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Multidimensional Poverty levels and trends in India: Next steps in analysing the global MPI

Sabina Alkire, OPHI, University of Oxford, UK

Tabitha, Kenya Rabiya, India Stéphanie, Madagascar Agathe, Madagascar Dalma, Kenya Ann-Sophia, Kenya Valérie, Kenya

I. India's results on the global stage

II. Subnational Trends

III. The 2019/21 global MPI results

The top line results for India were presented as a case study in the joint UNDP-OPHI Global MPI 2022 Report

Additional analyses was undertaken using online data tables on OPHI's website.

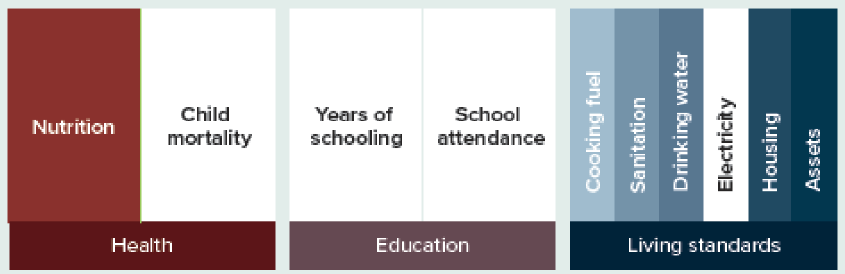
Details of data treatment for each country is found in: Alkire, S., Kanagaratnam, U., and Suppa, N. (2022). The global Multidimensional Poverty Index (MPI) 2022 country results and methodological note. *OPHI MPI Methodological Note 52.* Oxford Poverty and Human Development Initiative, University of Oxford. See also *Methodological Note 53* (on disaggregation) and *Methodological Note 54* (trends).

What is the global MPI? Start with Deepa.

People who are deprived in 33.3% or more of weighted indicators are identified as poor.

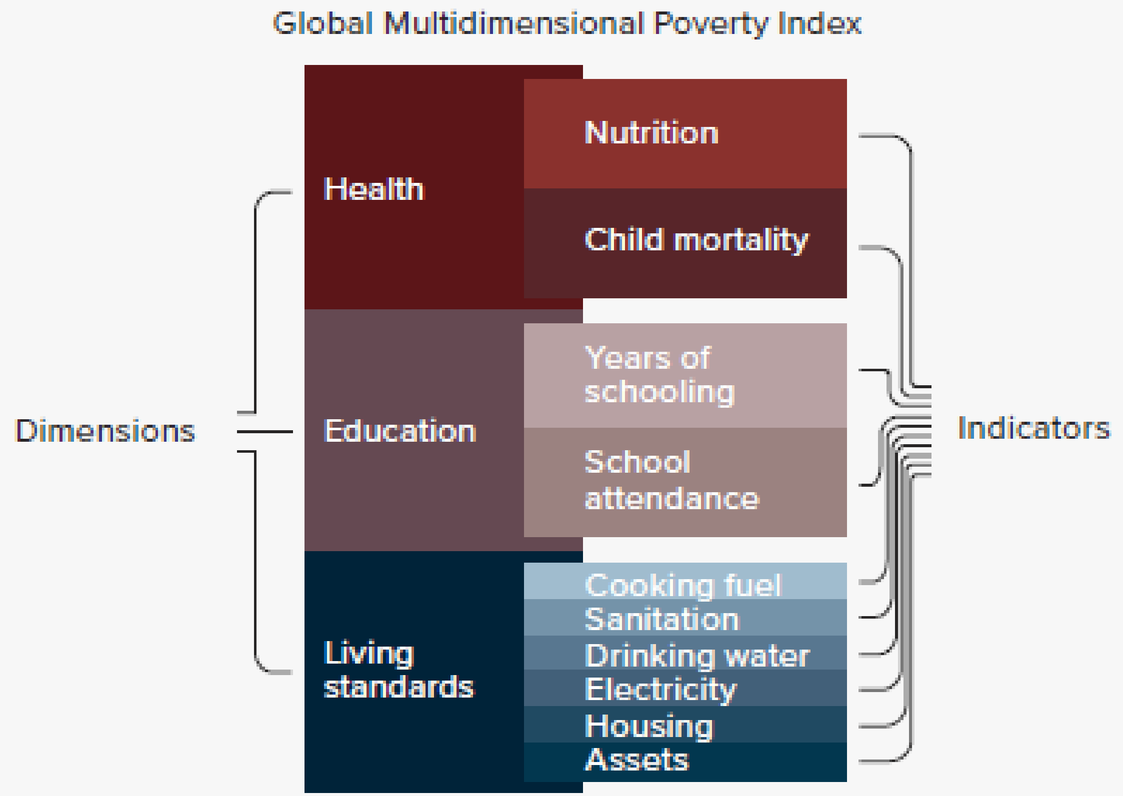
Deepa is poor, as she is deprived in 44.4% ≥ 33.3%

How the global Multidimensional Poverty Index measures Deepa's deprivations



Note: Indicators in white refer to a nondeprivation.

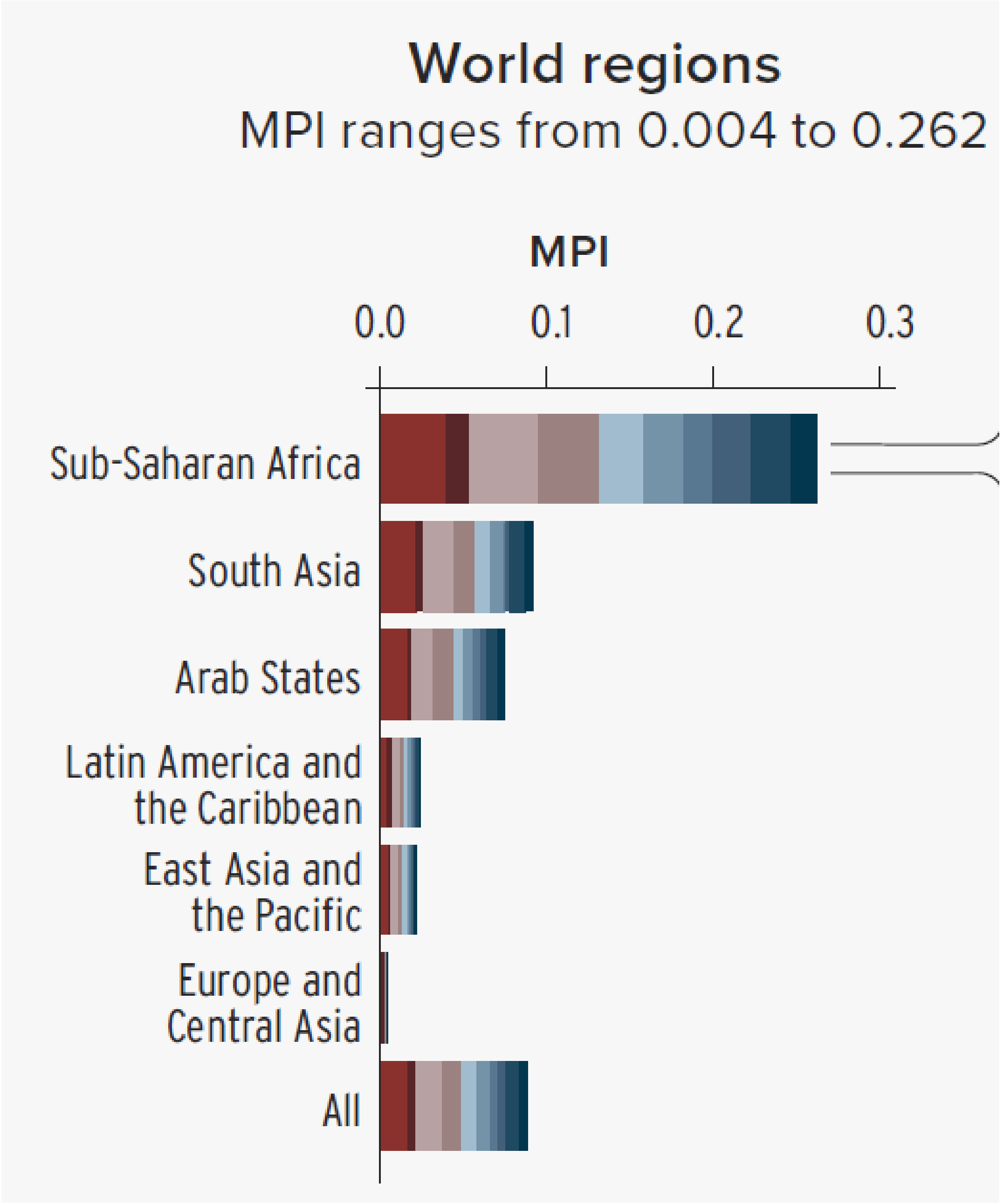
Figure 1 Structure of the global Multidimensional Poverty Index



Source: HDRO and OPHI.

OPHI
Oxford Poverty & Human Development Initiative

UNDP



The MPI stacks up the weighted deprivations of all poor people

If *any* deprivation of *any* poor person goes down, MPI goes down. Always.

Data

The 2023 global Multidimensional Poverty Index (MPI) uses the most recent comparable data available for **110 countries**

These countries are home to about **92 percent** of the population in developing regions.

Global MPI values, incidence and intensity of poverty, and component indicators are disaggregated for **1,281 subnational** regions as well as by **age** group, **rural-urban** area and **gender** of the household head.

The year of the surveys ranges from 2011 to 2021/2022.

Surveys used:

- Multiple Indicator Cluster Surveys: 54 countries
- Demographic and Health Surveys: 43 countries
- National surveys: 13 countries.

- **India's Global MPI uses DHS 2019/21 – the NFHS-5**

- **Trends over time are presented using NFHS-4 and NFHS-3 datasets, from 2015/16 and 2005/6**

Multidimensional Poverty in 2023

Across 110 countries,**1.1 billion** out of 6.1 billion people are poor.

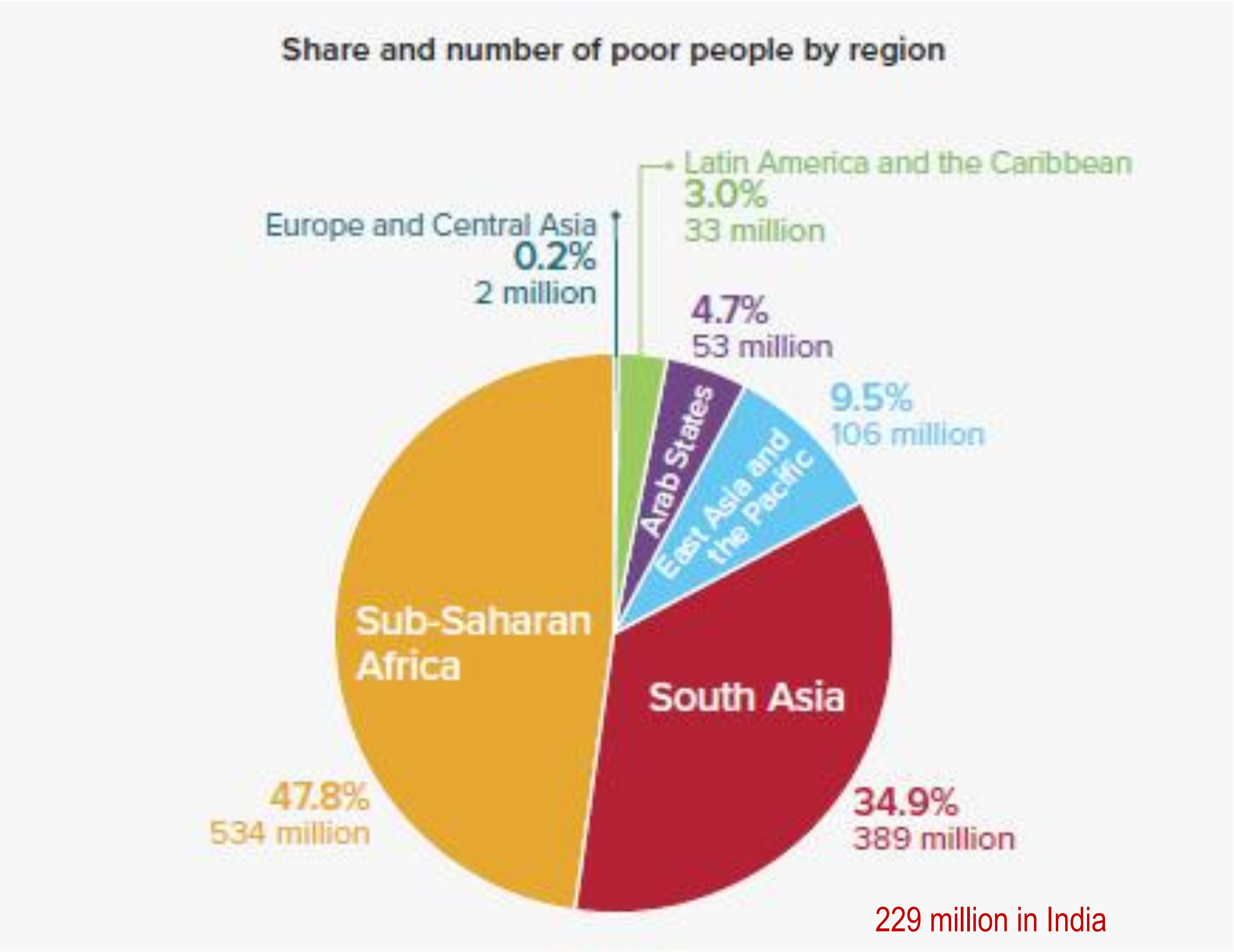
Just over 18% are estimated to live in acute multidimensional poverty.

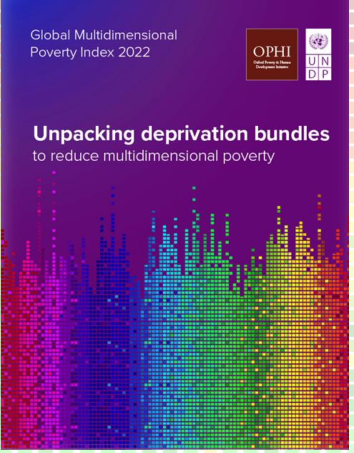
Half of the 1.1 billion poor people (566 million) **are children** under 18 years of age.

Multidimensional Poverty in 2023

Multidimensional poverty is widespread: 730 million poor people live in middle-income countries and **387 million** live in low-income countries.

Most poor people live in Sub-Saharan Africa & South Asia.



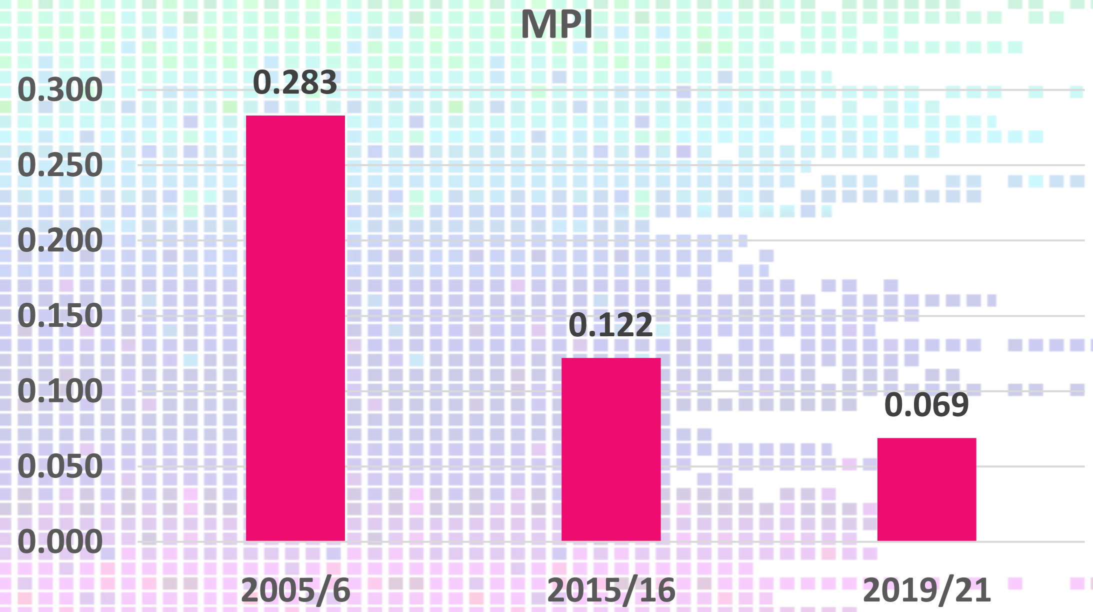


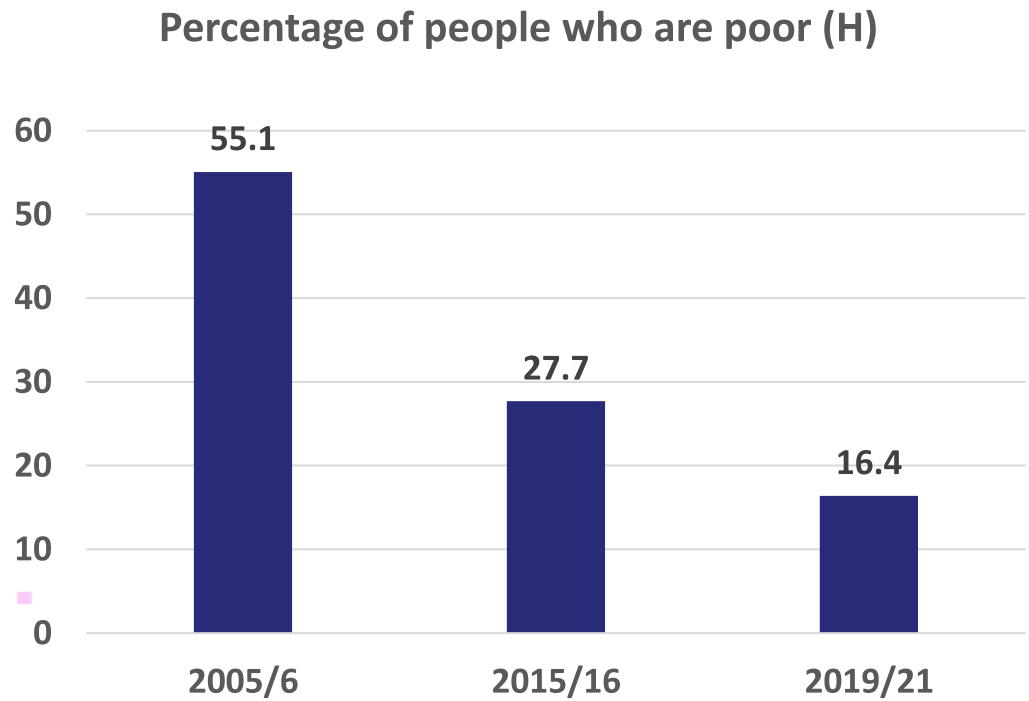
The 2022 global Multidimensional Poverty Index Report, issued jointly by UNDP and OPHI on 17 Oct 2022 announced that

IN THE 15 YEARS 2005/6 TO 2019/21...

