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The global Multidimensional Poverty Index (MPI) 2025: Disaggregation results and methodological note

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Attribution

The estimates of the global MPI and its partial indices are disaggregated by several different population groups. This includes by age groups (the global MPI 2025 release 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.

During her tenure as the team lead of the global MPI 2018–2024, Dr Usha Kanagaratnam developed Stata scripts (do-files) for data cleaning and indicator construction, which were then applied to the underlying microdata of each country survey. Additionally, Dr Kanagaratnam led the construction of the variables required for disaggregation analysis. For this 2025 round of update, the authors used the cleaned microdata produced by Dr Kanagaratnam for 96 countries and adapted the do-file by Dr Kanagaratnam to 13 of the new and updated surveys.

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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) 2025. The 2025 MPI disaggregation results are based on the most recent data from 109 countries, covering 6.3 billion people. We estimate the MPI and its associated statistics by four age categories (0–9 years, 10–17 years, 18–59 years, and 60 years and over) as well as two broad age categories covering children aged 0–17 years and adults 18 years and older, by rural and urban areas and gender of the household head. The MPI is also computed for 1,359 subnational regions across 101 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 such disaggregation.

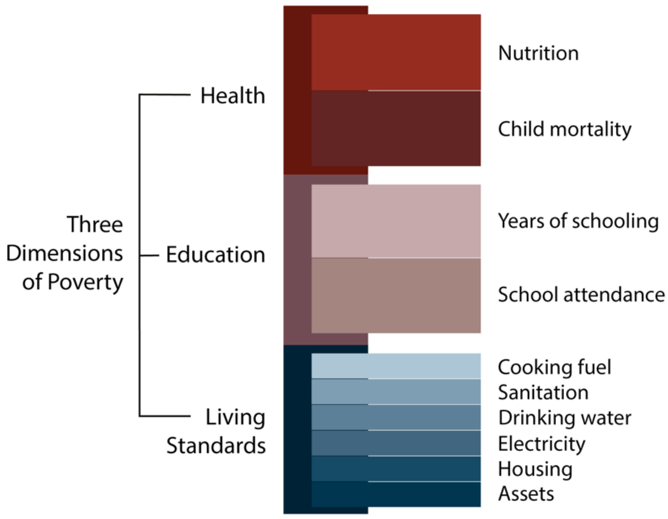
This note is structured as follows. Section 2 presents the global MPI structure and indicator definitions[1] and Section 3 outlines the global MPI and its partial indices that we estimate and publish. Section 4 details the disaggregation methodology and Section 5 elaborates on the toolbox designed to estimate the global MPI. Section 6 outlines the principles and decisions that underlie our disaggregation work. Section 7 summarises the country-specific decisions that were applied for the new or updated datasets in this round. Section 8 concludes.

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 approach to poverty measurement developed by Alkire and Foster (2011). The global MPI is composed of three dimensions (health, education and living standards) and 10 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, et al., 2022; Alkire and Kanagaratnam, 2021; Alkire and Jahan, 2018; Vollmer and Alkire, 2022).

[1] This methodological note builds on previous methodological notes by Alkire, Kanagaratnam and Suppa between 2018 and 2024, with the year, datasets, country-specific adjustments and country briefings updated where required. The text in this section draws on methodological notes published for each update of the global MPI (see previous updates by the authors in 2024, 2023, 2022, 2021, 2020 and 2019) and the book by Alkire et al. (2015).

Figure 1. Composition of the global MPI – dimensions and indicators



Source: OPHI 2018

The global MPI begins by establishing a deprivation profile for each person, showing in which of the 10 indicators they are deprived. 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 the information available 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. The 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, round trip.[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 five years of age (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 Body Mass Index (BMI) cutoff is below minus two standard deviations. Adults aged 20–70 years (229–840 months) are considered undernourished if their 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 15–49. In most surveys, men have also provided information on child mortality, but this lacks the date of birth and death of the child. Hence, the indicator is constructed solely from mothers' responses. 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 six 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 six years or more of schooling, the household is not deprived.

