Food and Agriculture Organization of the United Nations

Using poverty maps for FAO projects

What is a poverty map?

Poverty maps show the incidence of poverty and/or the distribution of the poor in given geographical spaces (e.g. country, region, or district). They provide a snapshot of poverty at the territorial level, communicating large amounts of information in a more compact way than tables (e.g. poverty profiles). Poverty maps also allow for linking poverty to geospatial variables, such as agroclimatic characteristics.

This note provides essential and practical information from the second chapter of the "FAO Toolkit on Poverty Analysis". It focuses on maps based on quantitative data. For an overview of qualitative and participatory methods for mapping, see Davis (2003).

When and why using a poverty map?

A poverty map can be useful in many ways. In general, the higher its resolution (i.e. the level of geographical disaggregation), the more a poverty map can guide territorially-specific poverty reduction interventions. Here are some examples:

- **Geographical targeting** – If resources are limited, poverty maps can serve as the first level of targeting to help focus strategies, programmes, and projects where the poor population is concentrated, compatible with other objectives of the intervention.
- **Country policy dialogue** – A poverty map can help shift attention away from a single national poverty figure, catalyse local stakeholders to participate in policy debates, and build consensus for interventions in more remote rural areas.
- **Support to subnational planning and multisectoral coordination** – If governments can identify where the poverty challenge is greater, they can allocate resources more efficiently. For example, poverty maps can support subnational planning as an input into formulas to adjust funding based on the poverty level of administrative units.
- **Linking poverty, climate change and natural resource management** – Poverty maps open the way to relate poverty to geospatial characteristics, including infrastructure, agroclimatic characteristics and availability of natural resources. Analysis based on these linkages can enable the design of interventions that consider the environmental characteristics and the development potential of the areas where the rural poor live.

How to build a poverty map?

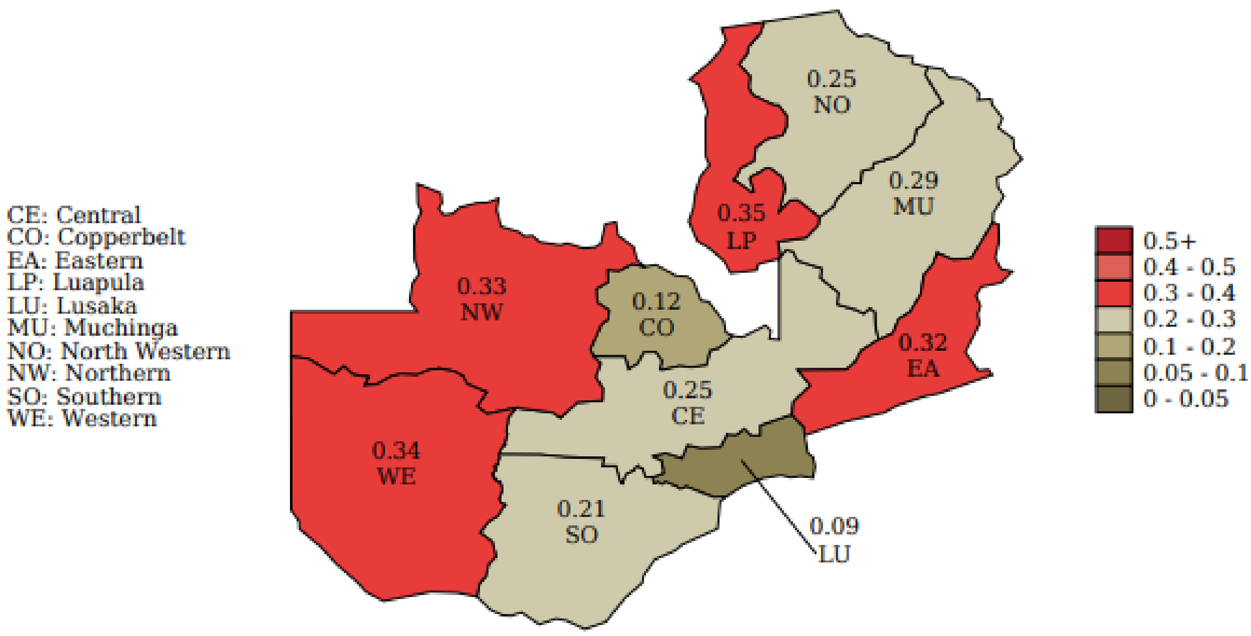
There are various approaches to build poverty maps, with recent developments in new techniques.