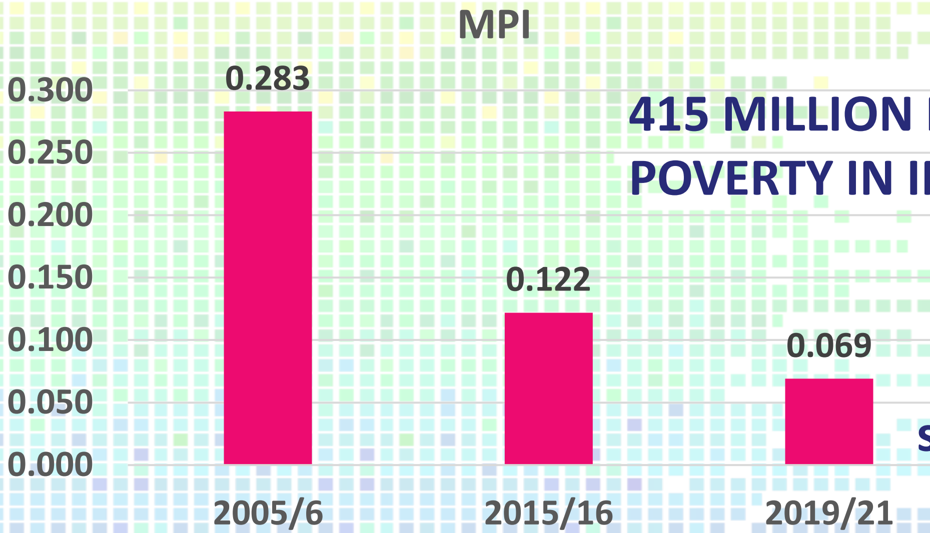
415 MILLION PEOPLE LEFT POVERTY IN INDIA

(229 Million were still poor)





IN THE 15 YEARS 2005/6 TO 2019/21…



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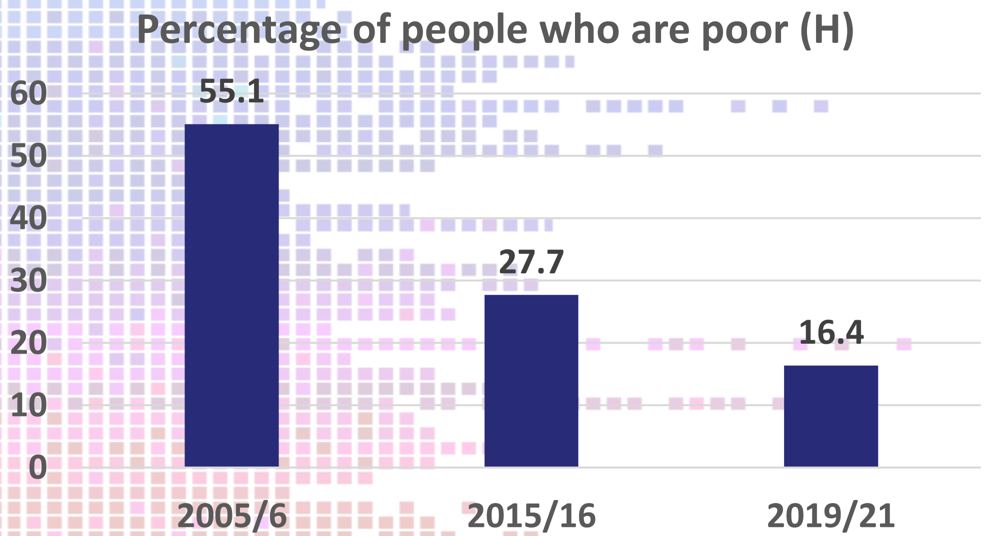


The SDGs call all countries to halve poverty in all its dimensions within 15 years. India's global MPI progress shows this is possible – and at scale.

MPI and Incidence both more than halved in 15 years. These and intensity and Severe poverty all had significant reductions each period.

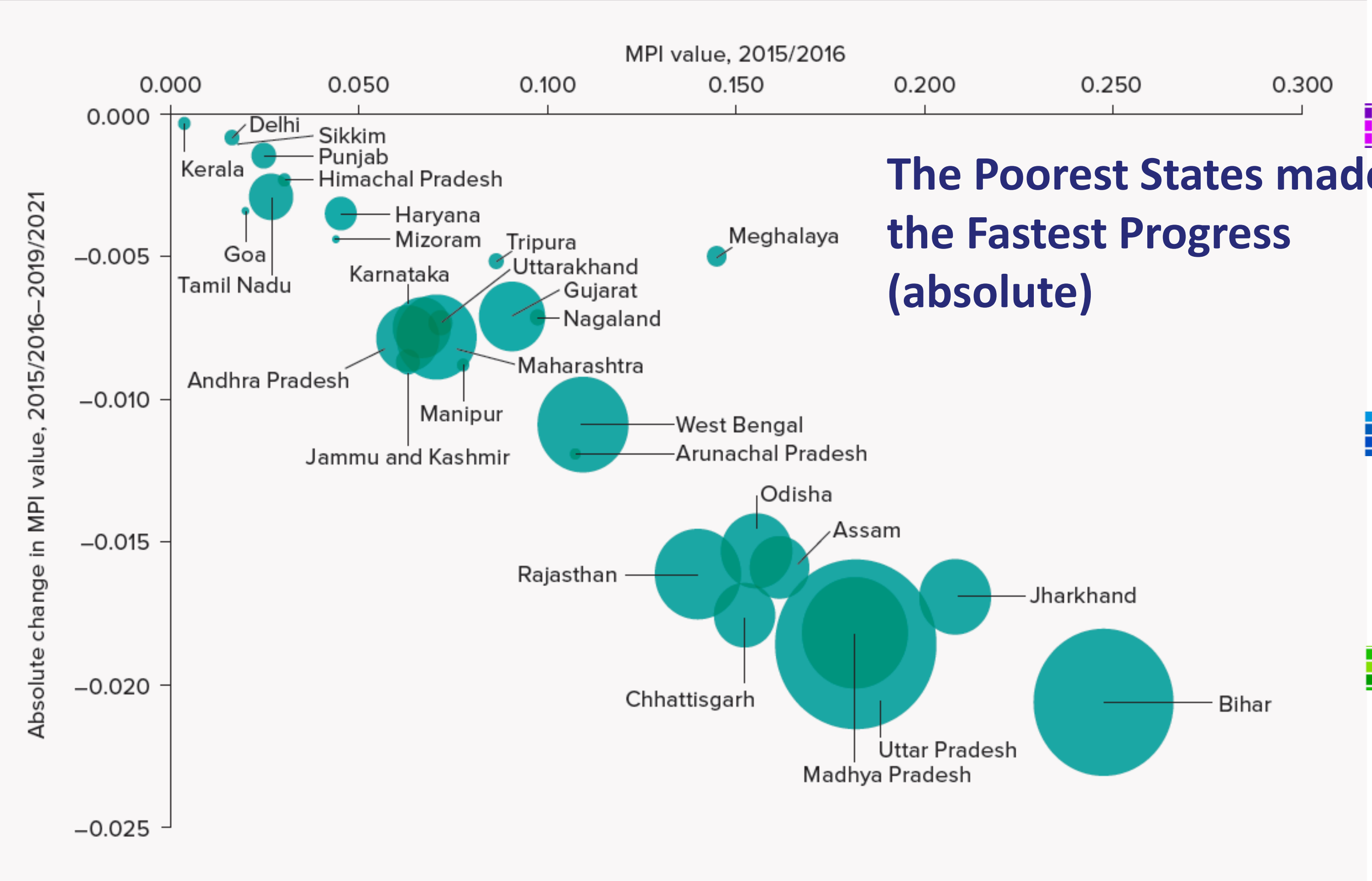
All ten indicators significantly reduced – led by **progress in sanitation, cooking fuel and housing**

Severe Poverty reduced: 27.8 to 8.7 to 4.2

Vulnerability stable: 17.0 to 18.9 to 18.7

Within Country Trends in India

Figure 8 The poorest states in India saw the fastest absolute reduction in Multidimensional Poverty Index (MPI) value from 2015/2016 to 2019/2021



Note: The size of the bubble is proportional to the number of poor people in 2015/2016.
Source: Alkire, Kanagaratnam and Suppa 2022c.

India's **poorest groups,** including its children, rural areas, states, and scheduled tribes had the fastest absolute reduction 2005/6 to 2019/21

Bihar's incidence fell from **77%** in 2005/2006 to **52%** in 2015/2016 to **35%** in 2019/2021.

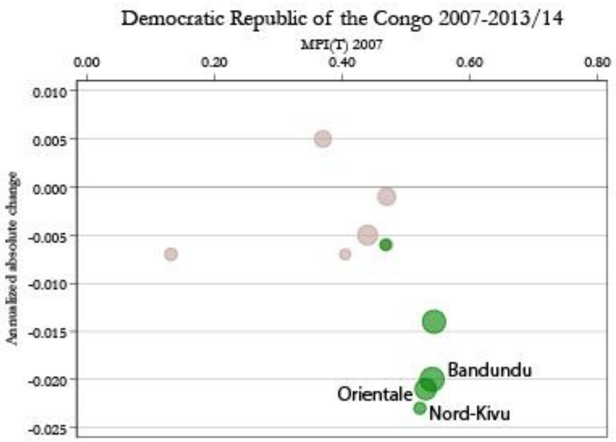
Jharkhand fell from **75%** to **46.5%** to **31%** percent in the same period.

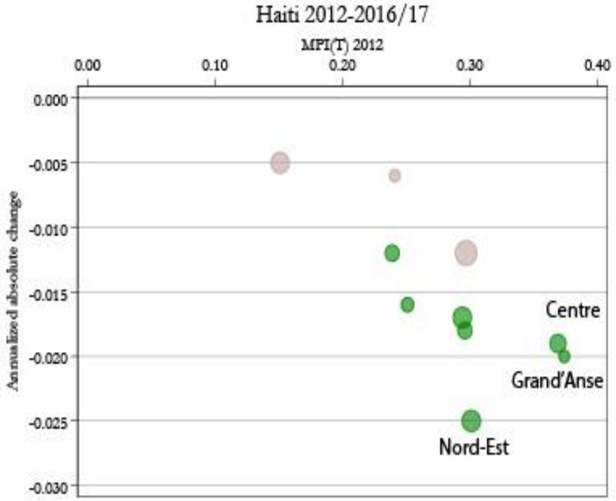
Madhya Pradesh, from 69% to 41% to 24%

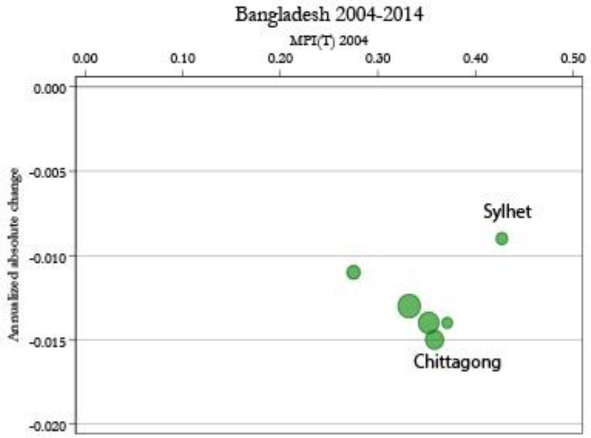
Uttar Pradesh from 69% to 41% to 23%

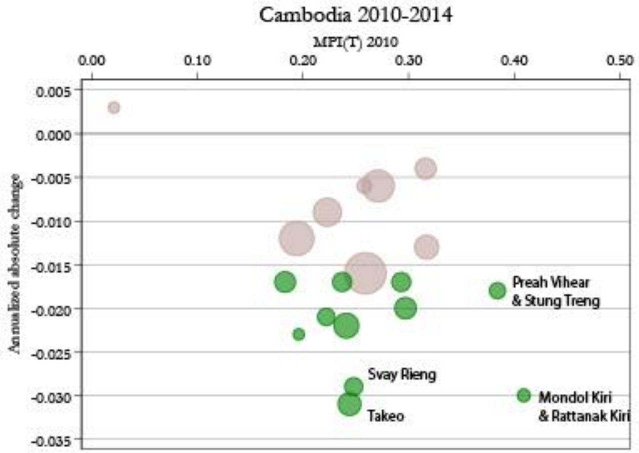
In Relative Terms: Goa reduced MPI the fastest, followed by Jammu and Kashmir, Andhra Pradesh, Chhattisgarh and Rajasthan.

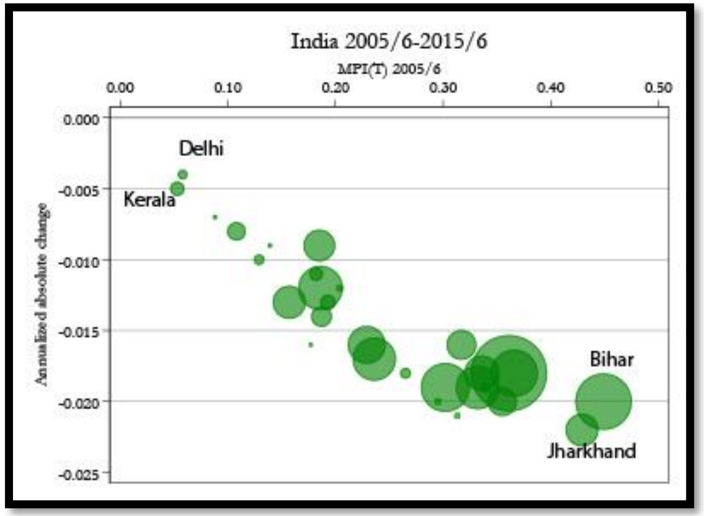
Not all countries show such clear and significant pro-poor trends.

