 Traditional Authority (TA)
           9 Government
          10 Neighbor
          11 Politician
          12 Paramount chief
          13 Commercial farmer/investor
          14 Other (specify)
          15 Don't Know/Refuse to answer

.
```

5.1.3 Merging Datasets

Since the LGPI 2019 dataset is organized by various topics across three countries within five regions (Malawi, Zambia, and Kenya), as elaborated in Section 8, it is essential to have the capability to merge datasets across different topics and/or to create subsets of the dataset focusing on a specific location (e.g., Country) and topics. Note that our location variables, which are present in the **BASE** dataset, encompass a range of location identifier variables at different administrative levels. These span from broader categories like the country (identified by country name) to more specific ones like the village name (anonymized).

There are three primary types of merging that may be necessary for effectively utilizing the LGPI 2019 dataset. Below, we provide illustrative examples demonstrating how to merge datasets across different topics and how to create subsets of the dataset for specific countries or regions.

1) Different Topics covering all the three countries

To merge household datasets containing diverse topics, such as the CONE and SERV datasets, from all three sampled countries (Malawi, Zambia, and Kenya), the `merge` command in Stata can be used by employing 'SbjNum' as the unique household identifier.
The procedure involves the following command sequence:

```
use "FILEPATH/dat1.dta"
merge 1:1 SbjNum using "FILEPATH/dat2.dta"
save "FILEPATH/newdat.dta"
```

where `dat1` is the first dataset and `dat2` is the second dataset. This creates a new dataset called `newdat`.

NOTE: In instances where certain standalone sub-datasets, or their combinations, result in a high number of variables, users of Stata/BE may encounter limitations, as this version supports only up to 2,048 variables. To circumvent this issue, it is advisable to select only the necessary variables from the provided RDS format in R (as explained below) and then save the resulting subset as a DTA file for use in Stata.

2) Creating/utilizing Sub-datasets for Specific Countries/Regions within a single or multiple topics

Depending on the purpose of combining sub-datasets, the process in this section usually involves two main steps: initially merging the datasets and subsequently applying selective filters to concentrate on the desired geographical areas.
For example, to create (or utilize) a subset of the LAND dataset specifically targeting the Zambian and Malawian border areas, the first step is to merge the primary LAND dataset with the `BASE|`[3] dataset. Secondly, selectively filter the merged dataset to isolate the areas of interest. The command for this operation is as follows:

```
use "FILEPATH/dat1.dta"
merge 1:1 SbjNum using "FILEPATH/dat2.dta"
```

where `dat1` is the first dataset(e.g.,LAND) and `dat2` is the **BASE** dataset. Next, utilize the appropriate location variables based on your specific needs. For instance, you can utilize the LGPI Region variable labeled 'base_q58' to filter observations from the border regions of Malawi and Zambia. An example of using the 'keep' command to achieve this and save the file is as follows:

```
Keep if base_q58 ==5| base_q58 ==3

save "FILEPATH/dat2.dta"
```

where dta2 is the sub dataset containing only Malawi and Zambia Boarder.

You can also work with the original merged file mentioned in item number 1 above without discarding the remaining observations, by directly applying appropriate filtering in your analysis command. For instance, if you wish to run a regression analysis focusing solely on Malawi and Zambia, you can use the 'if' option in the command line to implement this filtering, as demonstrated below:

```
reg y x1 x2 if base_q59 ==2| base_q59 ==3
```

where y, x1, and x2 are the variables you selected for the analysis and base_q59 is a factor variable containing the country name.

3) Merging Household and Village Level(MUNI and FACT) datasets

If you need to perform multilevel analysis or a similar hierarchical data task, it is essential to integrate the household data with village-level datasets (namely Municipal and Factual data). This integration should be done using the 'Village' variable, which serves as an anonymized Village ID.

```
merge 1:1 Village using "FILEPATH/dat2.dta"
```

where `dat2` is the MUNI or FACT dataset. The procedure for this integration should follow the same preliminary steps as detailed in the preceding sections.

5.2 R

5.2.1 Importing

- Save the R file (.rds) to your directory of choice.
- Set your working directory to where the file is stored: *setwd("filepathname")*
- Read in the R file: *readRDS("filename.rds")*

5.2.2 Encoding of Variables

If you would like to see all levels of a particular variable use the *levels(x)* function. See the example below.