[4] The data sources for the age that children start compulsory primary school are Demographic and Health Surveys (DHS) or Multiple Indicator Cluster Surveys (MICS) survey reports, and the UNESCO Institute for Statistics data browser (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] A household is considered deprived if the floor is made of natural materials (mud/clay/earth, sand or dung) or if the 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

In the global MPI, a person is identified as multidimensionally poor (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, or the average percentage of weighted deprivations experienced by poor people. We then compute the adjusted poverty headcount ratio (M_0) 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. The global MPI identifies individuals as vulnerable to poverty if they are not poor but are close to the poverty threshold; that is, if they are deprived in 20% to 33.33% of weighted indicators. The method also applies a higher poverty cutoff to identify those in severe poverty, meaning those deprived in 50% or more of the weighted indicators.

The Alkire-Foster method 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. While above we described MPI to be the product of H x A, the MPI can equivalently be computed as the weighted sum of the censored headcount ratios of all MPI indicators.

The censored headcount ratio shows the extent of deprivations among poor people 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, as 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 Alkire-Foster 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 population subgroups 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 and 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 people in the subgroup. In addition, we compute the weighted **contribution of each indicator** to poverty for each subgroup.

The survey datasets used in the global MPI 2025 were collected in different years, ranging from 2013 to 2024. 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 2023 population as reported in World Population Prospects 2024 (UNDESA, 2024). We compute population size for subgroups using a combination of the population share and the 2023 population to facilitate comparisons of the number of poor people in each subgroup.

All disaggregated estimates are based on the global MPI specification outlined in Alkire et al. (2025a).

5. Tool to estimate the global 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), H (headcount ratio), 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, urban and rural 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 measures specified in Alkire et al. (2025c) and across the national levels 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 the following age groups: 0–9 years, 10–17 years, 18–59 years, and 60 years and over; and children aged 0–17 years and adults 18 years and older. We use information on 'age of household members' from the household roster to construct the age groups. Age is a self-reported category across most surveys, except 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 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 109 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 and rural areas

We disaggregate the MPI and its partial indices by urban and rural areas in 107 countries; for one country (Argentina) we disaggregate by only urban area; and for Nauru and Seychelles, we are not able to disaggregate by area due to limitations in the sample stratification.

The definitions 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 107 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 defines 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 urban–rural units, we make use of the additional information for disaggregation. In the case of the Palestine MICS 2019–20 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 2019–20 did not cover rural areas, due to the cost of surveying these areas, as well as the small rural population in the country (9% of the total population) (UNICEF and SIEMPRO, 2021). The MPI estimation at the area level in Argentina is therefore restricted to urban areas.

In the case of Nauru and Seychelles, the sample is self-weighting at the national level. This means any estimation based on this dataset is restricted to the national level. Following this, information on urban and rural areas is also not included in the Nauru MICS 2023 and Seychelles QFLS 2019 datasets by the survey providers.

6.3 Disaggregation by subnational regions

In this 2025 round, we disaggregate the MPI and its partial indices by 1,359 subnational regions in 101 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 had been specified in previous rounds of the global MPI: the national poverty headcount ratio (H) and the MPI must be large enough (H more than 1.5% and MPI greater than 0.005) to allow for a meaningful subnational analysis. Since 2018, our estimates have been reported along with standard error 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 2025, 101 country surveys fulfilled this criterion. Four countries – Armenia, Nauru, Seychelles and Tuvalu – have sample sizes that are representative at the national level but not at the subnational level. Hence, these 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% of the original sample after dropping observations that had missing data in any of the 10 global MPI indicators. This is because a lower

[2] See Alkire and Santos (2014); Alkire et al. (2011).

[3] A criterion that matters for poverty trends is that regions must be harmonised for comparability over time. This is covered in detail in Methodological Note 63 (Alkire et al. 2025c).

sample size may affect accurate comparability across subnational estimations. We identified four countries that did not meet this cutoff (Table 2). The sample drop across these four countries ranges between 17% and 22%. Collectively, these four countries represent under 1% of the 6.3 billion people covered in the global MPI 2025.