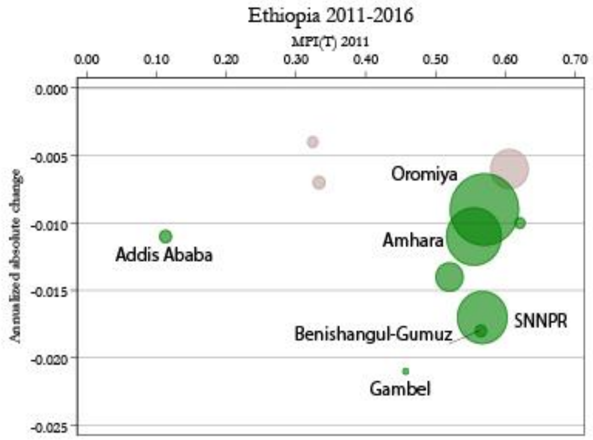


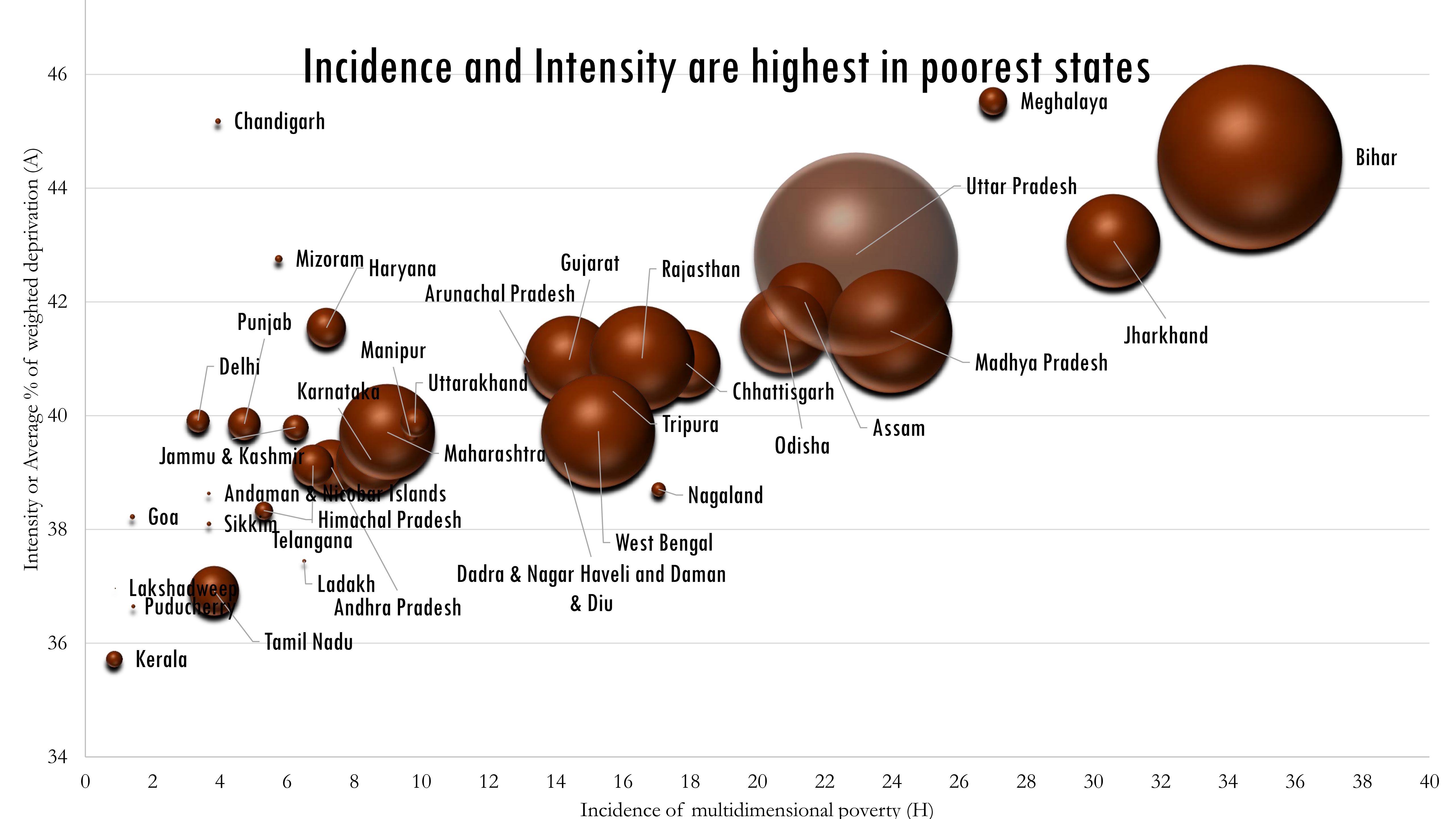




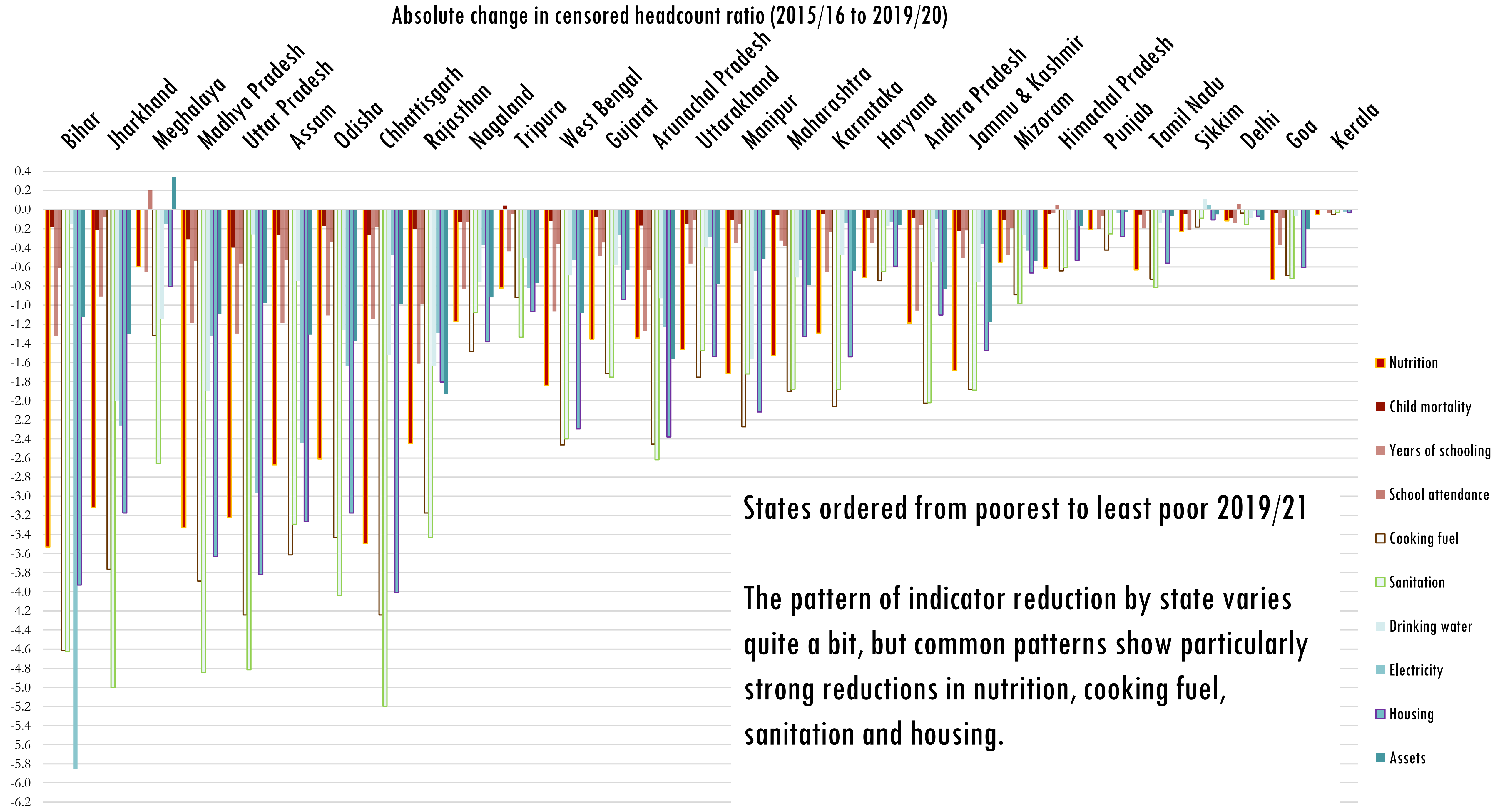








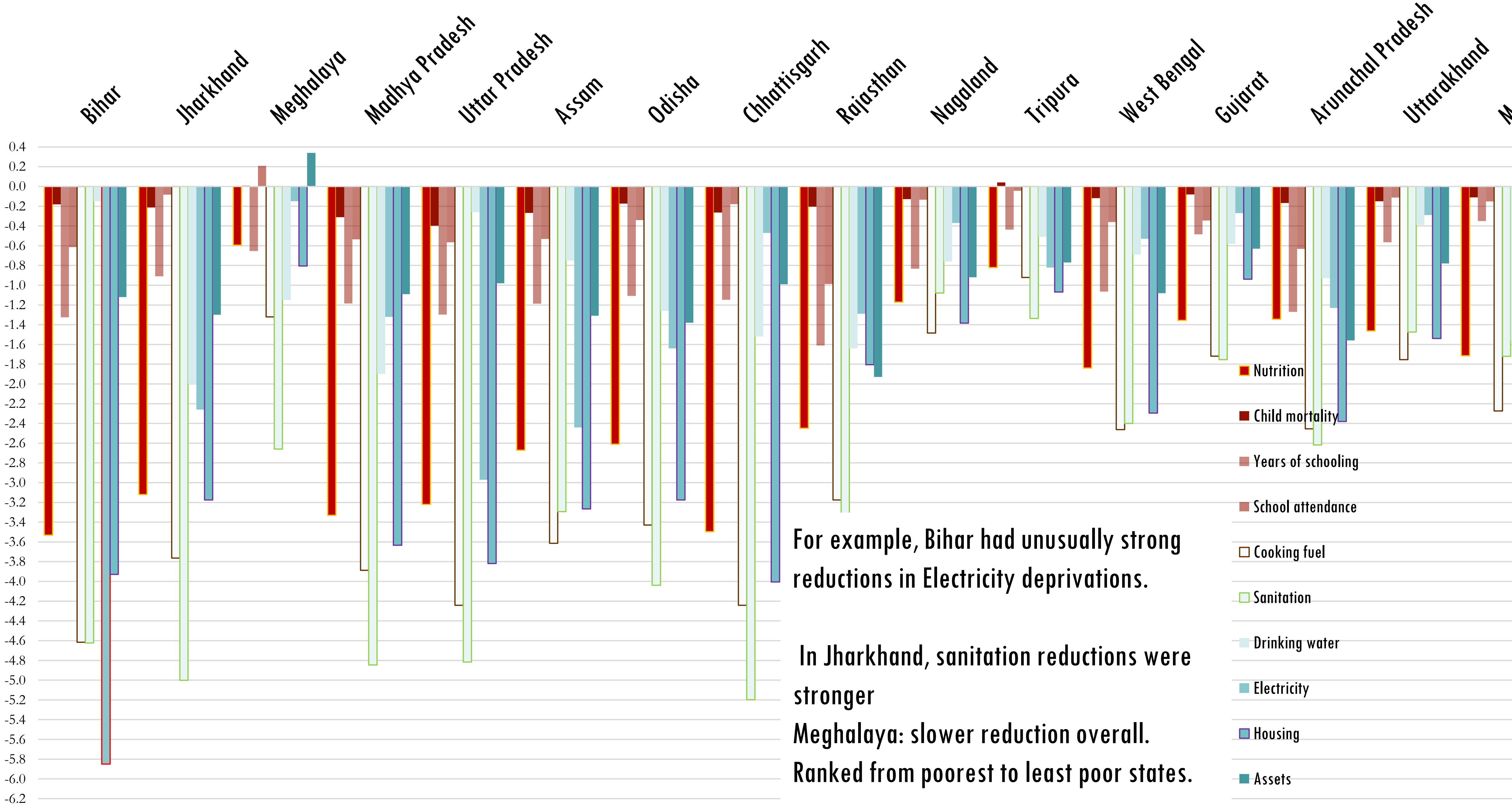
Incidence and Intensity are highest in poorest states
Intensity or Average % of weighted deprivation (A)
Incidence of multidimensional poverty (H)
34
36
38
40
42
44
46
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
34
36
38
40
Chandigarh
Meghalaya
Bihar
Uttar Pradesh
Mizoram
Haryana
Gujarat
Rajasthan
Arunachal Pradesh
Punjab
Jharkhand
Manipur
Madhya Pradesh
Delhi
Uttarakhand
Chhattisgarh
Karnataka
Tripura
Assam
Odisha
Jammu & Kashmir
Maharashtra
Nagaland
Andaman & Nicobar Islands
Goa
Himachal Pradesh
Sikkim
Telangana
West Bengal
Dadra & Nagar Haveli and Daman & Diu
Ladakh
Lakshadweep
Andhra Pradesh
Puducherry
Tamil Nadu
Kerala



States ordered from poorest to least poor 2019/21

The pattern of indicator reduction by state varies quite a bit, but common patterns show particularly strong reductions in nutrition, cooking fuel, sanitation and housing.

Absolute change in censored headcount ratio (2015/16 to 2019/20)



For example, Bihar had unusually strong reductions in Electricity deprivations.

In Jharkhand, sanitation reductions were stronger

Meghalaya: slower reduction overall.

Ranked from poorest to least poor states.

The fastest reduction of MPI and H are similar but not the same.

Fastest MPI	Fastest Incidence
Bihar	Chhattisgarh
Uttar Pradesh	Bihar
Madhya Pradesh	Uttar Pradesh
Chhattisgarh	Madhya Pradesh
Jharkhand	Jharkhand
Rajasthan	Odisha
Assam	Assam
Odisha	Rajasthan
Arunachal Pradesh	Arunachal Pradesh
West Bengal	West Bengal
Manipur	Manipur
Jammu & Kashmir	Jammu & Kashmir
Andhra Pradesh	Karnataka
Maharashtra	Andhra Pradesh
Karnataka	Maharashtra
Uttarakhand	Uttarakhand
Nagaland	Gujarat
Gujarat	Nagaland
Tripura	Meghalaya
Meghalaya	Tripura
Mizoram	Goa
Haryana	Mizoram
Goa	Haryana
Tamil Nadu	Tamil Nadu
Himachal Pradesh	Himachal Pradesh
Punjab	Punjab
Sikkim	Sikkim
Delhi	Delhi
Kerala	Kerala

Rural and Urban trends

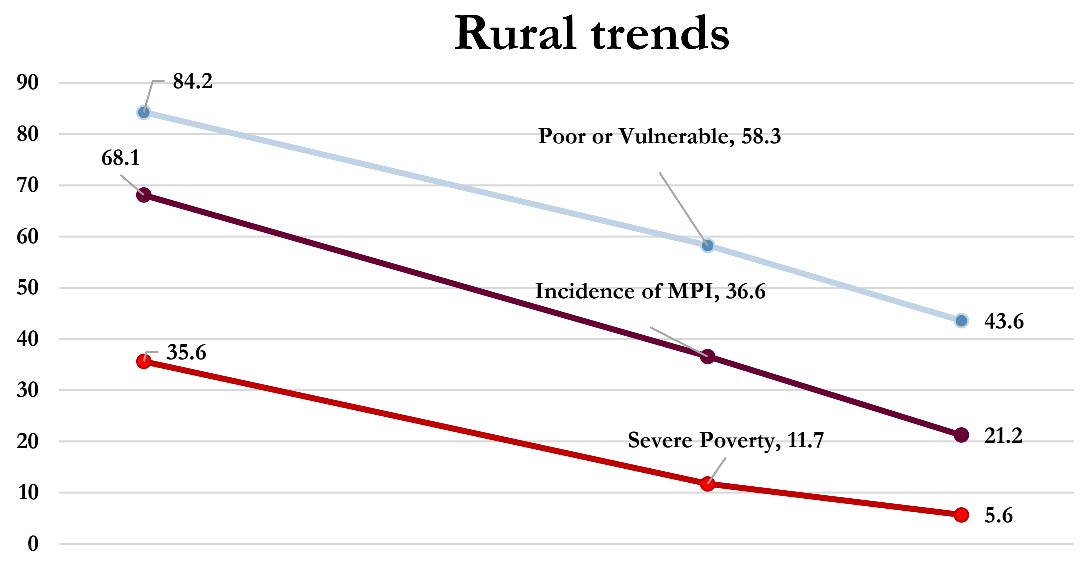
Rural and Urban areas had significant decreases in H, A and MPI and Severe MPI both periods.

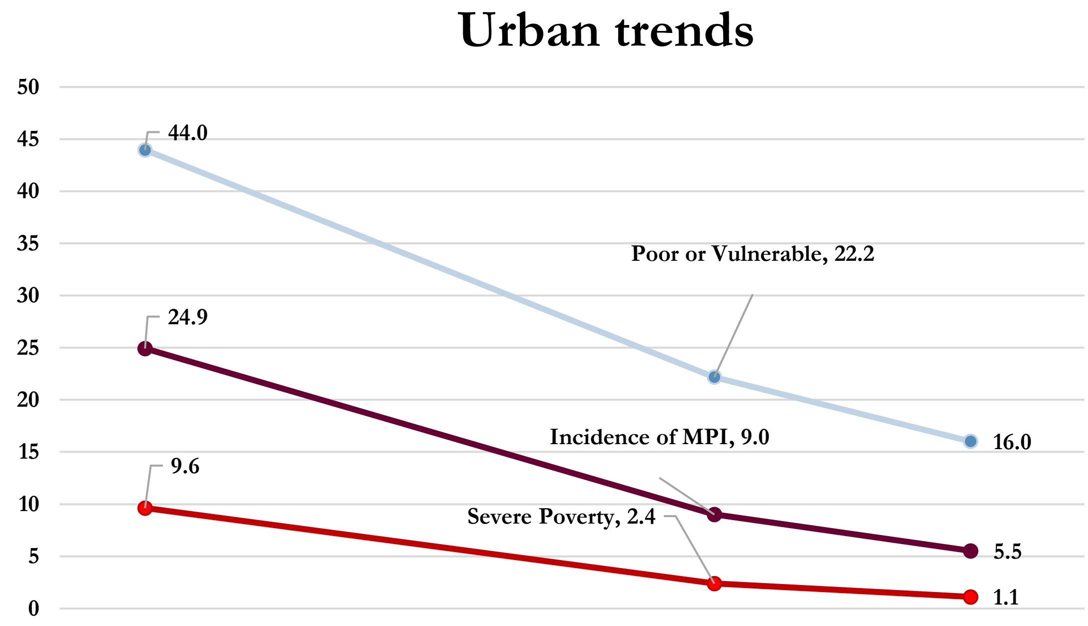
Rural areas had significant <u>increases in Vulnerability</u> both periods; in urban, it decreased

The number of MPI poor people decreased from 557 to 332 to 207 million in rural areas; in urban areas it fell from 88 to 39 to 24 million.