```
> levels(mydat$LAND_Q8)
 [1] "Village/Town Council"                  "Spouse's parents"
 [3] "Spouse's other relatives"              "Chief"
 [5] "Village Head/Neighborhood Block Leader" "Assistant chief/Group Village Head"
 [7] "Local elder"                           "Traditional Authority (TA)"
 [9] "Government"                            "Neighbor"
[11] "Politician"                            "Paramount chief"
[13] "Commercial farmer/investor"            "Other (specify)"
[15] "Don't Know/Refuse to answer"
```

5.2.3 Merging Datasets

Similar to the examples provided for Stata users, R Studio users might encounter three primary types (or similar versions) of merging that are essential for effectively utilizing the LGPI 2019 dataset. Below, we offer a few illustrative examples demonstrating how to merge datasets across various topics and how to create subsets of the dataset for specific countries or regions using R.

1) Different Topics covering all the three countries

To merge datasets like CONE and SERV for all sampled countries using the unique identifier 'SbjNum', use the merge() function in R.

Load datasets in your working directory first:

```
dat1 <- readRDS("FILEPATH/dat1.rds")
dat2 <- readRDS("FILEPATH/dat2.rds")
```

Then combine the datasets using the unique identifier:

```
newdat <- merge(dat1, dat2, by="SbjNum")
```

where `dat1` is the first dataset and `dat2` is the second dataset. This creates a new dataset called `newdat` is essentially the two original datasets put side-by-side.

2) Creating/utilizing Sub-datasets for Specific Countries/Regions within a single or multiple topics

To accomplish this task, start by combining the LAND and BASE datasets. After this, apply the necessary filters. The following example illustrates the process of generating a subset from the LAND dataset, particularly focusing on the border regions of Zambia and Malawi:

```
dat1 <- readRDS("FILEPATH/dat1.rds")
dat2 <- readRDS("FILEPATH/dat2.rds")
newdat <- merge(dat1, dat2, by="SbjNum")
```

where `dat1` is the first dataset(LAND) and `dat2` is the **BASE** dataset.

```
subset_data <- newdat[newdat $base_q58 %in% c(3, 5), ])
```

where `base_q58` is a factor variable containing the LGPI region identifier.

3) Merging Household and Village Level(MUNI and FACT) datasets

Similar to the items explained in section 5.1.3 above you can combine the household and village-level datasets(MUNI & FACT) using the Village Variable as follows:

```
newdat <- merge(dat1, dat2, by="Village")
```

where `dat1` is the first dataset and `dat2` is the **MUNI or FACT** dataset.

Important: Always ensure that any location filtering requirement involves the combination of household sub-datasets with **the BASE sub-dataset**

5.3 Supplementary Data Access Options

The Local Governance and Development Institute is currently working on creating a data access tool that will be integrated into its website. Once finished, this tool will offer a variety of features, such as multiple filtering and downloading options, a tool for searching variables, visualization capabilities, and further insights, with a primary emphasis on the datasets we have accumulated over time.

At present, the tool enables users to explore various combinations and downloading possibilities for the LGPI 2019 dataset. We encourage researchers and data users to frequently visit our data access page https://gld.gu.se/ for the most recent updates and the introduction of new tools.

6 Data Cleaning

This chapter outlines the procedure used to clean the data from the LGPI 2019.

6.1 Dropped Observations

The reasons that an observation may have been completely eliminated from the dataset are:

1. The observation was incomplete. We defined incomplete observations as those who did not have complete demographic data and/or did not answer both the first and last questions of the survey.
2. The observation, while complete, is located too far from the original sampling frame. We define too far as being more than 1 kilometer away from any square kilometer in the sampling frame.
3. The observation, was not done during the official sampling time period. Kenya/Zambia: May 29, Malawi: Sept 23
4. There was no GPS data available for the observation.
5. The implementation partner told us the observation needed to be dropped due to a confirmed quality issue.

Table 1: Breakdown of Observations

	No GPS Data	Incomplete Obs	Too Far Away	Outside Fielding Period	Partner Drop	Usable Obs
Kenya	2	21	39	1	20	3788
Zambia	2	303	136	10	0	9864
Malawi	2	139	9	69	0	10302

6.2 Don't Know and Refuse to Answer Responses

For many of the questions, both multiple choice and free response, "Don't Know" or "Refuse to Answer" are possible answer choices. Throughout the survey we see this type of answer choice in the following ways:

- Don't Know
- Refuse to Answer
- Don't Know/Refuse to Answer

It should be assumed that if "Don't Know/Refuse to Answer" is given as an answer choice, the designers of the survey determined that there was insufficient insight to recording "Don't Know" and "Refuse to Answer" separately.

7

Sampling Plan of LGPI 2019

The sampling of the LGPI was performed independently in 5 regions across 3 countries: Kenya, Zambia, and Malawi. We name the 5 regions:

- Nairobi
- Lilongwe
- Malawi Border
- Lusaka
- Zambia Border

The maps below show the areas canvased by the LGPI 2019 survey. Figure 1 shows all of the areas included in the LGPI 2019 survey. The bull's eye shaped areas correspond to the Nairobi, Lilongwe, and Lusaka regions. Figure 2 and Figure 3 show the Malawi/Zambia and Kenya sampling areas in more detail.

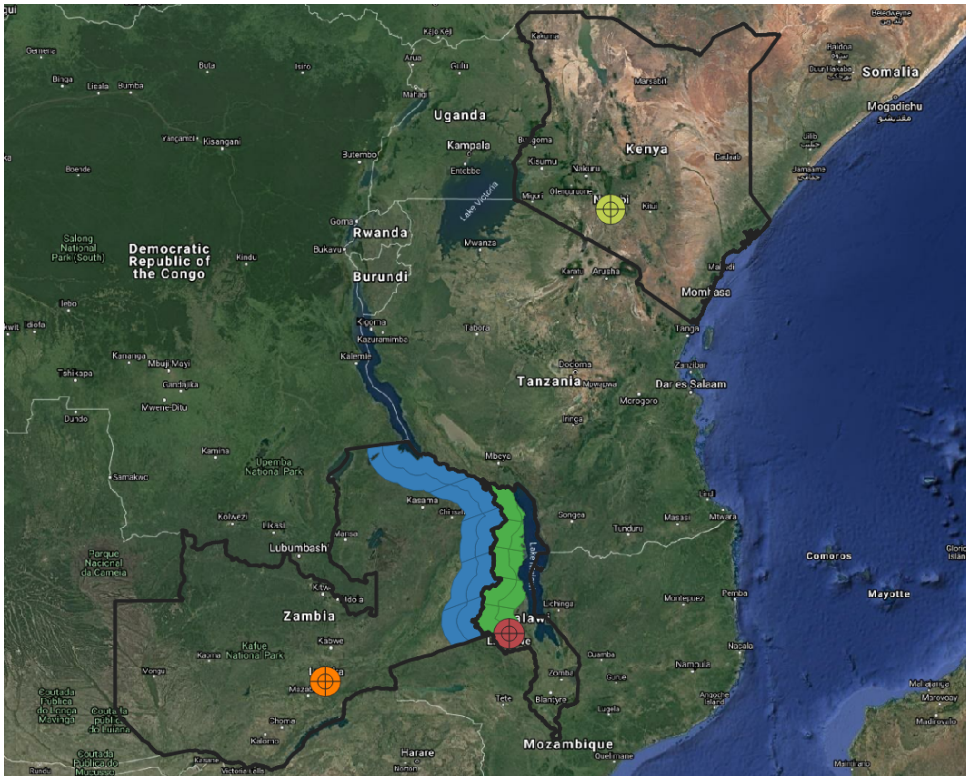


Figure 1: LGPI 2019 Sampling Areas

