OPHI MPI Methodological Note 59

The global Multidimensional Poverty Index (MPI) 2024 disaggregation results and methodological note

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Attribution

The estimates of MPI and its partial indices are disaggregated by several different population groups. This includes by age groups (OPHI's Table 3), urban and rural areas (Table 4), subnational regions (Table 5) and gender of household head (Table 7). All Tables based on disaggregated analysis are produced by the authors.

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1. Overview

This Methodological Note presents the methodology and technical decisions that underlie the published **disaggregation** results (age groups, rural and urban areas, subnational regions and gender of household head) of the global Multidimensional Poverty Index (MPI) 2024. The 2024 MPI **disaggregation** results are based on the most recent data from 112 countries, covering 6.3 billion people. We estimate the MPI and its associated statistics by four age categories (0 to 9 years, 10 to 17 years, 18 to 59 years, and over 60 years) as well as two broad age categories covering children aged 0 to 17 years and adults 18 years and older, by rural and urban areas, and gender of the household head. In addition, the MPI is also computed for 1,359 subnational regions across 102 countries to show disparities in poverty within countries. Subnational disaggregations are published when the survey used for the global MPI is representative at the subnational level and the retained sample permits.

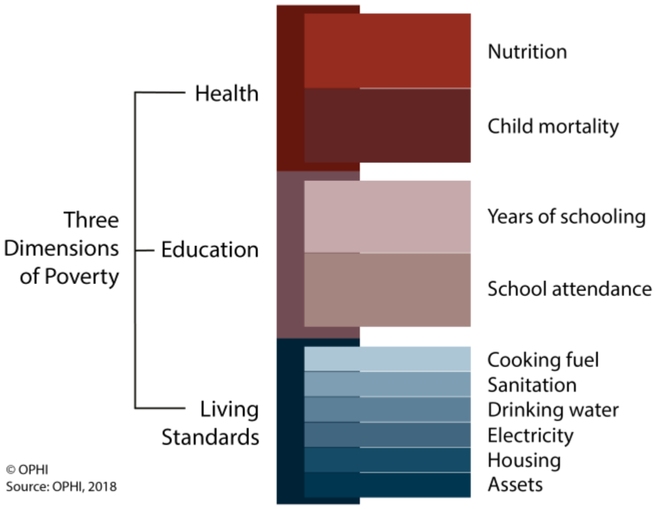
This document is structured as follows. Section 2 presents the global MPI structure and indicator definitions. [1] Section 3 provides an outline of the global MPI and its partial indices that we estimate and publish. Section 4 outlines the disaggregation methodology. Section 5 outlines the principles and decisions that underlie our disaggregation work. Section 6 summarises the country-specific decisions that were applied for the new or updated datasets in this round. We conclude with brief closing summary.

2. The global MPI structure

The global MPI, published annually since 2010, captures acute multidimensional poverty in developing regions of the world (Alkire and Santos, 2014 & 2010). This measure is based on the dual-cutoff counting methodology developed by Alkire and Foster (2011). The global MPI is composed of three dimensions (health, education, and living standards) and ten indicators (Figure 1). Each dimension is equally weighted, and each indicator within a dimension is also equally weighted. In 2018, the first major revision of the global MPI, that is, the adjustments in the definition of five out of the ten indicators was undertaken (see Alkire, Kanagaratnam, Nogales and Suppa, 2022; Alkire and Kanagaratnam, 2021; Alkire and Jahan, 2018; Vollmer and Alkire, 2022).

[1] The text in this section draws on methodological notes published for each update of the global MPI (see past updates by the authors including 2023, 2022, 2021, 2020 and 2019) and the book by Alkire, Foster, Seth and others (2015). It is useful to include similar text in each methodological note, to provide an overview of the global MPI structure, as well as MPI and its partial indices to first-time users of the global MPI data.

Figure 1. Composition of the Global MPI – Dimensions and Indicators



The global MPI begins by establishing a deprivation profile for each person, showing which of the 10 indicators they are deprived in. Each person is identified as deprived or non-deprived in each indicator based on a deprivation cutoff (Table 1). In the case of health and education, each household member may be identified as deprived or not deprived according to available information for other household members. For example, if any household member for whom data exist is undernourished, each person in that household is considered deprived in nutrition. Taking this approach – which was required by the data – is intuitive and assumes shared positive (or negative) effects of achieving (or not achieving) certain outcomes. Next, looking across indicators, each person's deprivation score is constructed by adding up the weights of the indicators in which they are deprived. The indicators use a nested weight structure: equal weights across dimensions and an equal weight for each indicator within a dimension.