All 10 indicators had significant reductions in both rural and urban areas.

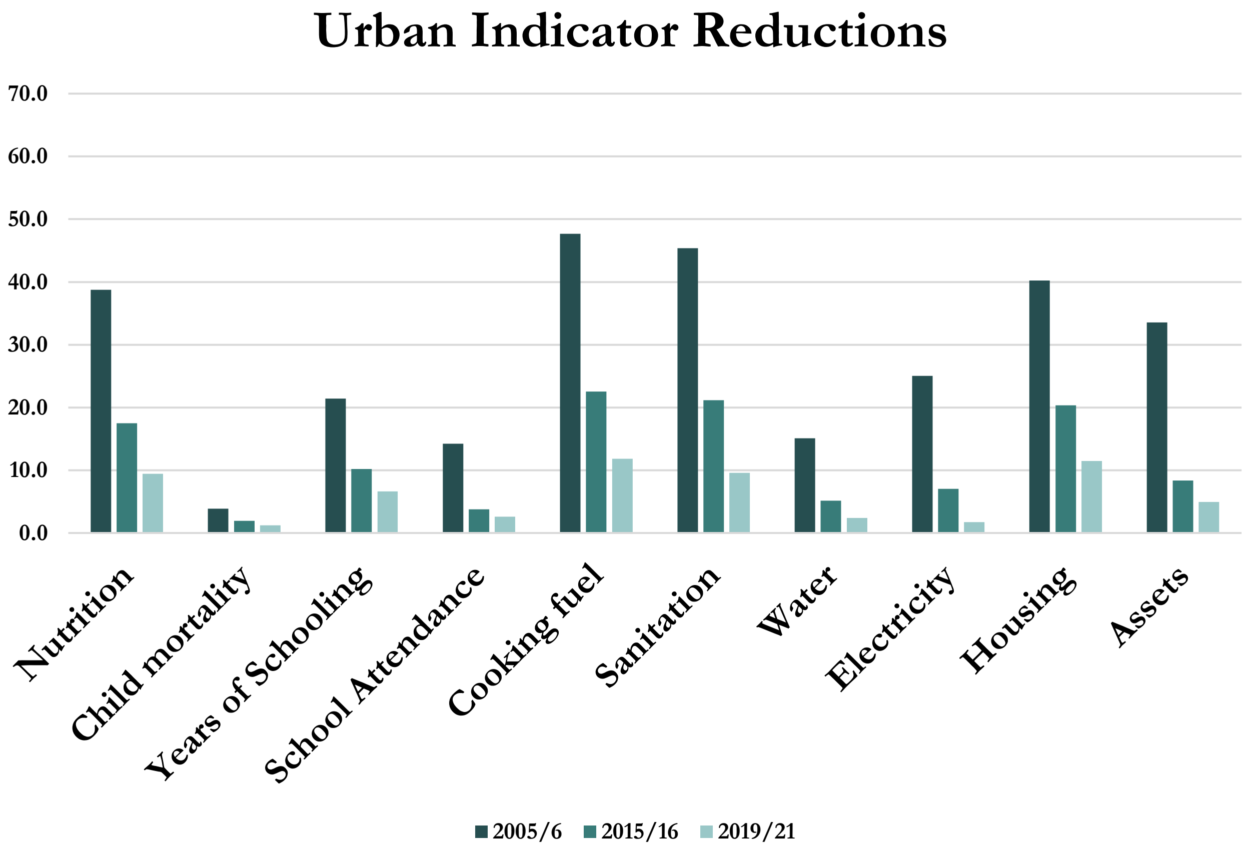
The population shares were relatively stable: 70:30; 68:32; 69:31.

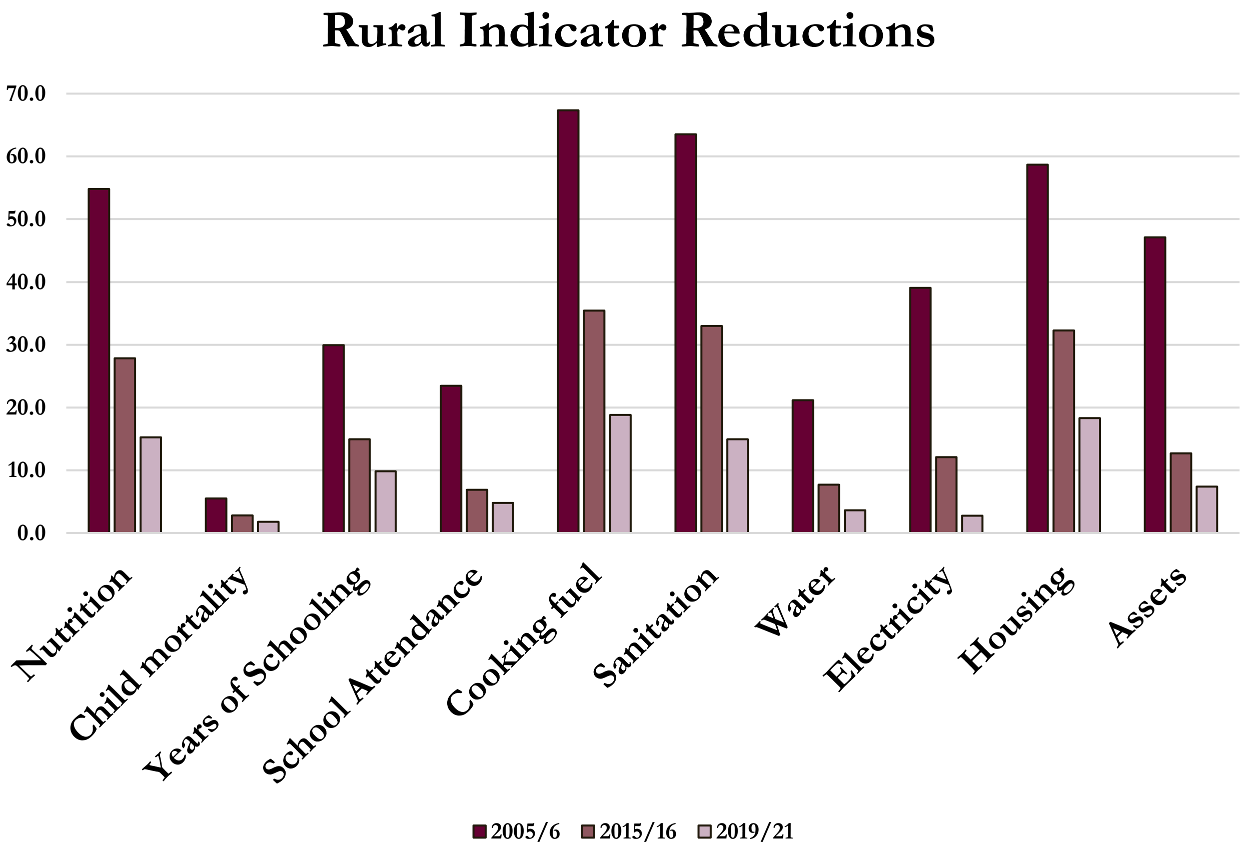




Indicator reductions by rural and urban areas:

All 10 indicators had significant reductions in both rural and urban areas in both periods.





Are Rural Areas being left behind 2015/16 to 2019/21?

It depends on how you measure. Absolute: **no**; Relative: **yes**; share of poor **yes**

- In **absolute** terms, annualised MPI reduction was faster in rural areas than urban areas (we prioritise absolute reductions as in this case, each person counts equally)

Absolute	2005/6-15/16	2015/16 – 2019/21	Relative 2005/6-15/16	2015/16 – 2019/21
Rural:	**-0.019**	-0.016	**-7.6**	-12.3
Urban:	-0.008	**-0.004**	-10.5	**-11.2**

- In **relative** terms, reduction was fastest in urban areas in the most recent period (relative is usually faster in less poor places as there's less poverty to start with)

- The **percentage of poor people** living in rural vs urban areas increased in rural:

	Rural	Urban
2005/6	86%	14%
2015/16	89%	11%
2019/21	**90%**	**10%**

§ Trends among children vs adults

In 2005/6, 46% of poor people were children; in 2015/16 it was 42.9%; in 2019/21, it was 42.4%.

Children, Adults, & 0-9, 10-17, 18-59, & 60+ all had significant decreases in H, A, MPI, and Severe MPI in both periods 2005/6 – 2015/16 – 2019/21

Children had significant increases in Vulnerability both periods; in adults, it decreased in the latest period

The number of poor children fell from 297 to 159 to 98 million (harmonised MPI)

So 138 million children left poverty 2005/6 to 15/16

And 61 million children left poverty 2015/15 to 19/21

In total, 199 million children left poverty in 15 years

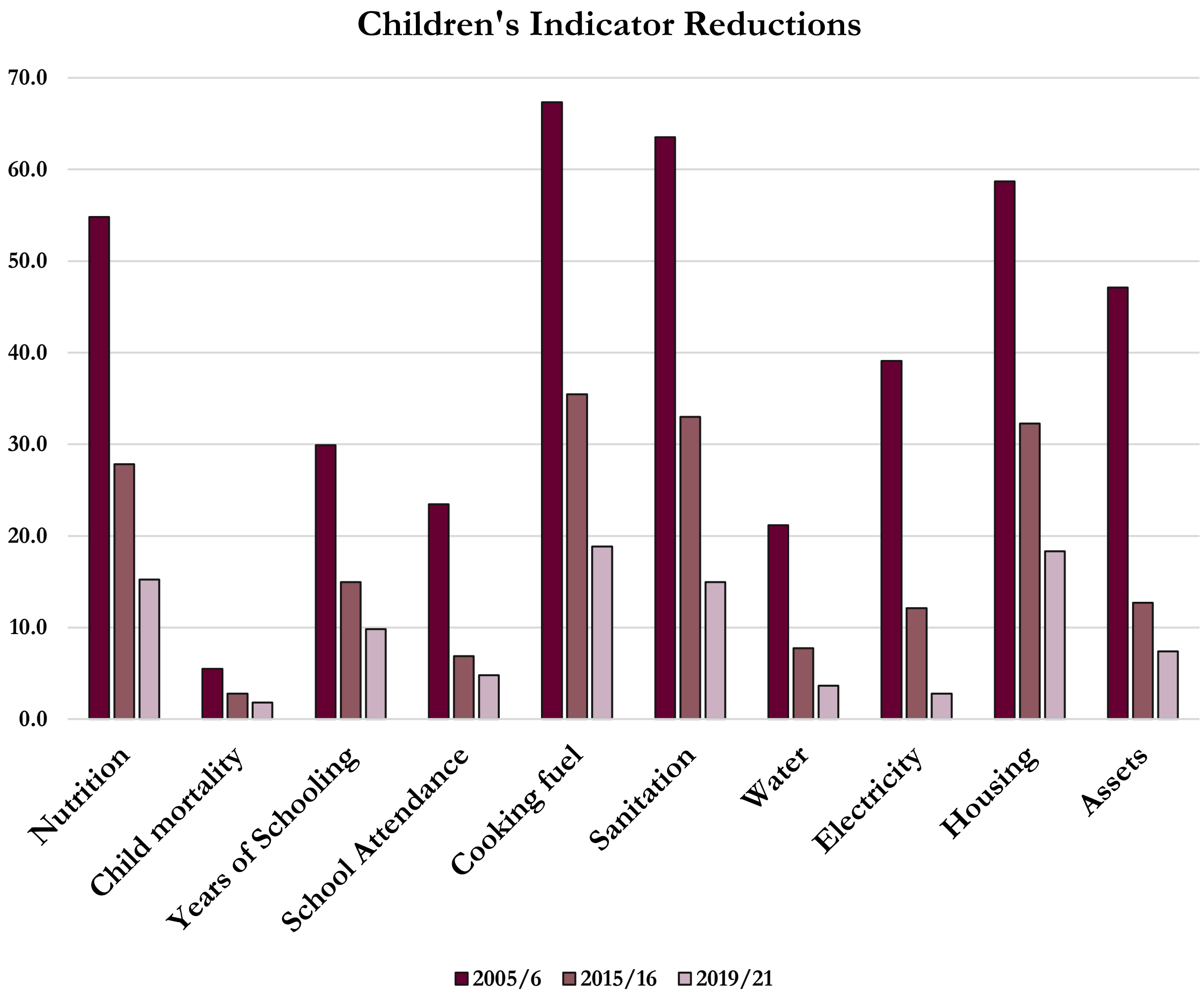
The number of poor adults fell from 348 to 212 to 133 million.

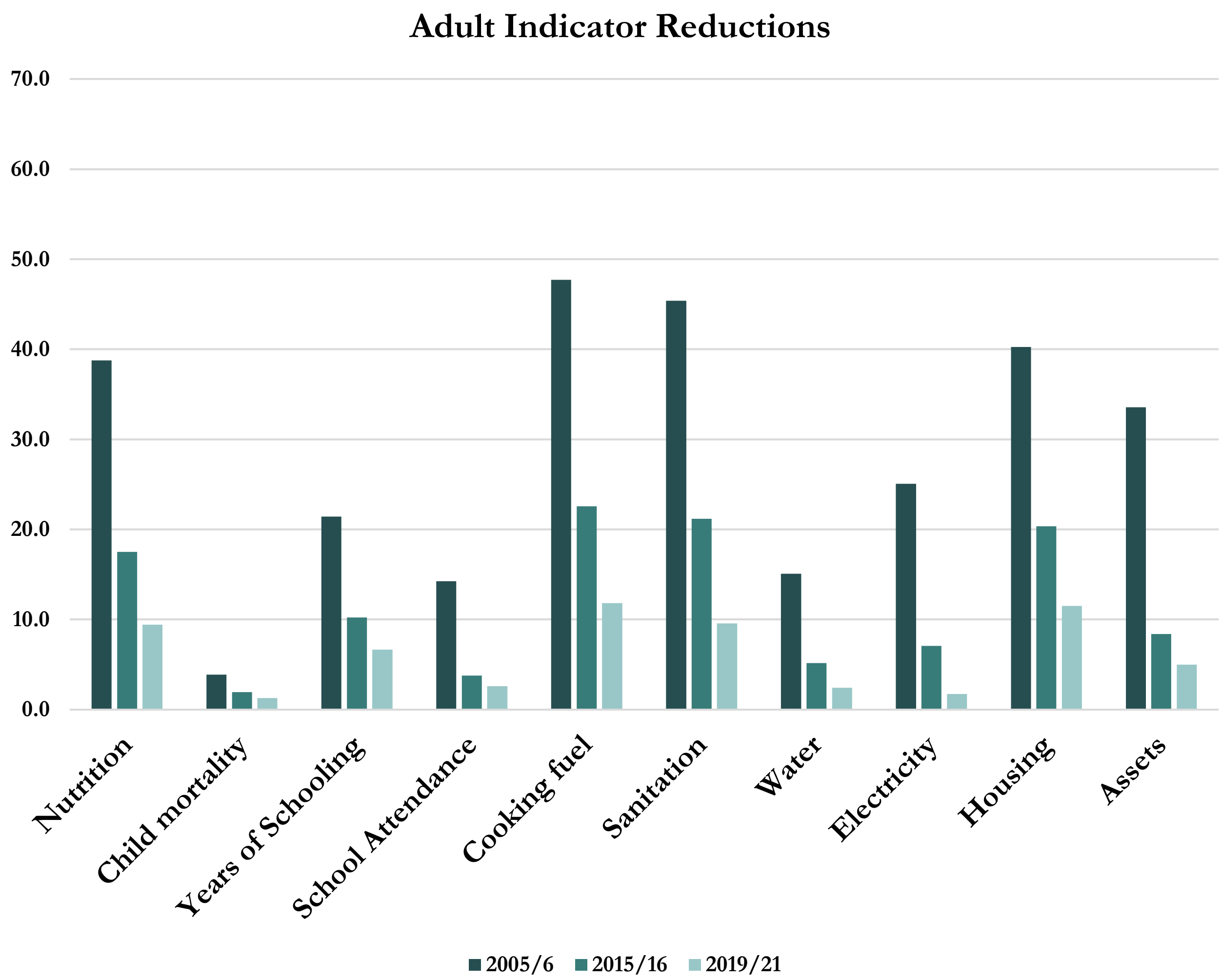
In total, 216 million adults left poverty in 15 years.

Important note: population shares changed visibly: from 40:60 to 34:66 to 32:68

Indicator reductions for children aged 0-17 vs adults age 18+:

All 10 indicators reduced significantly in both age groups in both periods.





Are Children being left behind 2015/16 to 2019/21? (no)

It depends on how you measure: Absolute: **no**; Relative: **yes**; share of poor **no**

- In **absolute** terms, annualised MPI reduction was faster among children than adults

Absolute	2005/6-15/16	2015/16 – 2019/21	Relative 2005/6-15/16	2015/16 – 2019/21
Children:	**-0.018**	-0.014	**-7.3**	-10.7
Adults:	-0.014	**-0.010**	-8.3	**-12.4**

- In **relative** terms, reduction was fastest among adults in the most recent period (relative is commonly faster in less poor groups)

- The **percentage of poor children** decreased : from 46% to 42% over 15 years.