Direct mapping

Poverty estimates are normally obtained from household socio-economic surveys, such as the Living Standards Measurement Study (LSMS) and the Demographic and Health Surveys (DHS). To build a poverty map, once the poor are identified, a measure of poverty is aggregated for each spatial unit of interest and then represented in a map. However, national household surveys are usually designed to be statistically representative at the national and, at most, first administrative level. If the aim is producing a poverty map of the first-level administrative units of a country (e.g. regions), direct mapping from a national household survey might be a feasible option. However, this approach is not satisfactory for:

- Producing a map representing poverty at lower-level administrative units. For example, a poverty map of the municipalities within a district.
- Producing a poverty map based on a disaggregation other than the country's administrative units. For example, a map of poverty based on agro-ecological zones, watershed areas, or socio-cultural and economic characteristics.

Example of direct poverty mapping - Multidimensional poverty index by province, Zambia 2018



Source: Oxford Poverty and Human Development Initiative (2020)

What to do in these cases? There are a few options:

- **Use census data** – Censuses are administered to all households in a country and do not involve problems of statistical representativeness. However:
  - census data are often not available for poorer countries and/or are outdated (censuses are usually run every ten years);
  - only a few censuses collect the information on income or consumption needed to measure monetary poverty. If they do, this measure is not as reliable as income captured in a national household survey. However, most censuses include enough variables to construct ad-hoc multidimensional poverty indexes (e.g. asset indexes) at village or district level.
- **Conduct a local household survey** – This could be a valid option if the area of interest is relatively small (e.g. for targeting a project within a district) but might involve substantial costs. These can be lowered using a poverty measure with lighter data requirements (e.g. an asset index or a number of questions to proxy poverty). In general, it is not advisable to conduct a new household survey only to produce a map. However, baseline surveys requested by donors in the context of projects may represent an opportunity to collect the necessary information to map poverty.
- **Use an imputation technique combing data sources** – These are described in the reminder of the note.

Tips for poverty mapping

- Produce separate maps to show the prevalence and the density of poverty. Often, more densely populated areas of a country have a larger number of poor people than more scarcely populated places with higher prevalence of poverty.
- In addition to a map of poverty incidence, produce maps of other poverty indicators (e.g. the poverty gap).
- If possible, generate poverty maps using different measures of welfare (such as consumption or assets indices) and compare them. This is a way to check the robustness of your map.
- After producing the map, try to identify spatial clusters of poverty (e.g. contiguous areas with high level of poverty). This can ease interpretation and help identify opportunities for policy interventions beyond pre-defined administrative units (for example identifying areas that are poor due to their common agro-climatic features).
- Report measures of uncertainty such as standard error if the mapped poverty figures are estimates (i.e. whenever the map is not based directly on census data).
- If you are comparing a map of poverty with maps of other geographically based variables, do not interpret visual correlations as causal relations. Comparing maps can be a useful exploratory analysis, but establishing causal relationships require rigorous statistical analysis.
- If the main goal is identifying where the poor live, it is not necessary to update poverty maps often (e.g. every three to five years is enough). Although poverty levels change over time, its spatial distribution tends to be more stable.

Mapping with imputed data: Small Area Estimation (SAE)

Imputation techniques simulate a measure of poverty for a given individual, household, or geographical area based on a model. Small Area Estimation (SAE) is a family of imputation techniques that combine survey and census data to create detailed poverty maps.

Imagine a household survey that includes representative data on age, sex, education, and income of households. A census instead has data on age, sex, and education on every single household, but not income. The idea is using the household survey data to build a model that links income information to the other variables available in the census. With this model, a value for income can be predicted for each observation of the census based on their sex, age, and education.

There are different SAE techniques, but the procedure can be summarized in four steps:

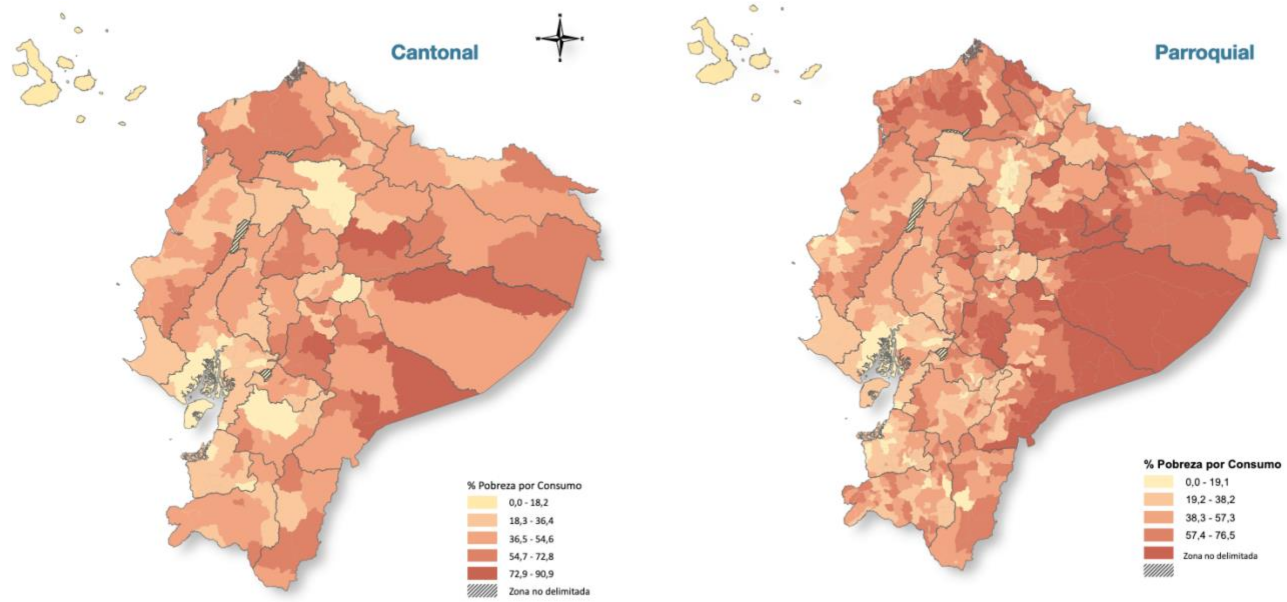
1. Use a household survey to build a model that links a welfare measure (e.g. income or consumption) to a set of explanatory variables that are common to both the survey and the census.
2. Apply the estimated parameters to the explanatory variables in the census to predict a welfare value for each observation unit.
3. Use the predicted welfare variable to estimate poverty for small areas (e.g. districts, municipalities, or communities).
4. Present the estimates through a map.

What does the quality of the estimates depend on? There are various factors involved:

- **Degree of disaggregation** – The more disaggregation, the less precision. There is often a trade-off between precision and policy needs.
- **Underlying model** – Precision depends on how good the model is (i.e. its explanatory power).
- **Temporal distance between the survey and the census** – It is important to use a survey and a census that are as close as possible in time (the distance should not be more than 3/5 years) as significant changes in the characteristics of the population are more likely to occur within a wider time period.

In all cases, it is highly advisable to discuss and validate the poverty estimates with local stakeholders.

Example of SAE – Incidence of monetary poverty in Ecuador, 2014 (two administrative levels)



Source: Molina et. al (2014)

How to build a map that focuses specifically on rural poverty?

A first approach is mapping poverty separately for geographic areas that are classified as rural. Another is mapping poverty separately for subsets of the population such as agricultural households (see for example the poverty map of Brazil developed by Soares *et al.* (2016)). In both cases, SAE offers the possibility of building a model that predicts poverty taking into account aspects that are particularly relevant for the livelihoods of the rural poor. This can be done by combining an agricultural or household survey with an agricultural census.

Mapping with imputed data: non-traditional data sources

The imputation method presented above relies on a population or agricultural census, which may be outdated or not available. This means that it is often not possible to generate detailed poverty maps for years and countries not covered by census data.

New methods that combine geo-referenced household survey data (e.g. from LSMS or DHS surveys) with non-traditional data sources such as geospatial, mobile phone data, and text data are creating opportunities to map poverty at a higher resolution, with increased coverage, at a higher frequency, and with a special focus on rural areas.

These methods use models that link a poverty measure from a geo-referenced household survey to variables from other databases (e.g. on temperature, precipitation, and leaf coverage). Then, the level of poverty of small areas which are not covered by the household survey is predicted with the model. For example, Steele *et al*. (2017) integrated environmental and mobile phone data to create a high-resolution poverty map of Bangladesh.

Some methods apply machine learning too. For example, Yeh *et al*. (2020) used a machine learning model to predict an index of wealth across about 20,000 African villages from publicly available nightlight and daytime satellite imagery. For more details consult box 2.8 of the forthcoming FAO Toolkit on Poverty Analysis.

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