Table 1. Global MPI – Dimensions, Indicators, Deprivation Cutoffs, and Weights

Dimensions	Indicator	Deprived if…	SDG area	Weight
Health	Nutrition	Any person under 70 years of age for whom there is nutritional information is **undernourished**.[1]	SDG 2	1/6
	Child mortality	A child **under 18** has **died** in the household in the five-year period preceding the survey.[2]	SDG 3	1/6
Education	Years of schooling	**No** eligible household member has completed **six years** of **schooling**.[3]	SDG 4	1/6
	School attendance	Any school-aged child is **not attending** school **up to** the age at which he/she would complete **class 8**.[4]	SDG 4	1/6
Living Standards	Cooking fuel	A household cooks using **solid fuel**, such as dung, agricultural crop, shrubs, wood, charcoal, or coal.[5]	SDG 7	1/18
	Sanitation	The household has **unimproved** or **no** sanitation **facility** or it is improved but **shared** with other households.[6]	SDG 6	1/18
	Drinking water	The household's source of **drinking water** is **not safe** or safe drinking water is a **30-minute** or **longer walk** from home, roundtrip.[7]	SDG 6	1/18
	Electricity	The household has **no electricity**.[8]	SDG 7	1/18
	Housing	The household has **inadequate** housing materials in **any** of the three components: **floor**, **roof**, or **walls**.[9]	SDG 11	1/18
	Assets	The household does **not own more than one** of these **assets**: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck.	SDG 1	1/18

Notes: The global MPI is related to the following SDGs: No Poverty (SDG 1), Zero Hunger (SDG 2), Health and Well-being (SDG 3), Quality Education (SDG 4), Clean Water and Sanitation (SDG 6), Affordable and Clean Energy (SDG 7), and Sustainable Cities and Communities (SDG 11).

[1] Children under 5 years (60 months and younger) are considered undernourished if their z-score of either height-for-age (stunting) or weight-for-age (underweight) is below minus two standard deviations from the median of the reference population. Children 5–19 years (61–228 months) are identified as deprived if their age-specific BMI cutoff is below minus two standard deviations. Adults aged 20 to 70 years (229–840 months) are considered undernourished if their Body Mass Index (BMI) is below 18.5 m/kg^2.

[2] The child mortality indicator of the global MPI is based on birth history data provided by mothers aged 15 to 49. In most surveys, men have provided information on child mortality as well, but this lacks the date of birth and death of the child. Hence, the indicator is constructed solely from mothers. However, if the data from the mother are missing, and if the male in the household reported no child mortality, then we identify no child mortality in the household.

[3] If all individuals in the household are in an age group where they should have formally completed 6 or more years of schooling, but none have this achievement, then the household is deprived. However, if any individuals aged 10 years and older reported 6 years or more of schooling, the household is not deprived.

[4] Data source for the age children start compulsory primary school: DHS or MICS survey reports; and http://data.uis.unesco.org/.

[5] If the survey report uses other definitions of solid fuel, we follow the survey report.

[6] A household is considered non-deprived in sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared. If the survey report uses other definitions of improved sanitation, we follow the survey report

[7] A household is considered non-deprived in drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring, or rainwater. It must also be within a 30-minute walk, round trip. If the survey report uses other definitions of improved drinking water, we follow the survey report.

[8] A small number of countries do not collect data on electricity because of 100% coverage. In such cases, we identify all households in the country as non-deprived in electricity.

[9] Deprived if floor is made of natural materials (mud/clay/earth, sand or dung) or if dwelling has no roof or walls or if either the roof or walls are constructed using natural or rudimentary materials such as such as carton, plastic/ polythene sheeting, bamboo with mud/stone with mud, loosely packed stones, uncovered adobe, raw/reused wood, plywood, cardboard, unburnt brick or canvas/tent. The definition of natural and rudimentary materials follows the classification used in country-specific DHS or MICS questionnaires.