2005/6	46.0%	54%
2015/16	42.9%	57.1%
2019/21	**42.4%**	**57.6%**

India's 2019/21 MPI

India:

16.4% of people are MPI poor (H)
42.0% is the intensity (A)

MPI is 0.069 = 0.164 x 0.420

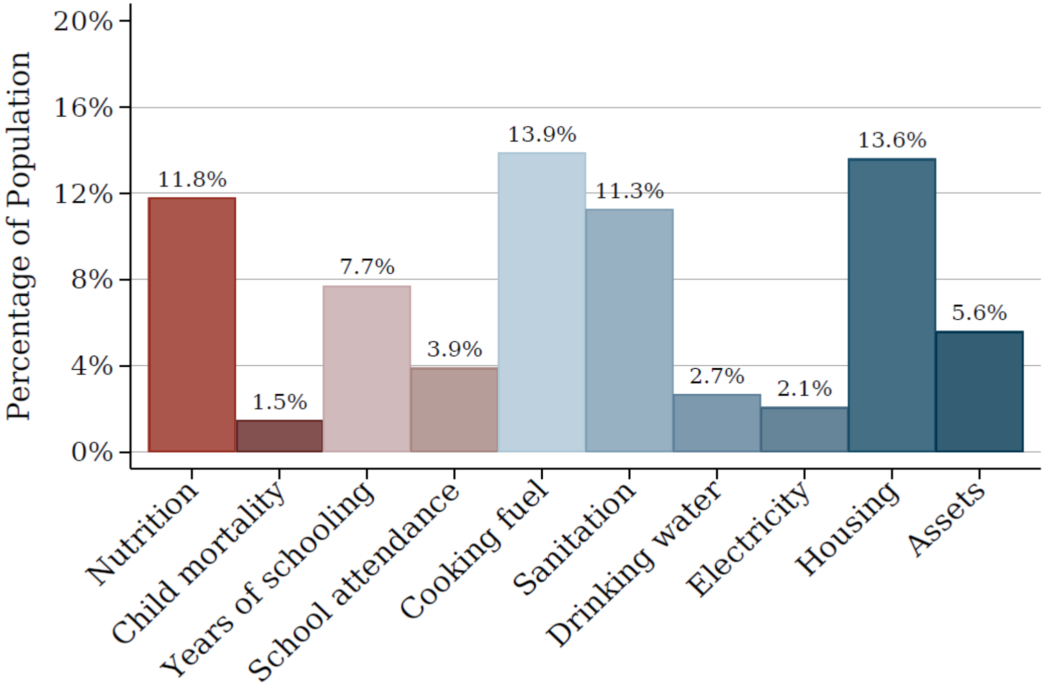
So 229 million people are MPI poor

Information by indicator,
Shows *how* people are poor

Deprivations in cooking fuel, housing and nutrition are highest.

Subnational Disaggregation –
Or by age, rural/urban, gender of hh head, showing *who* is poorest.

All are tracked over time



India is the only country in South Asia in which poverty is significantly **more prevalent among female-headed** than male-headed households (19.7% vs 15.9%)

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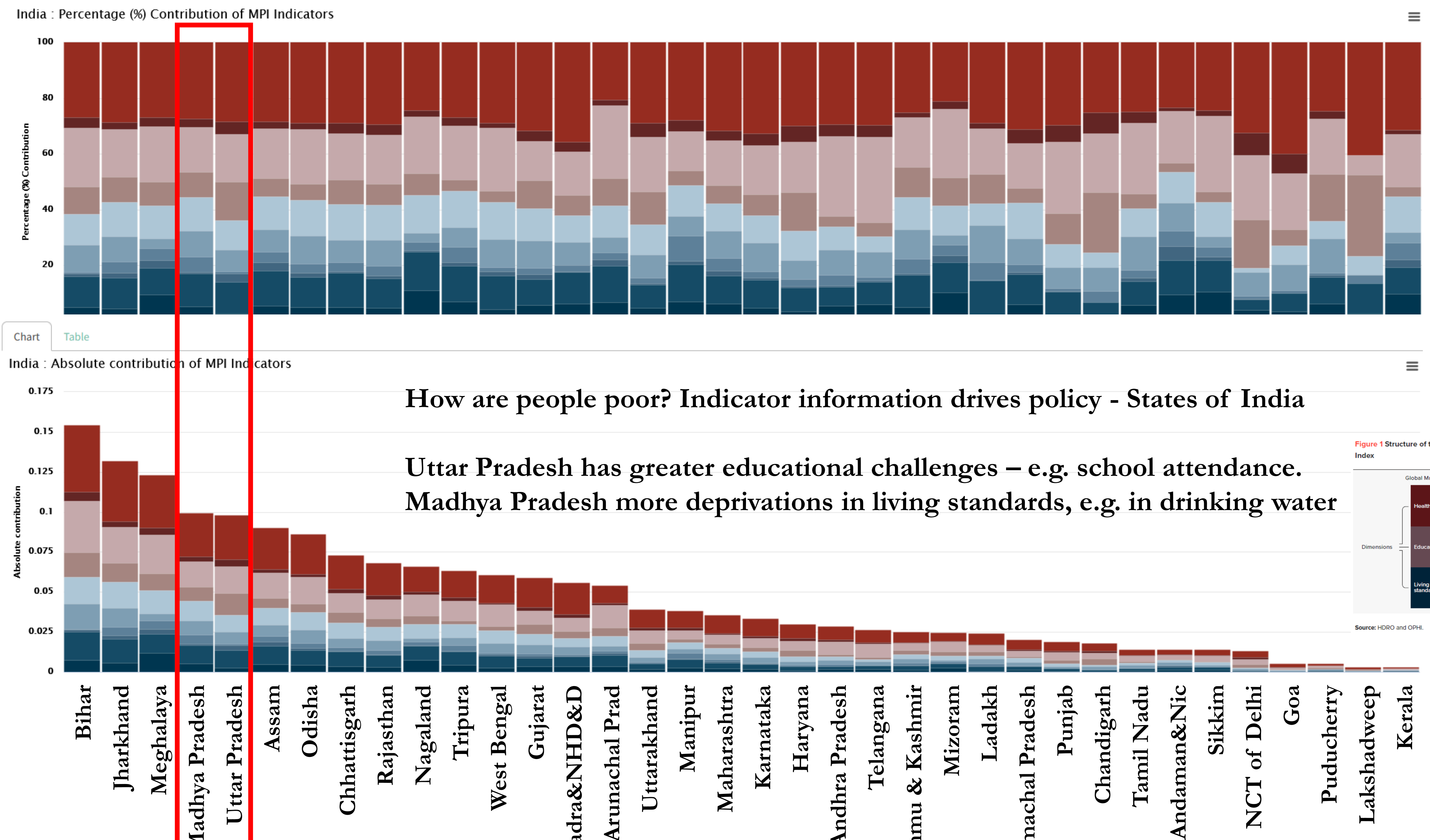
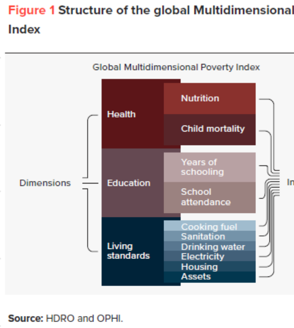


How are people poor? Indicator information drives policy - States of India

Uttar Pradesh has greater educational challenges – e.g. school attendance.
Madhya Pradesh more deprivations in living standards, e.g. in drinking water



Multidimensional Poverty in Children and Adults

	MPI	H	A	Vulnerable	Severe	Pop Share
Children	0.095	21.8	43.5	20.1	7.0	31.9
Adults 18+	0.057	13.9	40.8	18.0	2.9	68.1

The MPI poverty rate is
21.8% for children
13.9% for adults

32% percent of people are children – but
42% of poor people are children.

Deprivations in Nutrition and Housing are especially higher in children than among adults.

Among people aged 60+, the MPI is 0.060 compared to 0.056 for adults 18-59 and 0.095 for children. 15.7% of older adults are poor, compared to 13.6% of adults under 60.

Over 1 in 3 children are in Severe poverty – it's 1 in 5 for adults

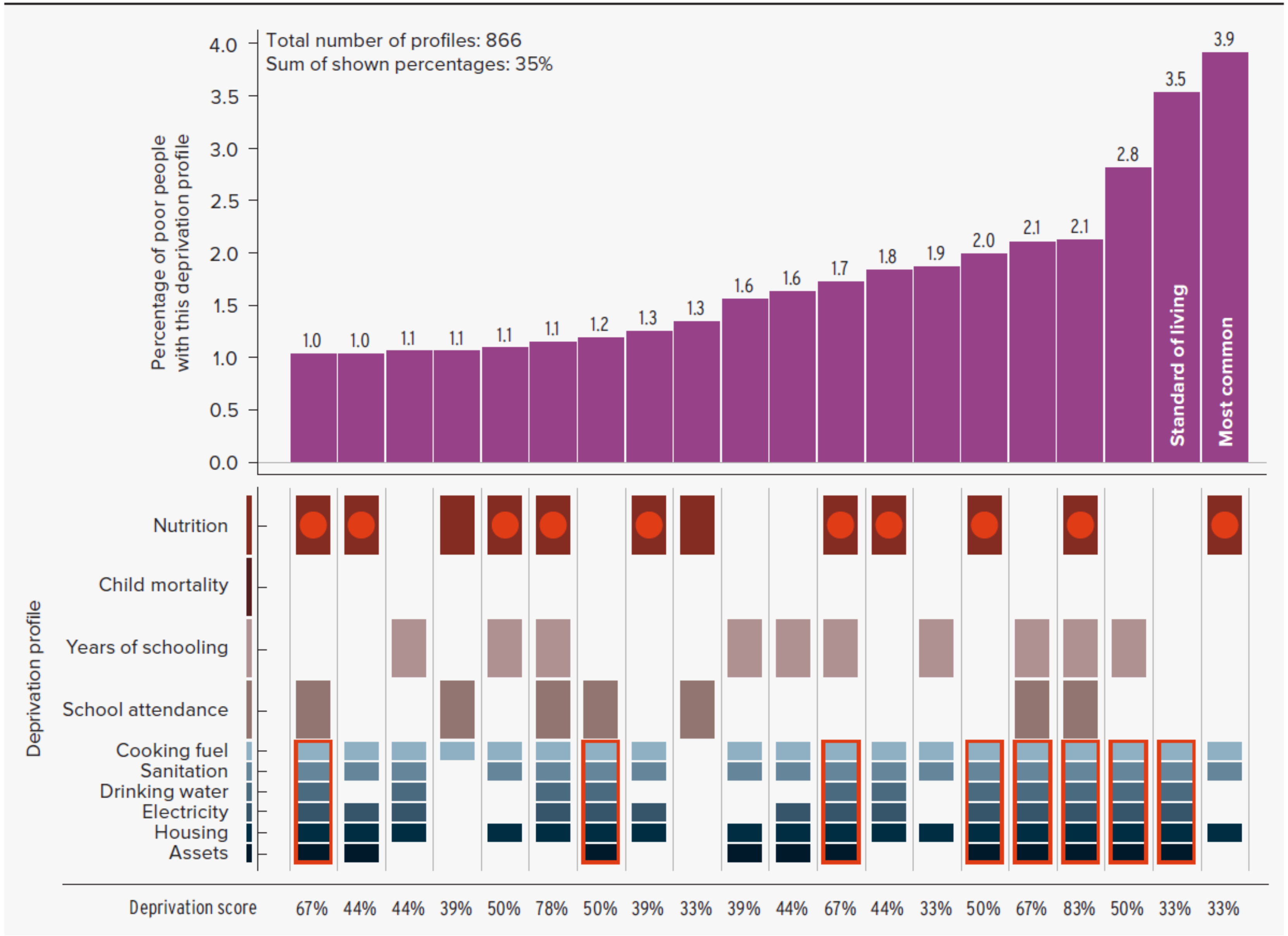
Terms:

Deprivation Profile: shows in which of the 10 indicators a person is deprived – e.g. 'all living standards indicators'. *Exhaustive*

Deprivation Bundle: some combination of indicators in which a person is deprived – e.g. water and sanitation. *May be selective*

Reported in terms of the number or percentage <u>of poor people</u> experiencing that bundle / profile.

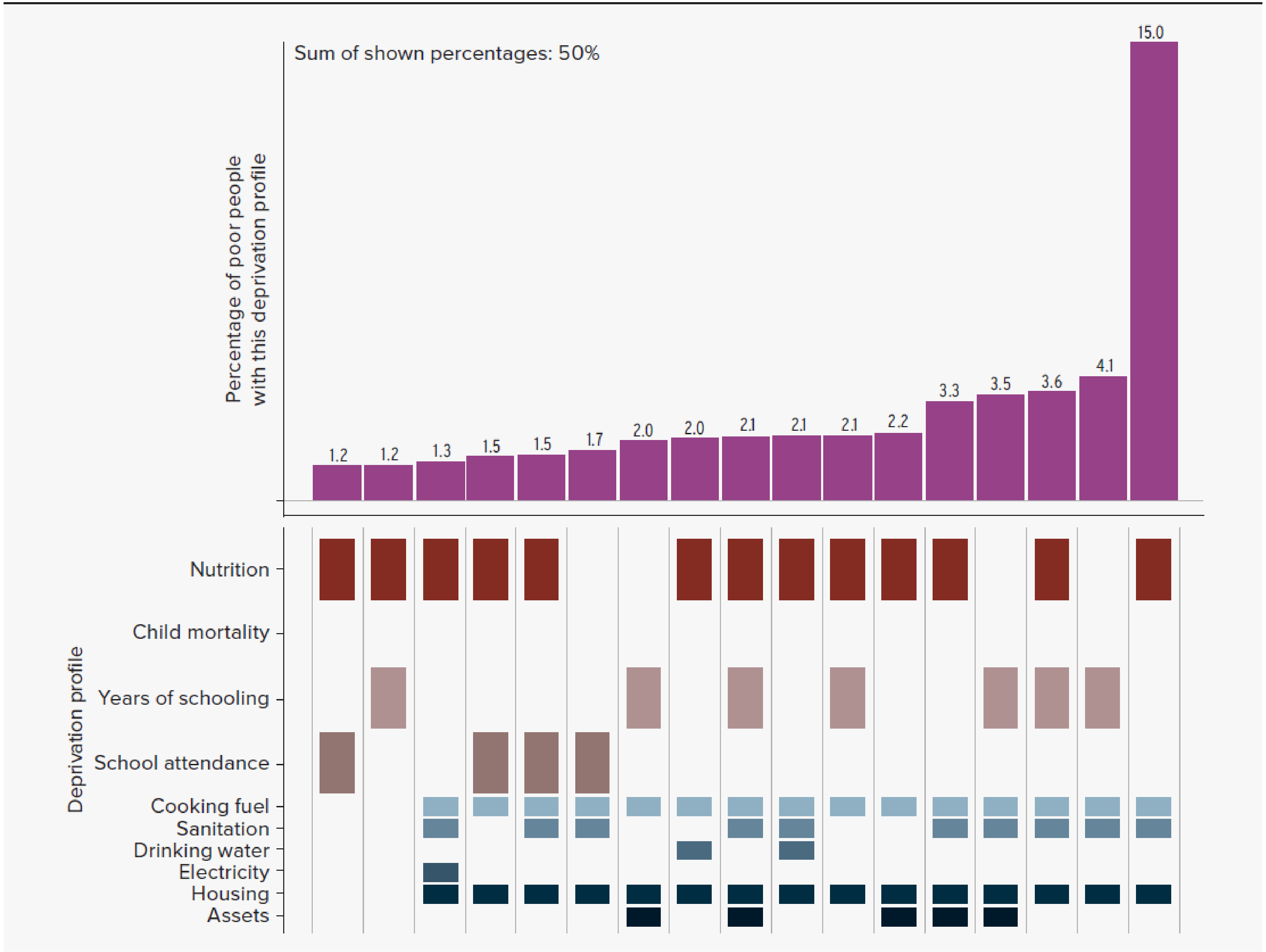
Figure 1 **The 20 most common deprivation profiles among poor people across 111 developing countries**



Note: The 10 deprivation profiles with a red dot in nutrition include the deprivations in the most common bundle (nutrition, cooking fuel, sanitation and housing), and the 8 deprivation profiles outlined in red include the deprivations in the second most common deprivation bundle (standard of living).

Source: Authors' calculations based on Alkire, Nogales and Suppa (2022) and microdata underlying the Multidimensional Poverty Index computations in table 1 at the end of the report.

Figure 9 **The most common deprivation profiles among poor people in India, 2019/2021**



The MPI poor people in India experience 652 deprivation profiles in total.

But half of the poor people experience one of the 17 deprivation profiles listed below.

In 2019/21 15% of all poor people – 34.3 million – were deprived in nutrition, cooking fuel, sanitation, and housing only.