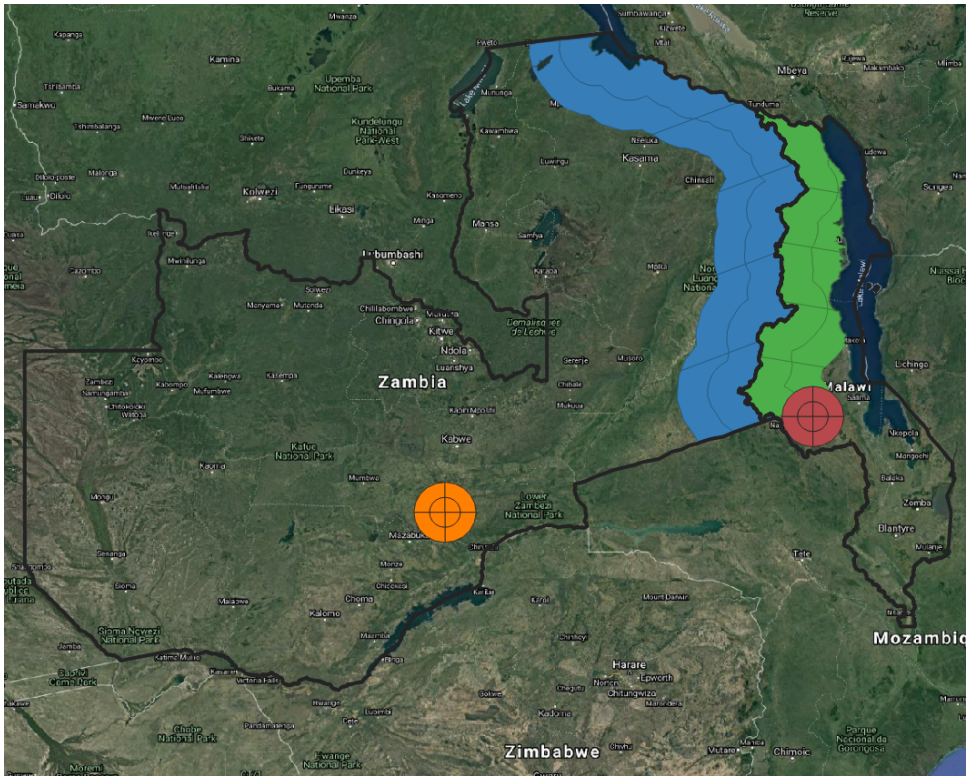


Figure 2: Malawi and Zambia Sampling Areas

Figure 3: Kenya Sampling Areas

As seen in Figure 1, there are two different types of regions in the sample. There are three capital regions (Nairobi, Lilongwe, and Lusaka) and two border regions (Malawi Border and Zambia Border). The LGPI 2019 survey utilized two sampling plans, one for the capital regions and one for the border regions. The two sampling plans are very similar with two major differences:

1. Definition of Bins
2. Selection Method for Choosing Square Kilometers

7.1 Overview of Sampling Plans

The sampling plans for the capital and border regions can be described as a multi-stage probability proportional to size sampling. Each sampling plan follows the same general steps:

1. Define the bins. (these are the strata)
2. Choose square kilometers within the bins using PPS. (stage 1)
3. In each selected sqkm, create a grid of hectares.
4. Remove all empty/underpopulated hectares from consideration.

5. Within each sqkm, randomly assign an order to the viable hectares using PPS (stage 2)

To see all the code used to create the sampling plan visit: https://github.com/senickel/sampling_documentation

and

https://senickel.github.io/sampling_documentation/index.html#prerequisites

The subsequent sections provide a detailed description of the sampling plan.

7.2 Defining the Bins

The LGPI 2019 Survey does not cover the entirety of any of the three countries included in the project. Therefore we must first define where in the country we will be conducting our survey. We call these large defining areas Bins. In the urban areas there are 8 bins and in the rural area there are 10 bins.

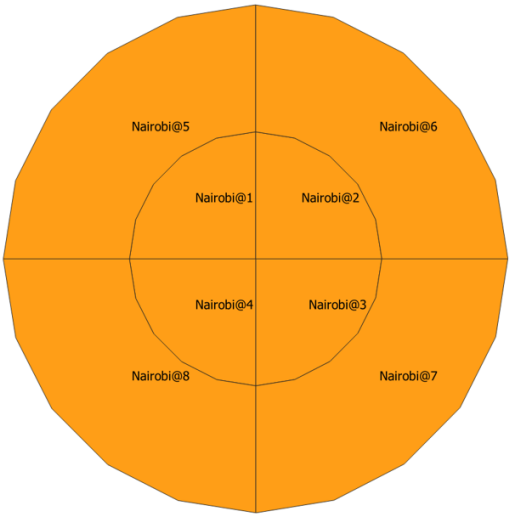
7.2.1 Creating Urban Bins

When surveying in a capital region, we want to ensure sampling of areas close to and further away from the city center. Therefore, we structure the capital region bins as a "bull's eye" over the city center. The bull's eyes are centered at the following locations:

- Nairobi: 36.81667 Longitude, -1.28333 Latitude
- Lilongwe: 33.783333 Longitude, -13.983333 Latitude
- Lusaka: 28.283333 Longitude, -15.416667 Latitude

Each bull's eye consists of two concentric circles: the first is 25km from the center and the second is 50 kilometers from the center. Then a vertical line and a horizontal line are drawn through the city center. The result is a marked off area like Figure 4. As seen in Figure 4, every bin is given a name of the form "RegionName@Bin#".

Figure 4: Sectors for the Nairobi sampling area.



7.2.2 Creating Rural Bins

When defining the bins for the border sampling plans, we employ a similar rule as the one used to create the capital region bins. To ensure that we sample areas both close to and far away from the border, we begin by defining two regions. The first is 50km from the border and the second is 50-100km from the border (as geography allows).

Then to ensure that we have equal sampling in the north-south direction we divide each of the first two regions into 5 smaller regions. The results for the two border regions are shown in Figures 5 and 6.

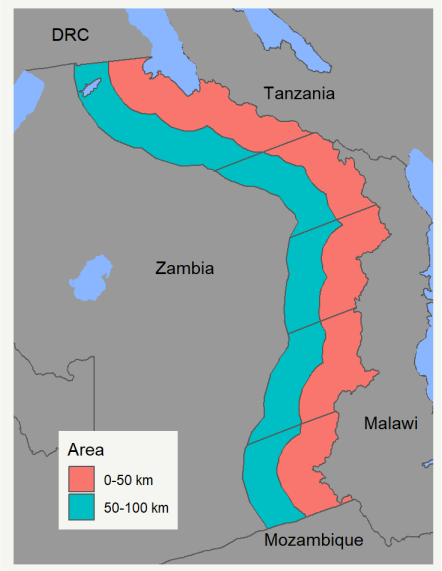


Figure 5: Bins for Zambia Border Region

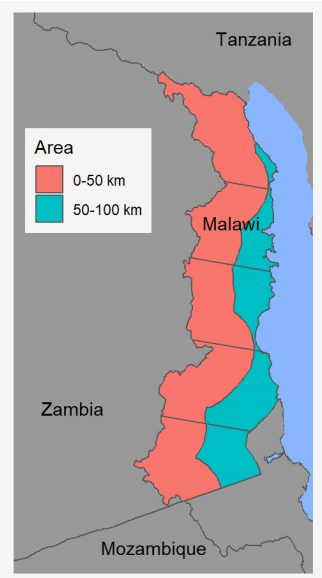