3. The global MPI and its partial indices

The global MPI person is identified as multidimensionally poor or MPI poor if they are deprived in at least one-third of the weighted MPI indicators. After the poverty identification step, we aggregate across individuals to obtain the incidence of poverty or headcount ratio (H) which represents the percentage of poor people in the population. We then compute the intensity of poverty (A), representing the average deprivation score of the poor. We then compute the adjusted poverty headcount ratio (M0) or MPI by combining H and A in a multiplicative form (MPI = H x A). A headcount ratio is also estimated using two other poverty cutoffs. Individuals are identified as vulnerable to poverty if they are close to the one-third threshold, that is, if they are deprived in 20 to 33.33 percent of weighted indicators. The tables also apply a higher poverty cutoff to identify those in severe poverty, meaning those deprived in 50 percent or more of the dimensions.

The AF methodology has a property that makes the global MPI even more useful—dimensional breakdown. This property makes it possible to consistently compute the percentage of the population who are multidimensionally poor and simultaneously deprived in each indicator. This is known as the censored headcount ratio of an indicator. The weighted sum of censored headcount ratios of all MPI indicators is equal to the MPI value.

The censored headcount ratio shows the extent of deprivations among the poor but does not reflect the weights or relative values of the indicators. Two indicators may have the same censored headcount ratios but different contributions to overall poverty, because the contribution depends both on the censored headcount ratio and on the weight assigned to each indicator. As such, a complementary analysis to the censored headcount ratio is the percentage contribution of each indicator to overall multidimensional poverty.

4. Subgroup disaggregation or decomposability

A component of the AF method is the link between overall poverty and poverty in different subgroups of the population. Population subgroup decomposability specifies that overall poverty (national level) is a population-share weighted sum of subgroup poverty levels. This principle is useful for identifying and reporting the poverty of different subgroups of the population in a country and comparing it with other subgroups and with aggregate national poverty.

Using the same procedure for national estimates, we disaggregate the country-level **MPI**, **H**, **A**, **vulnerable** to poverty and **severe poverty** by each population subgroup: age groups, urban-rural areas, subnational regions, and gender of household head. The population share for each subgroup is obtained by applying the sampling weight in the respective survey dataset to the final sample used for the computation of the reported statistics. We compute the **censored headcount ratios of each subgroup** to show the extent of deprivation among the poor in the subgroup. In addition, we compute the weighted **contribution of each indicator** to poverty for each subgroup.

The survey datasets used in global MPI 2024 are collected in different years. The survey used ranges between 2011-2012 to 2023. We rescale the sampling weights for each national survey so that they add up to the population of that country in the chosen common time period or reference year. This round, we rescaled the weights to add up to the 2022 population as reported in the World Population Prospects 2024 (UNDESA, 2024). We compute population size for subgroups using a combination of the population share and the 2022 population to facilitate comparisons of the number of poor in each subgroup.

All disaggregated estimates are based on the global MPI specification outlined in Alkire, Kanagaratnam and Suppa (2024a).

5. Tool to estimate MPI

The global MPI estimates are produced using the Stata package 'mpitb' which is documented in Suppa (2023). 'mpitb' facilitates the estimation of measures such as the MPI (adjusted headcount ratio), the H (headcount ratio), the A (intensity), the censored and uncensored headcount ratios, and percentage contribution of each indicator. `mpitb` supports estimations by population subgroups relevant to this methodological note, namely age groups, rural and urban areas, subnational regions and gender of household head. It is also possible to include any other subgroup disaggregations that are possible with the survey sample. `mpitb` supports the estimation of levels and change between time periods for each of the measure specified in Alkire, Kanagaratnam and Suppa (2024b) and across the different levels, namely national, and subgroups. `mpitb` also simplifies estimations and analyses in cross-country settings.

6. Disaggregation principles and decisions

6.1 Disaggregation by age groups

We disaggregate the MPI and its partial indices by these age groups: 0 to 9 years, 10 to 17 years, 18 to 59 years, and 60+ years, children aged 0 to 17 years and for adults 18 years and older. We use information on 'age of household members' from the household roster to categorise the age information into groups. Age is a self-reported category across most surveys. An exception is the survey for China where age was constructed using birth month and year information. In cases where respondents in the dataset have missing age information, we then exclude these respondents from the computation by age group, though they are included in the national MPI. The number of observations that are missing age data is less than 100 across the 112 countries. In this sense, this issue does not affect the population-share weighted sum of age group poverty levels when compared to overall poverty.