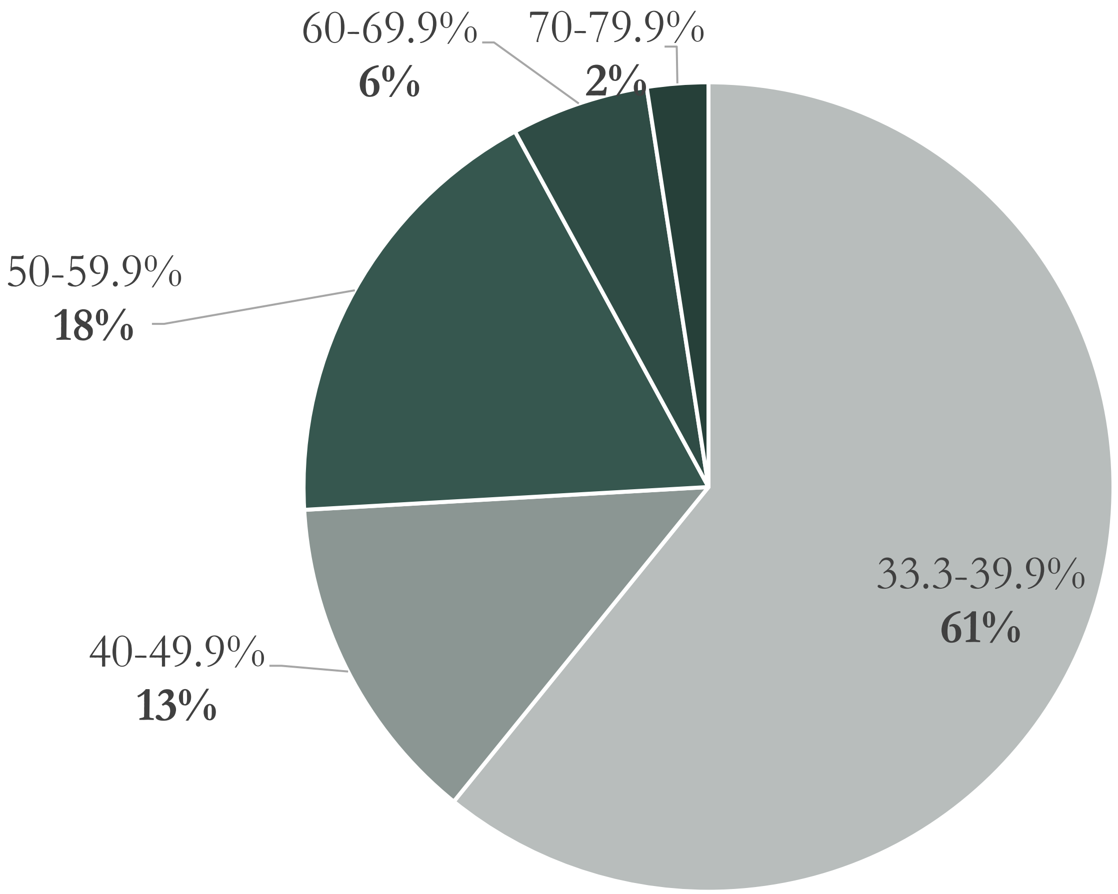
7 of these 17 common profiles include the 'most common deprivation bundle' – plus other deprivations.

Deprivation Scores of the MPI Poor 2019/21

The Figure shows the population of the poor in India 2019/21, organised by the value of the deprivation score of the poor.

What is clear is that 61% of poor people have a deprivation score between 33.3% and 39.9% - so they are close to the poverty line and might exit easily. And nearly three-quarters of poor people are deprived in less than 50%.

To continue the positive pro-poorest trend, attention is also needed to the last 26% (59 million) living in severe poverty, whose deprivation scores are 50% and above. The severe poor also have highest deprivations in nutrition, cooking fuel, housing and sanitation, so universal policies on these will likely benefit them also.



Technical Notes: Nutrition

Nutritional Deprivations among poor and non-poor

The MPI identifies people as poor if they are deprived in at least 33.33% of indicators – so nutrition plus a minimum of a) child mortality, school attendance, or years of schooling or b) 3 living standard indicators.

We define nutrition in terms of the percentage of the population living in a household in which at least one child under the age of 5 is underweighted or stunted, or one woman aged 15-49, or sampled male have a low body mass index (18.5 for people aged 20+ and age-specific for those 15-19). At a society-wide level (not considering multidimensional poverty – uncensored headcount ratio) this fell:

2005/6: 57.33%
2015/16: 37.60%
2019/21: 31.55%

Of the 31.55% of Indians in 2019/21 who live in a household in which at least 1 is nutritionally deprived

11.80% are **MPI poor**
12.53% are **Vulnerable** – having exactly one or two living standard indicator deprivations only in addition to nutrition (deprivation score of 20-33% but less than 33.33%)
7.22% are **Non-poor** – they are *only* deprived in nutrition, not in *any* of the other 9 indicators covered.

Technical Notes:

On comparisons of the annualised rate of change with other countries and between periods.

Annualised absolute change is the absolute change divided by the number of years. In the global MPI, if a survey spans 2 years, the 'policy' is to use the average. So 2005/6 would be 2005.5 and 2015/16 would be 2015.5   Published numbers in Table 6 rely on this approach.

To robustify this, we took the actual month of interview from each of the 3 waves, and computed annualised change more precisely using

1) the difference between the **mean month** of each survey.
2) the difference between the **median month** of each wave.

In both cases (mean and median month differences), the absolute annualised reduction in MPI was faster in 2005/6 to 2015/16 than during 2015/16 to 2019/21.

In both cases, also the absolute annualised reduction is slightly faster in both periods, so the published estimates reflect a lower bound.

Technical Notes:

On the number of 415 million leaving poverty
this requires applying the headcount ratio to a population figure. Which?

The current global MPI policy: In surveys that were fielded across two or three years the number of poor is estimated from the population data from the last survey year (2006, 2016, 2021).

In the case of NHFS, the population are not evenly distributed across years.
2005-2006: 92% of the weighted sample was interviewed in 2006
2015-2016: 62% of the weighted sample was interviewed in 2015
2019-2021: 50% of the weighted sample was interviewed in 2019

Hence we robustified this by cross-checking it against two options:

1. Using the year in which the **highest proportion of interviews** were held (2006, 2015, 2019)
2. Using the **second year of fielding**, whether fielded across 2 or 3 years (2006, 2016, 2020)

In both cases the number of poor leaving poverty increased (to 419 and 417 million respectively), so the published numbers represent a lower bound.

Technical Notes:

District level disaggregation for 2019/21 should be possible but has not yet been analysed. Trends may be possible for most districts that are present in both years.

Numbers changed since 2018 primarily due to **changes in UNDESA population estimations**. Example: in 2020, the estimated population of India in 2015/16 increased from 1,324,171 to 1,324,517. Minor changes in indicator policy are documented in methodological notes.

As other studies have outlined, the 2019/21 dataset **does not represent the post-covid situation**.
* Timing of Interviews: Fieldwork began July 2019. 71% of interviews were held between 7/2019 and 3/2020. The remaining 29% were held mainly from 11/2020 to 5/2021.

* All interviews were pre-covid in 17 states: Andhra Pradesh, Assam, Bihar, Goa, Gujarat, Himachal Pradesh, Jammu & Kashmir, Karnataka, Kerala, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura, West Bengal. In the remainder, interviews straddled the periods.

Next Steps for Analysis of Global Multidimensional Poverty Index data for India:

Determinants of Poverty reduction
Gender and Intrahousehold
Environment
Individual child MPI

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UNDP

Estimation Break-through

MPI toolbox for Stata now available on SSC

Nicolai Suppa
Last updated on Feb 1, 2023

After a considerable period of development `mpitb`, a toolbox to estimate and analyse multidimensional poverty indices (MPI) for Stata, is finally available on the Statistical Software Components (SSC) archive. You can download and install the toolbox by issuing `ssc install mpitb` in Stata.

The toolbox emerged from my work on the global MPI and various research projects. I frequently found myself to code solutions for the same problems again and again. As a consequence **key features** of the toolbox include

- the estimation of several indices of the Alkire-Foster framework (e.g., the adjusted headcount ratio, headcount ratio and intensity)
- the estimation of censored and uncensored headcount ratios as well as absolute and percentage contributions to the MPI for all indicators
- disaggregation of all indices by subgroups
- estimation of all indices for alternative parameter choices (e.g., weights, poverty cutoffs)
- estimation of changes over time is supported out of the box for many indices

This work is authored by Nicolai Suppa who co-leads global MPI estimations, and is all online`

- Developed in tandem with global MPI workflow
- A more general resource
- Paper: https://ophi.org.uk/rp-62a/

- Easily estimate key quantities out of the box including …
  - Standard errors
  - Disaggregation by subgroups (e.g. regions)
  - For parameter sets (weights, cutoffs, indicators)
  - Changes over time (absolute, relative, annualised or not)
- Facilitates generation of weights
- Avoid unnecessary estimations
- Produces structured results files
- Facilitates cross-country analysis

Determinants of India’s Poverty Reduction

The key unanswered question on the global stage:

How did India do it? How did it reduce MPI?

Such analysis requires panel data by state or district for a range of variables

- State GDP growth
- Public expenditure (not allocation) on MPI-related variables (but schemes vary)
- Service delivery (beyond expenditure) of MPI-related services
- Institutional strength and Accountability
- Investments by non-state actors – NGOs, private sector, etc
- Key events (disasters, population movements, employment shifts)

OPHI are interested to partner with actors who have detailed data or to learn of it; methodology is already published so the shortage is in data preparation.

Inclusive Absolute Well-being Changes: An Application with Multidimensional Cross-country Analysis

Sabina Alkire and Suman Seth

Table 2. Annualised Change in inclusive well-being, its decomposition and annualised bound-adjusted changes

		Year		Inclusive Well-being measure			Decomposition		Bound-adjusted change
Country	Region	1st	2nd	W_1	W_2	Δ	$\bar{\Delta}$	π	Δ_B
Afghanistan	SAS	2010-11	2015-16	29.3	35.2	1.18***	1.44***	-0.27***	1.67***
Bangladesh	SAS	2014	2019	54.9	64.9	2.00***	1.33***	0.66***	4.42***
India	**SAS**	**2005-6**	**2015-16**	**43.0**	**61.5**	**1.86*****	**1.39*****	**0.47*****	**3.25*****
Nepal	SAS	2011	2016	51.2	60.7	1.91***	1.23***	0.68***	3.90***
Pakistan	SAS	2012-13	2017-18	46.0	49.7	0.75***	0.70***	0.05	1.39***

Source: Authors' computations.

Statistical significance: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Notes: $W_1 = W(F_1; \omega^0)$ is the inclusive well-being measure in period 1; $W_2 = W(F_2; \omega^0)$ is the inclusive well-being measure in period 2; and Δ is the annualised absolute change.

Region abbreviations: ARS: Arab States; EAP: East Asia and the Pacific; ECA: Europe and Central Asia; LAC: Latin America and Caribbean; SAS: South Asia; SSA: Sub-Saharan Africa.

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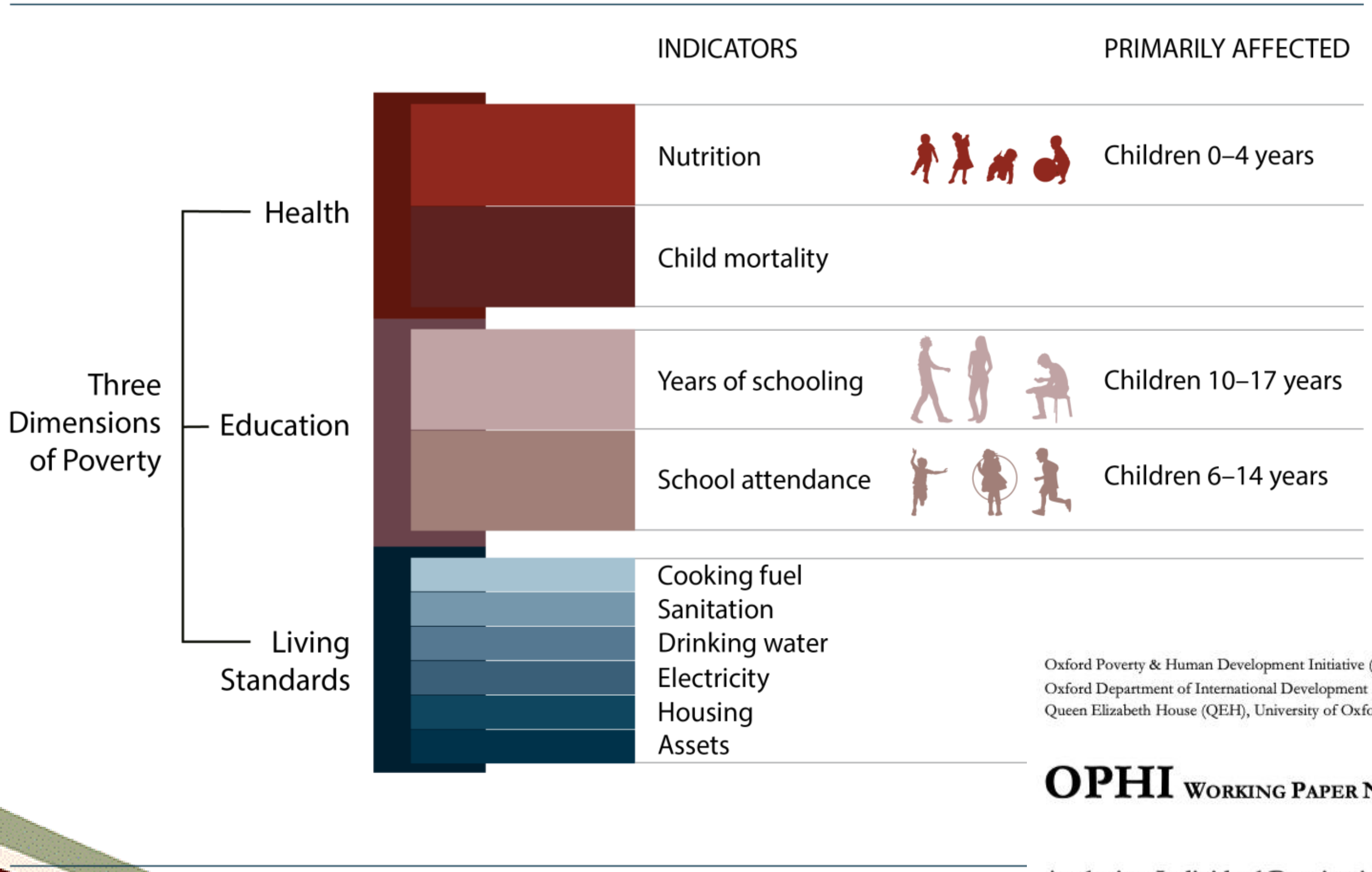
Gendered and Intrahousehold Analyses linked to MPI

Individual child information contained in the global MPI
Can be used to examine gender and intrahousehold patterns



Children vector graphics by Vector Open Stock

In new research, now going to scale across all global MPI countries we use underlying individual micro data to explore gendered and intrahousehold patterns of deprivation among children.

Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford

OPHI WORKING PAPER NO. 144

Analyzing Individual Deprivations alongside Household Poverty: Possibilities for Gendered, Intrahousehold, and Multidimensional Analyses

Sabina Alkire* and Rizwan Ul Haq**

January 2023

Let's look at gender among children – this is for 2015/16

Children who are MPI poor and deprived in school attendance and nutrition in South Asia, by gender (%)

Country	School-age boys/girls who are MPI poor and not attending school (%)		Boys/girls under 5 years of age who are MPI poor and malnourished (%)	
	Boys	**Girls**	**Boys**	**Girls**
Afghanistan	24.9**	44.0**	-	-
Bangladesh	12.1**	7.2**	30.6	31.0
Bhutan	8.7	7.8	24.2	24.3
India	6.1**	6.8**	27.6	27.8
Maldives	0.1	0.1	0.6	0.7
Nepal	3.1**	6.0**	25.5	27.0
Pakistan	19.7**	27.2**	26.6	27.8
South Asia	**9.0**	**10.7**	**27.7**	**28.1**

Note: * Gender differences are statistically significant at 5%;
** Gender differences are statistically significant at 1%.
Source: Authors' calculations based on surveys listed in Table 1.

There were significant gender disparities in poor children's school attendance – but not in undernutrition.

Figures show percentage of all children who are poor AND deprived, by gender.

Intrahousehold Inequality: where one child is deprived and another child in that household is not (India 2015/16)

Children experiencing intrahousehold inequality in South Asia with regard to school attendance and nutrition (%)

	Percentage of school-age children who reside in an MPI poor household where at least one school-age child does not attend school and another does	Percentage of children aged 0–4 who reside in MPI poor households where at least one child is malnourished and another is not
Afghanistan	34.3	-
Bangladesh	12.7	8.7
Bhutan	9.9	10.5
India	8.1	13.1
Maldives	0.3	0.4
Nepal	7.0	11.5
Pakistan	22.4	22.0
South Asia	**11.2**	**14.1**

Source: Authors' calculations based on surveys listed in Table 1.

Fully 13% of all children aged 0-4 are nutritionally deprived and share their household with another child also aged 0-4 who is not.