Figure 6: Bins for Malawi Border Region

7.3 Selection of Square Kilometers

The square kilometer sampling unit is used as a proxy of a community. Since boundaries of villages and communities are unclear and in some cases dynamic, we define a square kilometer area to be a community. Sampling these units will allow us to gather data from individuals living in close proximity to each other.

7.3.1 Capital Regions

We perform a stratified sample (stratum = bin) using PPS to select square kilometers (SQKM). First we create a grid of 1 kilometer squares over the bins and compute the expected population density for that areas using WorldPop data. We then sample a predetermined number of squares using probability proportional to size (where size = population density) sampling.

The number of square kilometers sampled was equal to the desired number of communities plus a small number of supplemental units. The supplemental units serve as backups in the case that a chosen square kilometer is not sufficiently populated to obtain the necessary number of observations.

7.3.2 Border Regions

The border regions are notably larger than the capital regions, so traveling through the region will be intensive and expensive for the enumerators. To help mitigate this issue, we

we sample 5 kilometer squares instead of sampling individual square kilometers. That is, we sample 25 square kilometers at a time. To do this we create a grid of 5km squares in each bin, and then using PPS select an appropriate number of 5km squares.

7.3.3 Sampled Square Kilometer Evaluation

Once the square kilometers have been sampled, they must be reviewed to ensure they are sufficiently populated. While PPS should minimize the probably of selecting underpopulated areas, there is still a small probability they could end up in the sample. A google map image of each selected square kilometer was reviewed to ensure the area was populated. If the area was not sufficiently populated it was removed from the sample.

7.4 Selection of Hectares

In every verified square kilometer from the previous step, we create a grid of hectares. Each hectares is checked visually to ensure it is populated. We then use PPS to randomly assign an order to the inhabited hectares within each square kilometer.

This second stage of sampling helps ensure that the entire square kilometer is being sampled and thus providing a more complete picture of the community.

7.5 Selection of Houses Respondents

This stage of the sampling plan was implemented on the ground by teams of enumerators. Teams were sent to a specified hectare by their team leader. They were instructed to enter the hectare using tablets to track their locations and confirm they were in the correct area. They would then go to the center of the hectare and then move outward in a random walk. Once a household had been selected (and agreed to participate) a Kish grid was used to randomly choose a respondent from all reported adults (at least 18 years old) in the household.

7.6 Reaching Target Number of Observations

Starting from the center of a hectare, the team of enumerators would go in separate directions to additional houses using a random walk. The team continued surveying in the hectare until at least 8 surveys had been completed. Once the hectare was completed, if the target number of observations for the current square kilometer had not yet been met,