6.2 Disaggregation by urban-rural areas

We disaggregate the MPI and its partial indices by urban and rural areas in 110 countries; for one country (Argentina) we disaggregate by only urban area; and for Seychelles we are not able to disaggregate by area due to limitation in sample stratification.

The definition of 'rural' and 'urban' are taken directly from the surveys used to construct the MPI; these definitions may vary across countries. The stratification used in the sample design of the datasets defines the geographic units within which the sample was designed. This determines the possibility for disaggregation by urban and rural areas.

Across the 110 country surveys with rural-urban disaggregation, the sample was designed to be self-weighting within urban areas and rural areas. The area variable in the datasets would define the urban and rural areas and we have used this variable for our disaggregation work. In addition, we refer to survey reports produced by data providers to ascertain the sample stratification. In cases where the sample design was stratified beyond the urban-rural units, we make use of the additional information for disaggregation. In the case of Palestine MICS 2019-2020 dataset, the sample was designed to be self-weighting within urban, rural and camp areas. The MPI estimation at the area level in this country is based on these three categories.

In cases where the sample design is stratified to certain areas, we restrict the disaggregation to the area that was sampled. The sample for Argentina MICS 2019-2020 did not cover rural areas mainly due to the cost of survey of these areas, as well as the low share of rural population in Argentina (9% of the total population) (UNICEF and SIEMPRO, 2021). The MPI estimation at the area level in this country is restricted to urban areas.

In the case of Seychelles, the sample is self-weighting at the national level. This means any estimation based on this country sample is restricted to the national level. Following this, information on urban-rural areas is also not made available in Seychelles QFLS 2019 dataset by the survey providers.

6.3 Disaggregation by subnational regions

In this round of publication, we disaggregate the MPI and its partial indices by 1,359 subnational regions in 102 countries. The decision whether national estimates could be disaggregated at the subnational level was determined by two criteria that were established in our earlier work.[2] These criteria were (1) the sample was representative of subnational regions; and (2) the sample size after the treatment of missing data was reasonably high.[3]

An additional criterion was specified in earlier rounds of the global MPI: the national poverty headcount ratio (H) and the MPI must be large enough (H more than 1.5 percent and MPI greater than 0.005) to allow for a meaningful subnational analysis. Since 2018, our estimates are reported along with standard errors estimates and confidence intervals. Poverty measures should be accompanied by standard errors to evaluate their precision and properly rank regions of a country. In cases where the subnational estimates are zero, the standard errors establish whether these are true zeros. As such this criterion is no longer required. We disaggregate by subnational regions of countries with low H and MPI.

The first criterion for disaggregation is that the survey report must establish that the sample is representative at the subnational level following the survey metadata on sample design. In 2024, 107 country surveys fulfilled this criterion. Five countries – Armenia, Bosnia and Herzegovina, Saint Lucia, Seychelles and Tuvalu – have sample sizes that are representative at the national level but not at the subnational level. Hence, these five countries were excluded at this stage.

The second criterion emphasises that the sample size after the treatment of missing data must be reasonably high at the national and subnational levels. For borderline cases, bias analyses are conducted to exclude those cases where the sample reduction leads to statistically significant bias. We specify the second criterion in three ways.

First, the national sample size must be at least 85 percent of the original sample after dropping observations that had missing data in any of the 10 global MPI indicators. This is because a lower sample size may affect accurate comparability across subnational estimations. Following this specific criterion, we identified four countries that did not meet this cutoff (Table 2). The sample drop across these four countries ranges between 17 to 22 percent. Collectively these four countries represent under 1 percent of the 6.3 billion people covered in global MPI 2024.

[2] See Alkire and Santos (2014); Alkire, Roche, Santos and Seth (2011).

[3] A criterion that matters for poverty trends is that regions must be harmonised for comparability over time. This we cover in detail in Methodological Note 60 (Alkire, Kanagaratnam and Suppa, 2024b) which focuses on subgroup disaggregation or decomposability over time.