Second, every subnational region in a country must have a retained sample size of at least 75% 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 five subnational regions across three countries fall short with respect to this sub-criterion (Table 3). The retained sample size across these five regions ranges from 56% to 75%.

Table 2. Global MPI countries with national sample size below 85% 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	2016–17	83	17
Montenegro	MICS	2018	80	20
South Africa	DHS	2016	78	22

Source: Alkire, Kanagaratnam and Suppa (2023).

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

Country	Survey	Year	Subnational region	Population share of region (%)	Total sample size used to compute the MPI (weighted) (%)	Total sample drop (weighted) (%)
Maldives	DHS	2016–17	Malé	41	75	25
Maldives	DHS	2016–17	Central Region	7	74	26
Montenegro	MICS	2018	Central Region	55	73	27
South Africa	DHS	2016	Gauteng	26	71	29
South Africa	DHS	2016	Western Cape	11	56	44

Source: Alkire, Kanagaratnam and Suppa (2024).

Third, a bias analysis test is carried out for each of the five regions whose retained sample size is lower than 75% of the original, and for countries where the retained national sample size is lower than 85% 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. If a systematic and statistically significant difference (at a significance level of 1%) is observed between the headcount ratios across these two groups, the region is considered to have failed the bias analysis test. If a region with a large population share (more than 20%) 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 to be people who are not poor.

Further, Malé and the Central Region collectively account for almost half of the population in Maldives (see 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 tests on all regions of Georgia, as Georgia has a weighted sample loss of 18% at the national level, meaning it was borderline whether it could be disaggregated at the subnational level. Two of the 10 subnational regions within the country (Kakheti and Shida Kartli) both had a retained sample of 77%. 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% and two of its subnational regions, home to 45% of the population, indicate biased estimates, we exclude Georgia from the subnational disaggregation.

Although subnational disaggregation is theoretically possible for 105 of the 109 countries, only 101 countries (with 1,359 regions) in this round of the global MPI satisfy the principles for subnational disaggregation and are therefore used for subnational analysis.

6.4 Disaggregation by gender of household head

Of the 109 countries included in the 2025 global MPI, disaggregated results by female-headed and male-headed households were produced for 108 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 dataset. Across all the surveys, household headship 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 datasets – sex and relationship to household head. In all datasets except one, sex is reported as a binary variable, hence the gender of the household head is reported as binary. In a small number of cases, the category 'household head' is not assigned to any household members. In such cases, if information about the spouse (male or female) was available, we replace them as the household head. Fewer than 50 observations were replaced across the 109 surveys. The replacement of the missing value made no difference to the final aggregate numbers.

7. Country-specific considerations for new or updated surveys

This section details the country-specific disaggregation decisions for each of the 13 new or updated countries included in the global MPI 2025.

7.1 Azerbaijan MICS 2023

The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, as well as for 13 economic regions. East Zangazur was excluded from the sampling due to the temporary deployment of Russian peacekeepers during the preparation of the sampling frame. We estimate the MPI and its associated statistics by provinces since the survey sample is representative at this level (State Statistical Committee of the Republic of Azerbaijan and UNICEF, 2024). We publish MPI estimates for all 13 economic regions, as well as for urban and rural areas.

7.2 Bangladesh DHS 2022

The sample design of the Bangladesh DHS dataset was designed to produce reliable estimates for both urban and rural areas, as well as for eight divisions (NIPORT and ICF, 2024). As such, the global MPI subnational estimates cover eight divisions of Bangladesh since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.3 Bolivia EDSA 2023

The Bolivia EDSA dataset was designed to produce reliable estimates from nine departments of the country as well as urban and rural areas (Instituto Nacional de Estadística, 2025). We publish MPI estimates and associated statistics for all nine departments, as well as for urban and rural areas.

7.4 Jordan DHS 2023

The Jordan Population and Family Health Survey dataset was designed to yield statistically reliable estimates for 12 governorates, and urban and rural areas within each governorate. Urban–rural and subnational estimates were therefore generated according to the sampling design (Department of Statistics and ICF, 2024). We publish MPI estimates and related statistical measures for all 12 governorates, including both urban and rural areas, as detailed in the survey report.