the team would move onto the next listed hectare for the current square kilometers as outlined in Subsection 7.4. The teams would continue to complete hectares until the target number of observations for a square kilometer had been met.

The target number of observations for each region were:

	Total # Obs	**# of SQKM**	**# Obs Per SQKM**	**# Obs Per Hect***
Nairobi	3750	150	25	8
Lusaka	4500	150	30	8
Zambia Border	6000	200	30	8
Lilongwe	4500	150	30	8
Malawi Border	6000	200	30	8

*–One will note that the number of observations per hectare does not equally divide the number of observations per square kilometer. This is due to a last minute change to increase the number of observations per hectare from 5/6 to 8. This was done to increase the chances that enumerators would be able to reach the target number of observations per square kilometer.

7.6.1 Team Size

It is important to note that the size of the teams sent to hectares was large enough to minimize the chances that a small number of enumerators complete all of the observations in a square kilometer. By doing so, we help address the issue of enumerator effects confounding with community (sqkm) effects.

7.6.2 Special Considerations

We now describe additional sampling rules that were implemented to help mitigate issues in the field.

<u>One–Hectare–West</u>

Justification: We added this rule as a way to combat the issue of low population density areas.

Rule: In the event that the team of enumerators could not obtain 8 observations in a given hectare, they were allowed to move one hectare west to make up the missing observations.

Implementation Period: This rule was in place in all regions throughout the entirety of the respective fielding period.

Adjacent–Square–Kilometer

Justification: During fielding in Kenya and Zambia it become apparent there were some issues with the population density of selected and rejected areas. Namely that many selected areas were not sufficiently populated and numerous rejected areas were in fact populated. This resulted in a large number of incomplete (number of obs < 30/25) square kilometers.

Rule: If after an entire square kilometer has been exhausted, the square kilometer is still not complete, then enumerators may go to any *adjacent* sqkm not in the sampling plan to obtain the remaining observations. Enumerators are instructed to obtain the observations as close to the border as possible.

Implementation Period: This rule was first implemented in Kenya and Zambia on July 27, 2019. It was implemented during the entire Malawi fielding.

Open–Square–Kilometer

Justification: During fielding in Kenya and Zambia we learned that many of the selected hectares were underpopulated while some of the rejected hectares were populated.

Rule: If after all hectares in a given sqkm have been exhausted the target number of observations for that sqkm have not been met, enumerators may go anywhere within the sqkm

Implementation Period: This rule was never used in Kenya. It was first implemented in Zambia on September 5, 2019. It was implemented during the entire Malawi fielding.