Second, every subnational region in a country must have a retained sample size of at least 75 percent of the original sample. A smaller sample creates a problem of representativeness for that subnational region, which may distort the subnational comparisons. Our analyses indicate that a total of five subnational regions across the three countries fall short with respect to this sub-criterion (Table 3). The retained sample size across these five regions ranges from 56 percent to 75 percent.

Table 2. Global MPI countries with national sample size below 85 percent of the original sample after missing data is treated.

Country	Survey	Year	Total sample size used to compute MPI (weighted)	Total sample drop (weighted)
Georgia	MICS	2018	82%	18%
Maldives	DHS	2016-2017	83%	17%
Montenegro	MICS	2018	80%	20%
South Africa	DHS	2016	78%	22%

Source: Alkire, S., Kanagaratnam, U., and Suppa, N. (2024a). The global Multidimensional Poverty Index (MPI) 2024 country results and methodological note. OPHI MPI Methodological Note 58, Oxford Poverty and Human Development Initiative, University of Oxford.

Table 3. Subnational regions of four countries with sample size below 75 percent of the original sample after missing data is treated.

Country	Survey	Year	Subnational region	Population share of region	Total sample size used to compute MPI (weighted)	Total sample drop (weighted)
Maldives	DHS	2016-2017	Malé	41%	75%	25%
Maldives	DHS	2016-2017	Central Region	7%	74%	26%
Montenegro	MICS	2018	Central	55%	73%	27%
South Africa	DHS	2016	Gauteng	26%	71%	29%
South Africa	DHS	2016	Western Cape	11%	56%	44%

Source: Author's computation.

Third, a bias analysis test is carried out for each of the five region whose sample size is lower than 75 percent and whose national sample size is lower than 85 percent of the original. We identify the major cause of the sample reduction (in this case, nutrition for all three countries listed in Table 3) and divide the entire sample into two groups based on this cause and check the headcount ratios of the other indicators across these two groups. Suppose there is a systematic and statistically significant difference (at a significance level of 1%) between the headcount ratios across these two groups. In that case, that region does not satisfy the bias analysis test. If a region with a large population share (more than 20 percent) within a country does not pass the test, we exclude the country from our subnational analysis.

Following this sub-criterion, we carried out the bias test for the five regions with a low retained sample. The results for the regions in Maldives, Montenegro, and South Africa, indicate that the likelihood of being deprived in child mortality (as well in other indicators) is not the same for those who are missing the nutrition indicator and those who are not missing this indicator. Those without a missing nutrition indicator are systematically more likely to be deprived in child mortality (or in other indicators). This suggests that the sampling structure would need to be revised to assure representativity as those who are dropped from the sample are likely the non-poor.

Further, Malé and the Central Region collectively account for almost half of the population in Maldives as listed in Table 3. Across the three major regions of Montenegro, the region of Central is the most populated – 55 percent of the population live in this region. The regions of Gauteng and Western Cape are home to one-third of South Africa's population. Following the bias observed, we exclude these countries from our subnational analysis.

In addition, we implemented bias test on all regions of Georgia. This is because Georgia has a weighted sample loss of 18 percent at the national level, leaving it at the borderline. Two of the 10 subnational regions within the country (Kakheti and Shida Kartli) had a retained sample of 77 percent each. Both regions had the highest missing values for nutrition and child mortality. Those without missing nutrition indicators are systematically more likely to be deprived in child mortality, suggesting that non-poor people are being excluded. Given that the national sample loss is more than 15 percent and two of its subnational regions, home to 45 percent of the population, indicate biased estimates, we exclude Georgia from subnational disaggregation.

In summary, although subnational disaggregation is theoretically possible for 107 of the 112 countries, only 103 countries satisfy the principles for subnational disaggregation. Of the 103 countries, we restricted the subnational estimation for one country – Mexico – because of an issue with the subnational variable identifier in the microdata.[4] So, while we could have included Mexico for subnational disaggregation, this was not possible at the time of publication. As such, in this round of global MPI, only 102 countries with 1,359 regions satisfy the principles for subnational disaggregation and are thus used for our subnational analysis.