Complex Combination: Pioneer Children

(live in a household where no adult has completed 6 years of schooling but a child has)

1 in 8 Children 10-17 are pioneers

And over one-quarter of pioneer children are poor:
10.6M / 37.5M

Country	Share of pioneer children among all children (10–17)	Total number of pioneer children	Share of pioneer boys/girls among all boys/girls (10–17)		What percentage of pioneer children are MPI poor?
			Male	Female	
Afghanistan	7.1%	519,338	9.3%	4.7%	42.0%
Bangladesh	14.4%	4,283,753	12.8%	16.0%	27.8%
Bhutan	13.3%	18,928	13.8%	12.9%	16.8%
India 2015/6	14.2%	29,740,901	13.9%	14.4%	28.9%
Maldives	5.0%	2,945	5.2%	4.7%	0.4%
Nepal	20.6%	1,121,774	18.7%	22.4%	23.4%
Pakistan	5.1%	1,788,269	5.7%	4.6%	19.6%
South Asia	**12.6%**	**37,475,910**	**12.8%**	**13.3%**	**28.4%**

Integrated Analysis: schooling, nutrition, & Pioneer (India = 2015/16)

Levels of deprivation in the school attendance and nutrition indicators in South Asia and their overlaps,

	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	South Asia
Malnourished child(ren) only	32,908,395	138,480	256,392,034	54,238	5,745,176	67,853,061	**363,091,384**
Out-of-school (OOS) child(ren) only	18,221,535	86,477	84,416,116	5,574	1,590,830	54,966,389	**159,286,921**
Pioneer child (ren) only	17,032,199	83,729	101,487,833	9,433	3,778,337	9,196,485	**131,588,016**
Malnourished child(ren) and OOS child(ren)	4,786,546	20,630	27,301,448	386	465,678	30,410,227	**62,984,915**
OOS child(ren) and pioneer child(ren)	2,483,966	9,241	13,305,253	386	239,318	3,013,974	**19,052,138**
Malnourished child(ren) and pioneer child(ren)	2,424,944	11,272	13,025,206	386	439,058	2,395,723	**18,296,589**
All three	573,412	2,155	2,804,052	-	22,832	1,101,260	**4,503,711**

Note: OOS = Out-of-school
Source: Authors' calculations based on surveys listed in Table 1.

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Global MPI, Multidimensional Well-being & Beyond GDP

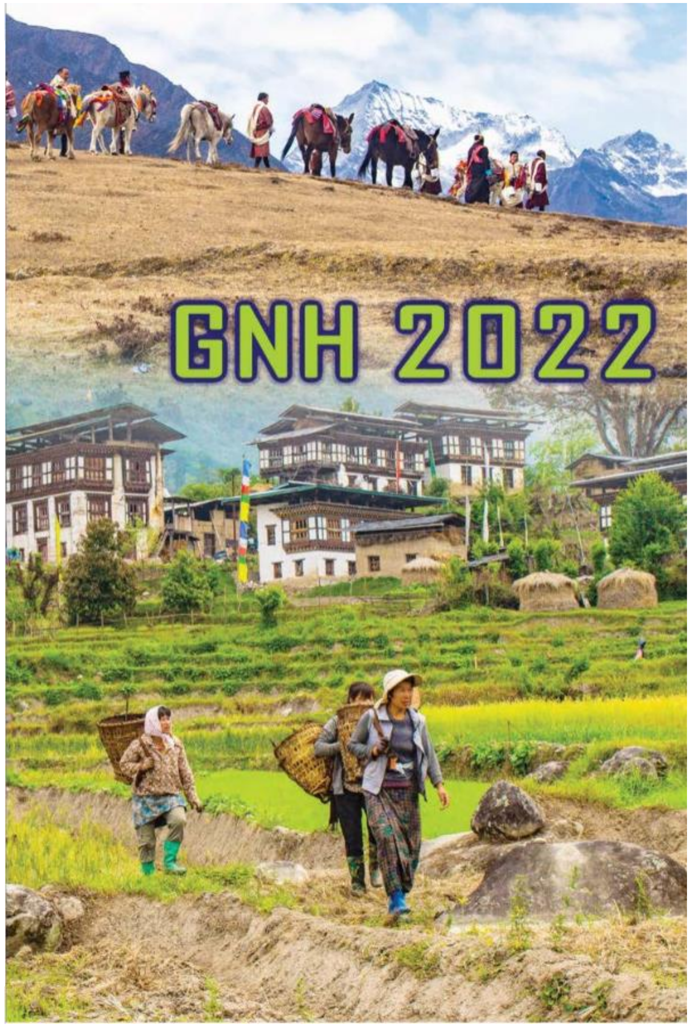
The UN Secretary General has initiated the move to measure well-being **Beyond GDP.**

The Global MPI is mentioned in the latest committee report (few indicators are). How do OPHI respond and proactively explore options?

Global MPI
Moderate MPI
Multidimensional Well-being Index (1-MPI)

In 2023, Bhutan launched its 2022 Gross National Happiness Index; Alkire and Kovesdi have drafted UK well-being metric combining Understanding Society data with the UK ONS well-being indicators. It illuminates very high disparities by ethnic and racial groups.

Would a well-being metric be of interest go to 'Beyond GDP' in India with disaggregation to district level, and mapping over to MPI?



Urgently needed: Multidimensional poverty data

Unfortunately, the "Data Revolution" seems to be leaving multidimensional poverty data behind.

- OPHI are organizing a simple ***Poverty Data Conference*** **7–9 Feb 2024** in Oxford, to convene actors working in data space.
- **We will propose brief survey questions that could be added to existing surveys for a genuinely global Moderate MPI** and seek critical engagement on content and process.

We will also seek to organize events in the upcoming **World Data Forum** regarding multidimensional poverty data.

Minor changes in MICS and DHS surveys would also radically empower future MPI analysis.

Consultations and engagement by other bodies (e.g. Eurostat, OECD, UNSD) would be essential to facilitate this process.

Vulnerable Groups: ~ People living with disabilities – updatable from 2024

Research Article

Hamill Institute on Disabilities

Journal of Disability Policy Studies
1–11

DOI: 10.1177/1044207320919942
jdps.sagepub.com
SAGE

How Poor Are People With Disabilities? Evidence Based on the Global Multidimensional Poverty Index

Monica Pinilla-Roncancio, PhD[1] and Sabina Alkire, PhD[2]

Table 3. Incidence (H), Intensity (A), and MPI for People Living in Households With and Without Disabled Members.

			Household *with* disabled members			Household *without* disabled members		
Country	% PWD	% PHWD	MPI	Incidence (%)	Intensity (%)	MPI	Incidence (%)	Intensity (%)
Algeria	1.5	7.5	0.011**	2.8**	38.85	0.005	1.3	39.1
Cambodia	5.2	17.5	0.136	31.1	43.9	0.148	33.4	44.4
Cameroon	—	26.2	0.367**	62.2**	59.0	0.310	54.3	57.1
Chad	—	19.7	0.565	89.1	63.4	0.549	86.6	63.4
Colombia	6.1	17.7	0.021*	6.1	39.9	0.262	5.2	41.2
DR	5.4	14.6	0.022	5.3	42.1	0.021	5.5	38.8
Ecuador	5.9	16.4	0.191**	4.9**	38.6	0.123	3.2	38.5
Gambia	2.7	16.1	0.342	62.9	55.1	0.32	59.8	54.3
Mexico	9.8	25.4	0.010	2.8	38.2	0.011	2.8	39.1
Uganda	4.2	14.5	0.398	76.5**	52.0	0.361	68.7	52.5
Yemen	3.6	17.9	.248	48.7	51.5	.233	45.2	50.9

Note. Statistical significance is tested with *t*-test for continuous variables and Pearson's chi-square test for binary variables. MPI = Multidimensional Poverty Index; PWD = people with disabilities; PHWD = people living in households with members with disabilities.
*Differences between groups are significant at 10%. **Significant at 5%.

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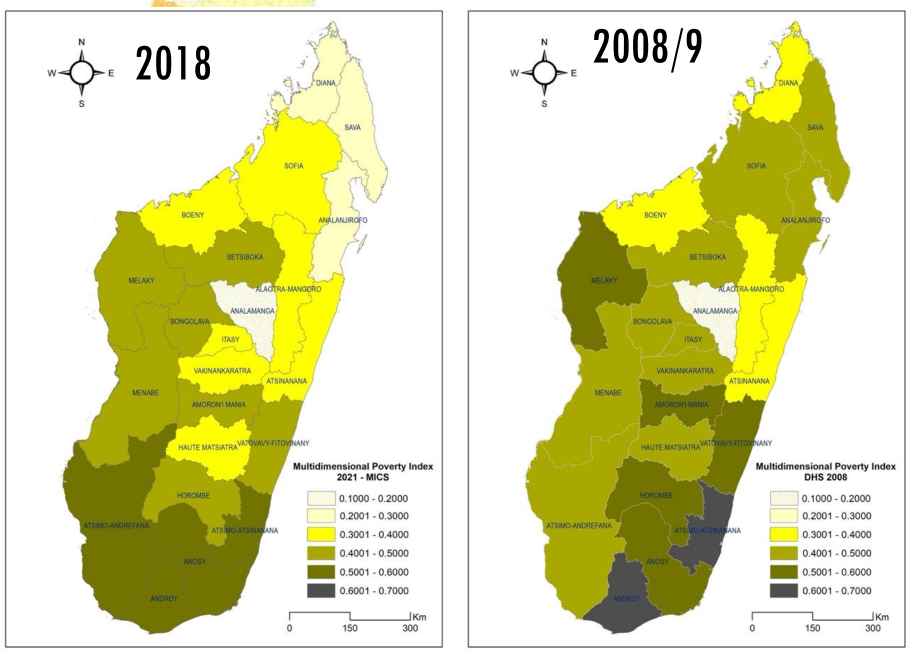
Environmental variables

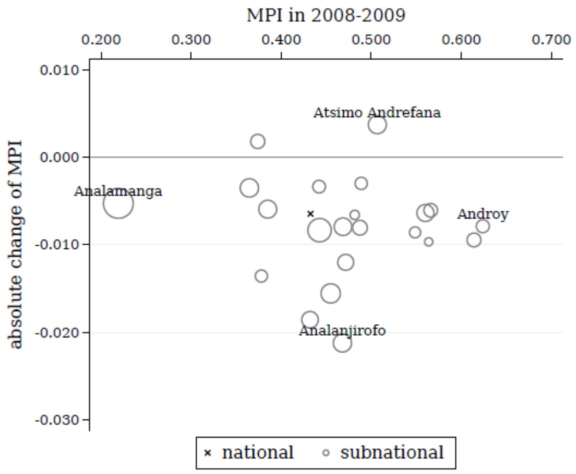
Madagascar in the global MPI

Figure 3. Incidence of MPI poverty by subnational region



Source: Christian Oldiges using data published by Alkire, Kanagaratnam and Suppa (2020).

Figure 11. Changes in MPI by subnational region



Notes: Absolute changes are expressed in units of MPI and annualised. Source: For 2008-2009 DHS, for 2018 MICS, own calculations.

- **From 2008/9 to 2018, the harmonised MPI_T reduced from 0.433 to 0.372;**
- **Incidence from 75.7% to 67.4%;** Intensity reduced significantly from 57.2% to 55.2%.
- But **the number of poor people increased**, from 16 to 18 million.
- In 2018, 18 of the 27 million people were poor.
- Only **10 of the 22 subnational regions** had statistically significant reductions at 95%.
- And absolute reduction in MPI across regions was **not pro-poorest**.

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How we incorporated environmental data

- Locating clusters
- Choosing environmental indicators
- Checking availability and download environmental data
- Determining the range of each environmental indicator and think about deprivation level
- Choosing spatial extraction method
- Extracting value by area
- Compiling values to feed the EMPI database
- Data analysis

Locating clusters

MICS 2018

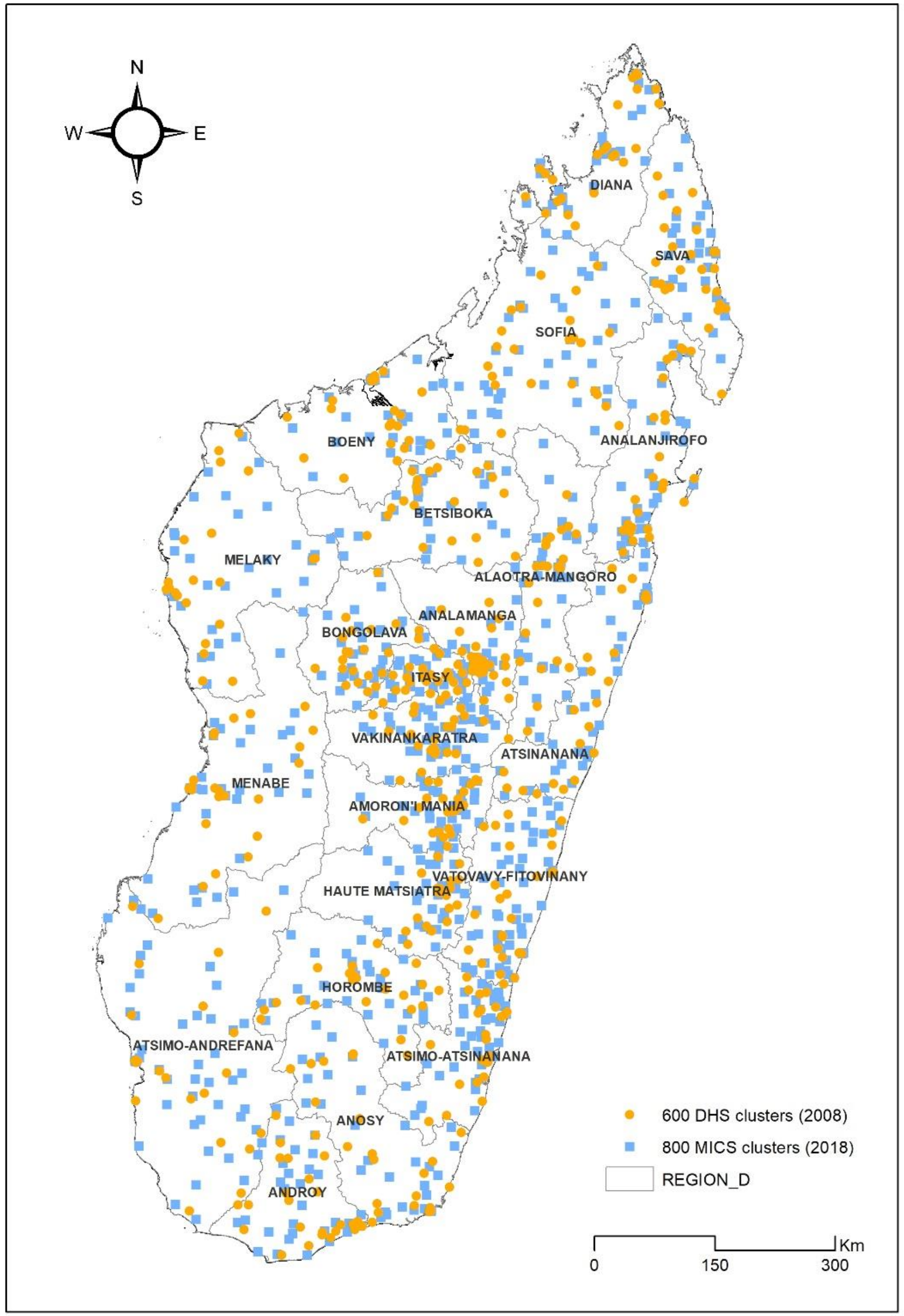
MICS_site	Longitude	Latitude
1	47.50285	-18.9036
2	47.51457	-18.9042
3	47.50847	-18.9074
4	47.51269	-18.9141
5	47.53947	-18.9174
6	47.56082	-18.9149
7	47.53499	-18.9293
8	47.53961	-18.9396
9	47.51694	-18.891
10	47.53048	-18.8995

DHS 2008

DHS_site	Longitude	Latitude
1	47.50036	-18.9088
2	47.49953	-18.9094
3	47.51908	-18.9045
4	47.50856	-18.9192
5	47.49968	-18.9236
6	47.52111	-18.9113
7	47.50696	-18.8882
8	47.50463	-18.9239
9	47.52438	-18.9085
10	47.528	-18.9291

Using Arc GIS 10.6 to convert table into vector 'points'