7.5 Kyrgyzstan MICS 2023

The sample design of this dataset ensured statistically reliable estimates at the nine regional levels, with disaggregation by urban and rural areas (NSC and UNICEF, 2024). Both subnational and urban–rural estimates are derived in accordance with the specification outlined in the survey report.

7.6 Lao PDR MICS 2023

The sample for Lao PDR was designed to provide statistically reliable estimates for both urban and rural areas, as well as for the 18 autonomous districts of Lao (Lao Statistics Bureau and UNICEF, 2025). The survey data classify rural areas based on household road connectivity, distinguishing between those with and without access to roads. For the global MPI, these two categories have been merged into a single rural category. 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 Lesotho DHS 2023

The Lesotho DHS was designed to produce a reliable estimate for 10 districts, as well as for rural and urban areas. MPI estimates are computed for 10 districts since the survey sample is representative at this level (Ministry of Health and ICF, 2024). Our MPI estimates, both at the district level and in urban and rural areas, are computed following the sampling specifications mentioned in the survey report.

7.8 Mexico ENSANUT 2023

The survey sample for the National Health and Nutrition Survey (ENSANUT) was designed to produce statistically representative estimates at the national and regional levels for urban and rural areas Shamah-levy et al. (2024), National Institute of Public Health of the Government of Mexico. Our estimates at the area level cover urban and rural areas. While the dataset includes a variable intended to identify 32 federal entities, their classifications are incomplete as they lack a value identifier in the microdata. Due to these inconsistencies, we report estimates only for Mexico's five major subnational regions, as well as urban–rural areas, adhering to the sampling specifications outlined in the survey report.

7.9 Nauru MICS 2023

The survey sample was designed to produce representative estimates at the national level. We do not report estimates for urban and rural areas because a geographical area identifier is not available in the microdata or report estimates for subnational regions as the survey is only representative nationally (Nauru Bureau of Statistics, 2024).

7.10 Niger ENAFEME 2021

The sample design for this national dataset was structured to produce robust estimates for eight administrative regions as well as urban and rural areas (Institut National de la Statistique (INS) and Utica International (2022). The subnational MPI and related statistics are produced for these eight administrative regions, along with urban and rural areas, in accordance with the sampling specifications to ensure representativeness.

7.11 Peru ENDES 2023

The sample for Peru ENDES is designed to provide representative estimates at the national level, for 24 administrative regions, and for the capital district of Callao (INEI, 2024). Our estimates at the area level encompass both urban and rural areas. We publish MPI estimates and associated statistics for all 25 administrative regions, as well as urban and rural areas.

7.12 Senegal DHS 2023

The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, and to facilitate disaggregation for 14 provinces (ANSD and ICF, 2024). As such, our subnational estimates cover the 14 administrative areas of Senegal. Our estimates at the area level cover urban and rural areas.

7.13 Vanuatu MICS 2023

The Vanuatu MICS survey was planned to produce representative estimates for urban and rural areas, and for each of the six provinces (Vanuatu Bureau of Statistics, 2024). Our subnational MPI and related estimates are generated for all six provinces, given that the survey sample is representative at this level. Our estimates at the area level cover both 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 2025 covers 109 countries, of which 13 countries have new or updated surveys. We compute estimates of the MPI and its partial indices by six major age groups, by rural and/or urban areas for 107 countries (excluding Seychelles and Nauru due to lack of data on rural–urban areas), and by the gender of the household head for 108 countries (excluding China due to lack of data on household head).

Our subgroup disaggregation also includes estimates of the MPI and its partial indices by 1,359 subnational regions across 101 countries (excluding four countries due to constraints in sample representation and four countries due to bias in regional estimates). Twelve out of 13 countries with new or updated surveys were included in our estimations at the subnational level. Collectively, these 12 countries account for 137 subnational regions that are home to 5.8% of the total global population who are poor (6.6 million poor people) – now with new or updated disaggregated estimates.

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