4 The region of Edo México was part of ENSANUT 2021. But Edo México was no longer part of ENSANUT 2022. It was not evident from the microdata and related survey documents if Edo México was excluded from ENSANUT 2022 sampling or was merged with neighbouring subnational region. This required cross-checks with microdata provider, which is on-going.

6.4 Disaggregation by gender of household head

Out of the 112 countries included in the 2024 global MPI, disaggregated results by female-headed and male-headed households were produced for 111 countries – all except China. Information on household head and relationship to head of household based on the household listing was not available in the China CFPS 2014 data set. Across all the surveys, household head is a self-reported category. The selection of a household head by householders may be based on a person's economic status (main provider), age hierarchy (older), or cultural preference (men). However, despite the variation in the definition of household head, the value of presenting a global account of multidimensional poverty by the gender of household head is considerable despite the limited comparability due to the mixed definition of headship.

In our microdata work, we constructed the 'gender of household head' variable using information drawn from two variables in the data sets - sex and relationship to household head. It is useful to summarise a couple of data decisions that we made. In a small number of cases, the category 'household head' is not assigned to any household members. In such cases, if information of spouse was available (male or female), we replace them as household head. The number of replacements made was less than 50 observations across the 111 surveys. The replacement to the missing value made no difference to the final aggregate numbers.

7. Country-specific considerations for new/updated surveys

This section details the country-specific disaggregation decisions for each of the 20 new or updated countries included in the global MPI 2024.

7.1 Afghanistan MICS 2022-2023

The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 34 provinces (UNICEF, 2023). We estimate the MPI and its associated statistics by provinces since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.2 Benin MICS 2021-2022

The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, and for the 12 department (INStaD, 2023). As such, the global MPI subnational estimates cover 12 departments of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.3 Bhutan BLSS 2022

The Bhutan Living Standard Survey (BLSS) micro data set is not available on an open access platform. Micro data was shared through a mutual agreement between the National Statistics Bureau (NSB) of Bhutan and OPHI. The BLSS 2022 survey covered 44 sampling strata (20 dzongkhags with urban and rural areas; and 4 thromdes with only urban areas) (NSB Bhutan, 2022, p.3). The sample in this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 20 dzongkhags (districts) and 4 thromdes (municipalities). We publish the MPI estimate and its associated statistics for all 24 subnational regions (districts and municipalities) as stated in the survey report; as well as urban and rural areas.

7.4 Burkina Faso DHS 2021

The survey sample was designed to produce representative estimates for the urban and rural areas, and for each of the 13 administrative regions (INSD and ICF, 2023). We produced our urban-rural estimates and subnational estimates accordingly. It is useful to note that due to the security context, the survey did not enumerate all areas of the Sahel and Eastern region of Burkina Faso (INSD and ICF, 2023). As such the survey findings may not be representative for these regions and should therefore be interpreted with caution. The sample drop across these regions was negligible, hence we continue to produce the subnational estimates for these regions.

7.5 Comoros MICS 2022

The sample of this dataset was designed to provide statistically reliable estimates at the national level, for urban and rural areas, and for the three major islands of the country (INSEED, 2023). Our urban-rural estimates and subnational estimates are based on the specification of the survey report.

7.6 Côte d'Ivoire DHS 2021

The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 14 autonomous districts of Côte d'Ivoire (INS and ICF, 2023). Two of the 14 autonomous districts include the cities of Abidjan and Yamoussoukro. We estimate the MPI and its associated statistics by districts since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.7 Eswatini MICS 2021-2022

The MPI estimates are computed for four regions since the survey sample is representative at this level (CSO Eswatini, 2024). Our estimates at the area level cover urban and rural areas.

7.8 Gabon DHS 2019-2021

The survey sample is representative for the urban and rural areas. At the subnational level, the sample is representative for nine provinces, as well as for the capital city of Libreville, and the port-city of Port- Gentil (DGS, 2023). We publish the MPI estimate and its associated statistics for all 11 regions, as well as urban and rural areas.

7.9 Ghana DHS 2022

The sample this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 16 administrative regions (GSS and ICF, 2024). We publish the MPI estimate and its associated statistics for all regions as stated in the survey report, as well as urban and rural areas.

7.10 Kenya DHS 2022

The sample for this dataset was designed to provide estimates for urban and rural areas, and for each of the 47 counties (KNBS and ICF, 2023). In 2010, Kenya's eight provinces were replaced by a system of 47 counties as the official administrative areas. Our subnational estimates cover 47 counties since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.11 Mexico ENSANUT 2022

The survey sample was designed to produce representative estimates at the national level, for urban and rural areas. Our estimates at the area level cover urban and rural areas. We do not report estimates for Mexico's major subnational regions due to an issue with the regional variable identifier in the microdata. This requires cross-checks with microdata provider, which are on-going. As such, Mexico was excluded from subnational estimation for the 2024 round.

7.12 Mozambique DHS 2022-2023

The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, and to facilitate disaggregation for 10 provinces (províncias) and 1 capital city (cidade), that is Maputo city (INE and ICF, 2024). As such, our subnational estimates cover a total of 11 administrative areas of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.13 Nepal DHS 2022

This survey was designed to produce representative estimates for urban and rural areas, and for each of the seven provinces (MOH, New Era, and ICF, 2023). Our subnational estimates cover all seven provinces of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas

7.14 Peru ENDES 2022

The survey sample is representative for the urban and rural areas, 24 administrative regions and the capital district of Callao. We publish the MPI estimate and its associated statistics for all 25 regions, as well as urban and rural areas.

7.15 Philippines DHS 2022

The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for 17 regions (PSA and ICF, 2023). The Philippines is subdivided into 17 regions – eight in Luzon, three in the Visayas, and six in Mindanao. These regions are not local government units, but their existence is primarily for administrative purposes. We estimate the MPI and its associated statistics by 17 regions since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.16 Tanzania DHS 2022

The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, for each of the 31 regions, and for the nine major zones. Our subnational estimates are limited to nine major zones of this country. This is because the survey report indicated that grouping the 31 regions into the nine major zones allowed a relatively large number of people in the denominator and a reduced sampling error (MOH Tanzania Mainland, MOH Zanzibar, NBS, OCGS, and ICF, 2022; p.13). Our estimates at the area level cover urban and rural areas.

7.17 Thailand MICS 2022

The survey sample is representative for the urban and rural areas, and five major regions (NSO Thailand, 2023). We publish the MPI estimate and its associated statistics for all five regions and urban and rural areas.

7.18 Trinidad and Tobago MICS 2022

The sample of this dataset was designed to provide statistically reliable estimates at the national level, for urban and rural areas, and for the five major regions of the country (CSO Trinidad and Tobago, 2023). Our urban-rural estimates and subnational estimates are based on the specification of the survey report.

7.19 Tunisia MICS 2023

The survey sample was designed to produce representative estimates for the urban and rural areas, and for each of the seven governorates. We produced our urban-rural estimates and subnational estimates accordingly. At time of publication, the survey report was not available on the MICS website. As such, the necessary quality checks were not implemented, namely the subgroup population share derived from our workline could not be compared to that reported in the survey report.

7.20 Yemen MICS 2022-2023

The sample this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 22 governorates, including the capital city Sana'a and Socotra Archipelago (CSO Yemen and UNICEF, 2023). We publish the MPI estimate and its associated statistics for all regions as stated in the survey report, as well as urban and rural areas.

8. Concluding remarks

This methodological note outlines the principles that underlie poverty estimation in different subgroups of the population, going beyond a national aggregate. The global MPI 2024 covers 112 countries, of which 20 countries have new or updated surveys. We compute estimates of MPI and its partial indices by six major age groups, by rural and/or urban areas for 111 countries (excluding Seychelles due to lack of data on rural-urban area), and by the gender of the household head for 111 countries (excluding China due to lack of information on household head).

In addition, our subgroup disaggregation also includes estimates of MPI and its partial indices by 1,359 subnational regions across 102 countries (excluding five countries due to constraints in sample representation, four countries due to bias in regional estimates and one country due to issues with variable identifier in the microdata). 19 of the 20 countries with new or updated surveys were included in our estimations at the subnational level. Collectively, these 19 countries accounted for 286 subnational regions that are home to 14 percent of the global poor (1.15 million people) – now with new or updated disaggregated estimates.

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