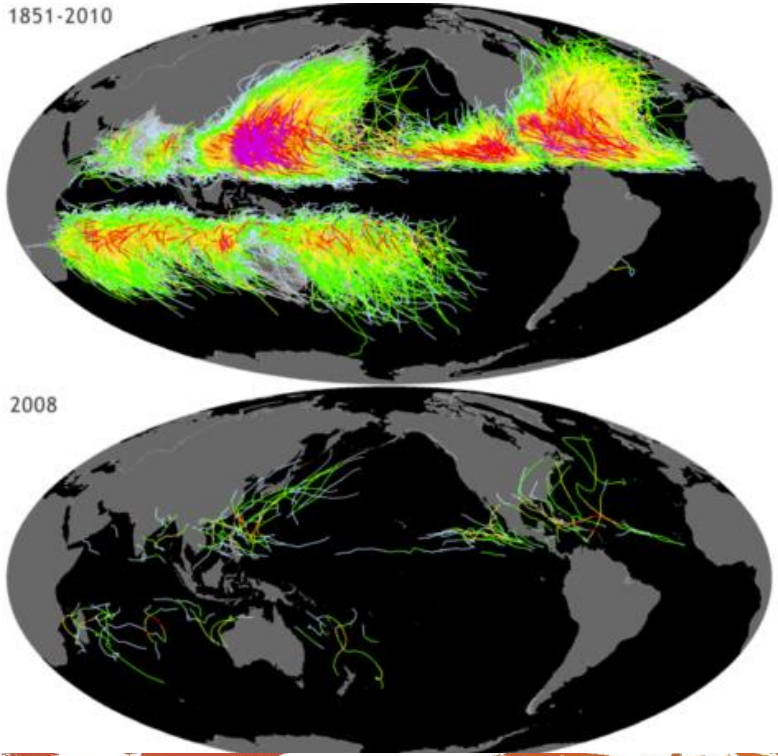
Total: 1,400 clusters

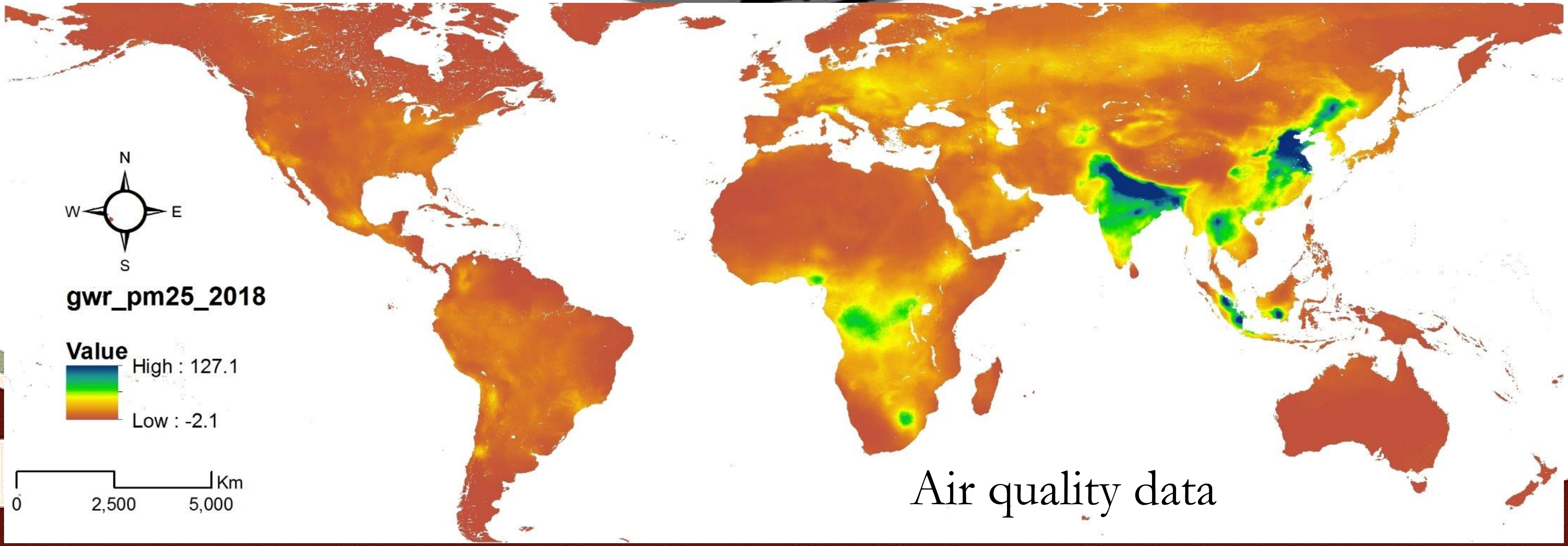


Choosing among Possible Environmental Indicators

1. Air Quality (outdoor) - SDGs 3, 7, 11
2. Storms - SDGs 11, 13
3. Fire - SDGs 11, 13, 15
4. Earthquakes - 11, 15
5. Forest Cover/Loss - SDGs 6, 13, 15
6. Soil Erosion SDGs 13, 15
7. Precipitation (Drought, Flooding) - SDGs 13, 15
8. Temperature - SDGs 13, 14, 15
9. Biodiversity Loss - SDGs 14, 15

Cyclone data



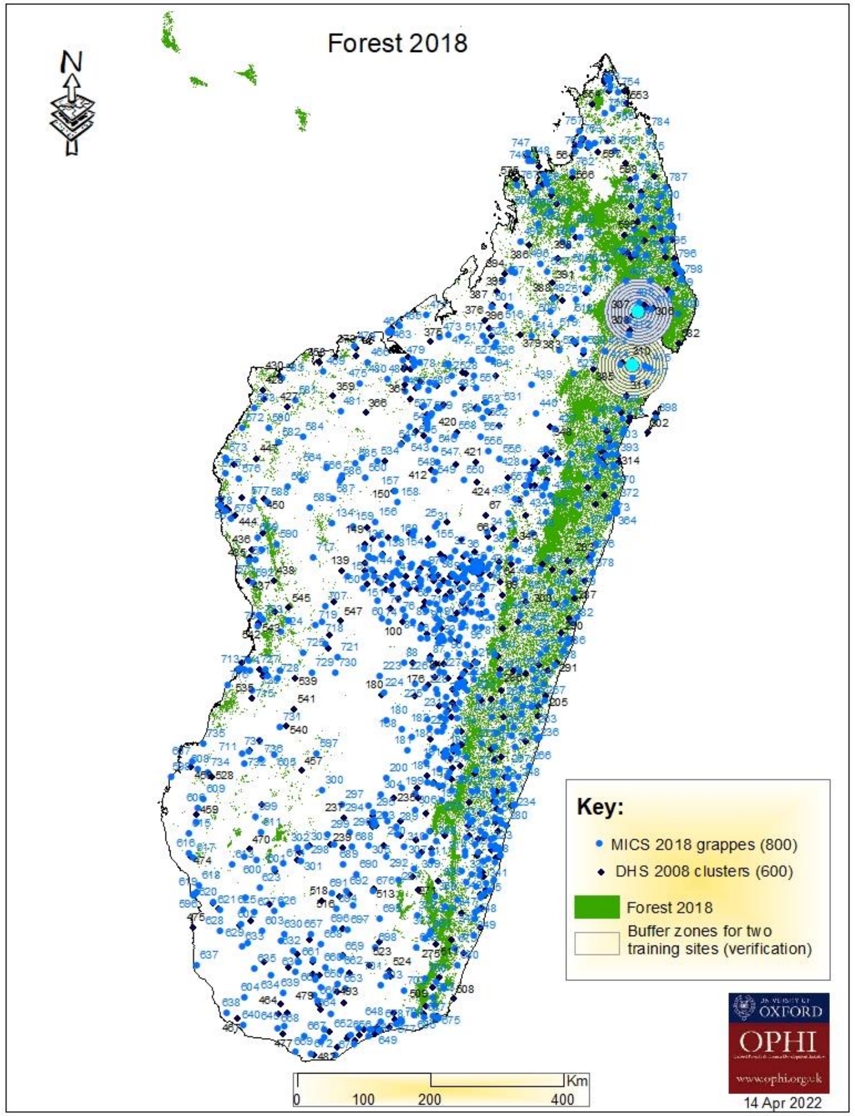


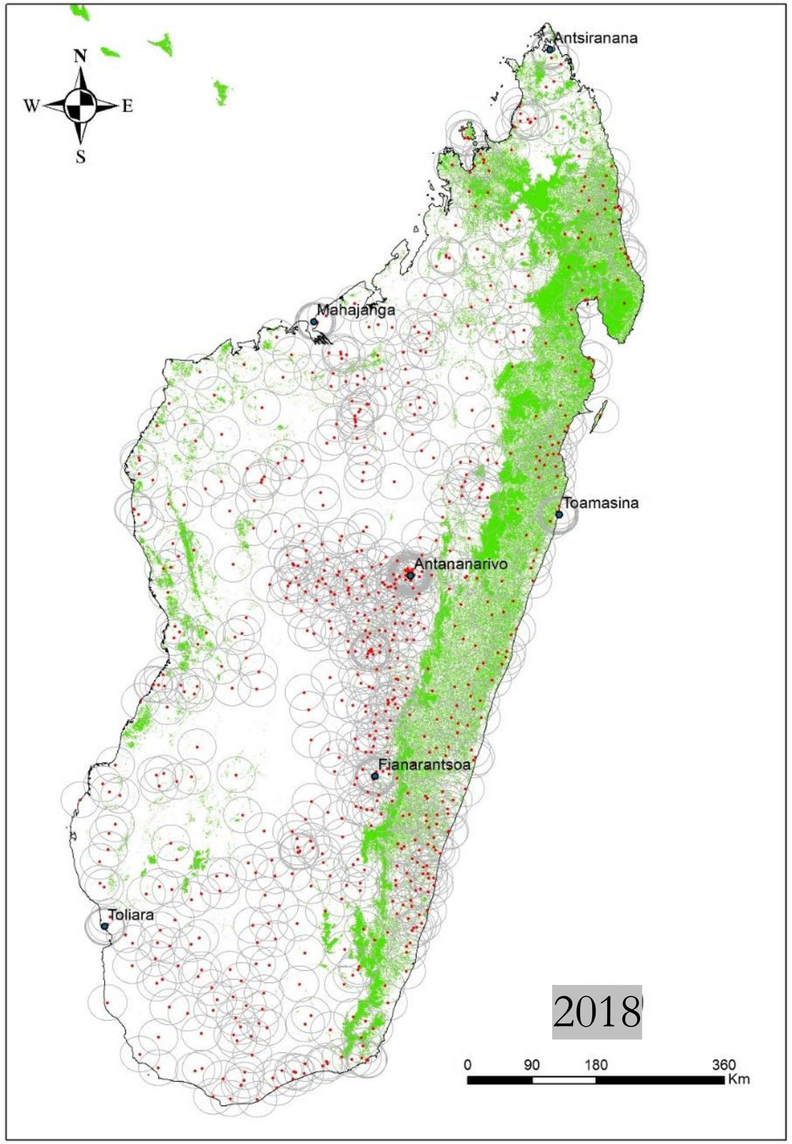
Air quality data

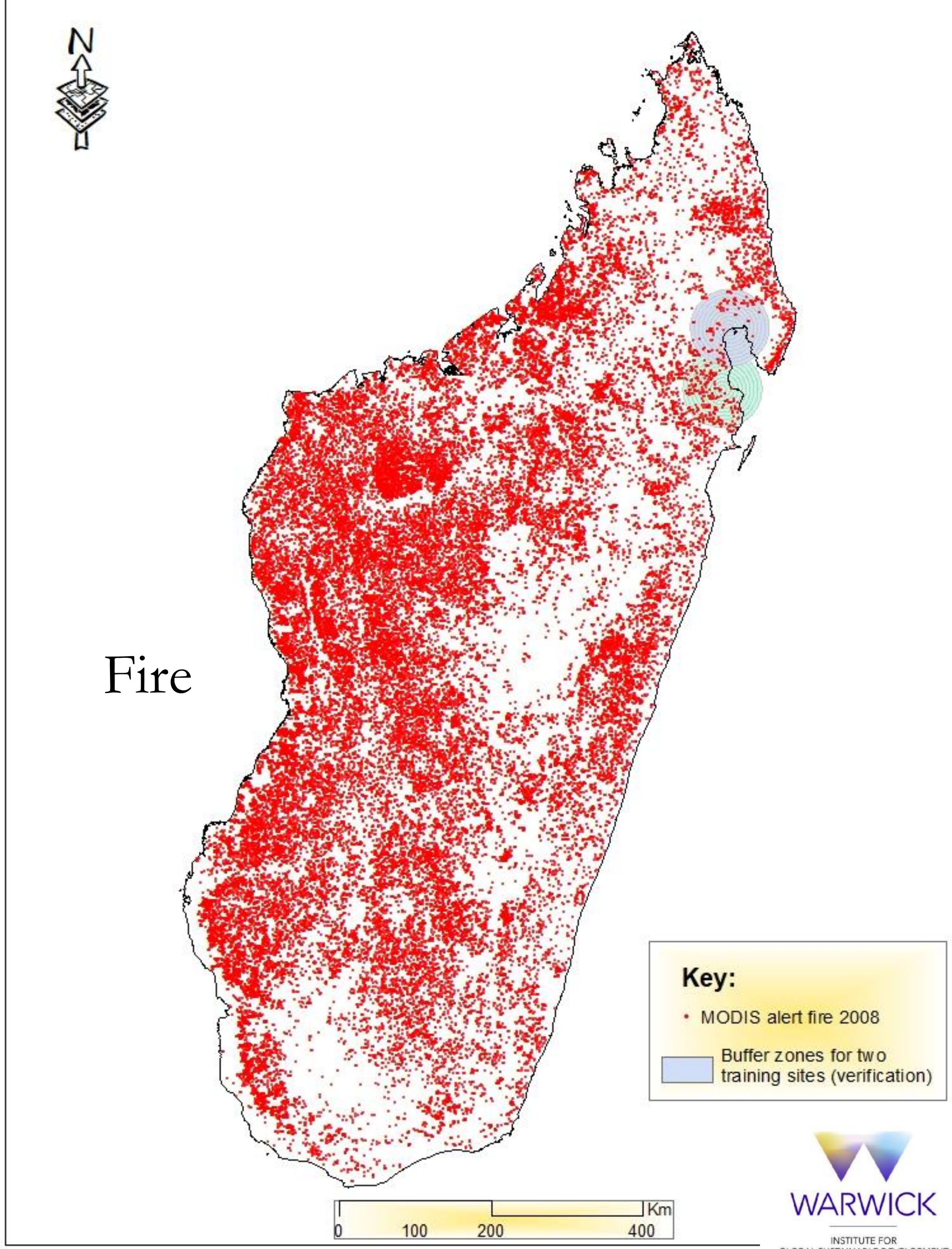
Determining the range of each environmental indicator, and deprivation

Variables	Affected range	Deprived if
Forest	10km radius	Less than 10% cover
Air quality	10km radius	Greater than 5 µg/m3
Cyclone	50km radius	One cyclone or more
Earthquake	10km radius	One earthquake or more
Fire	10km radius	3 active fires or more

Determining the range of each indicator







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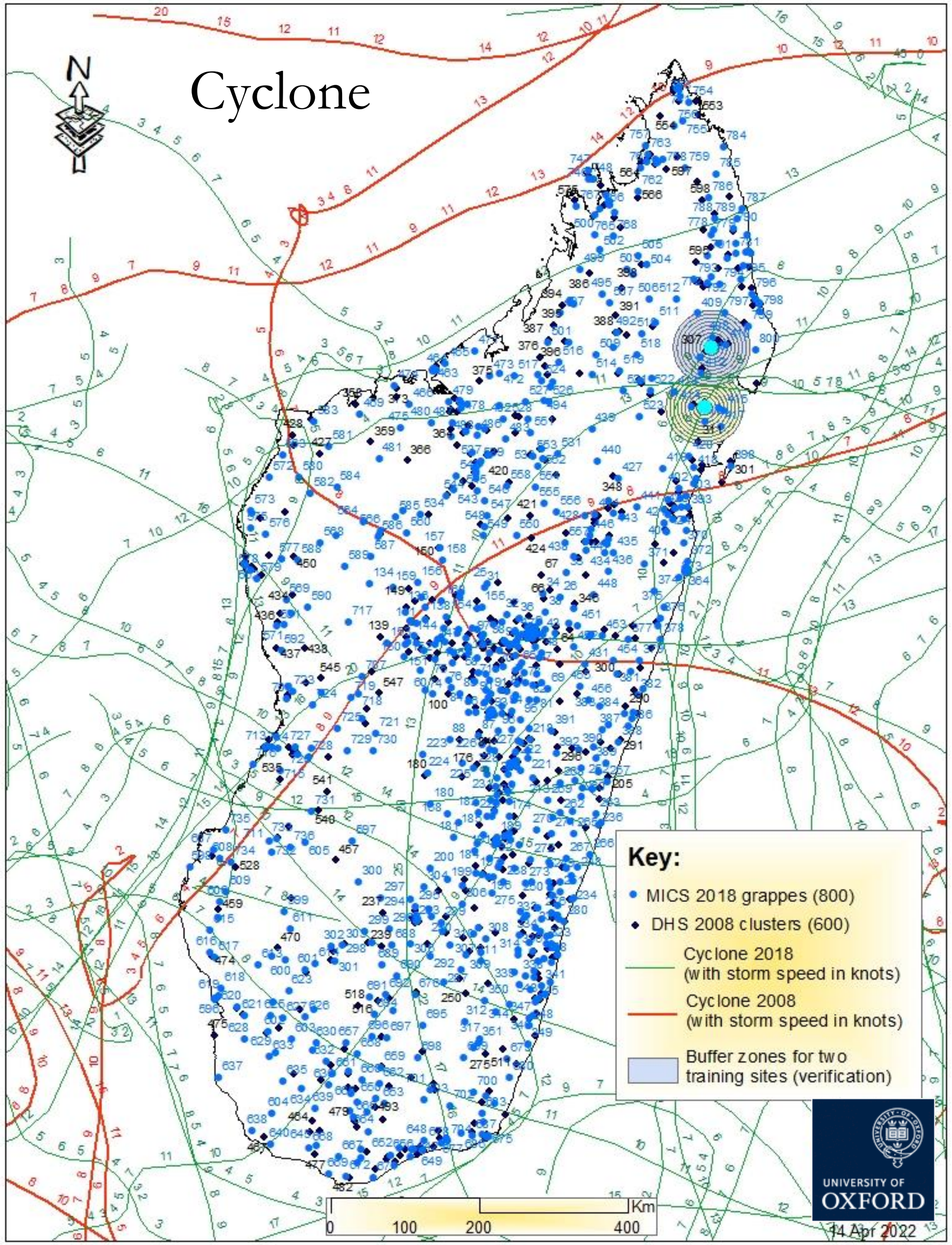

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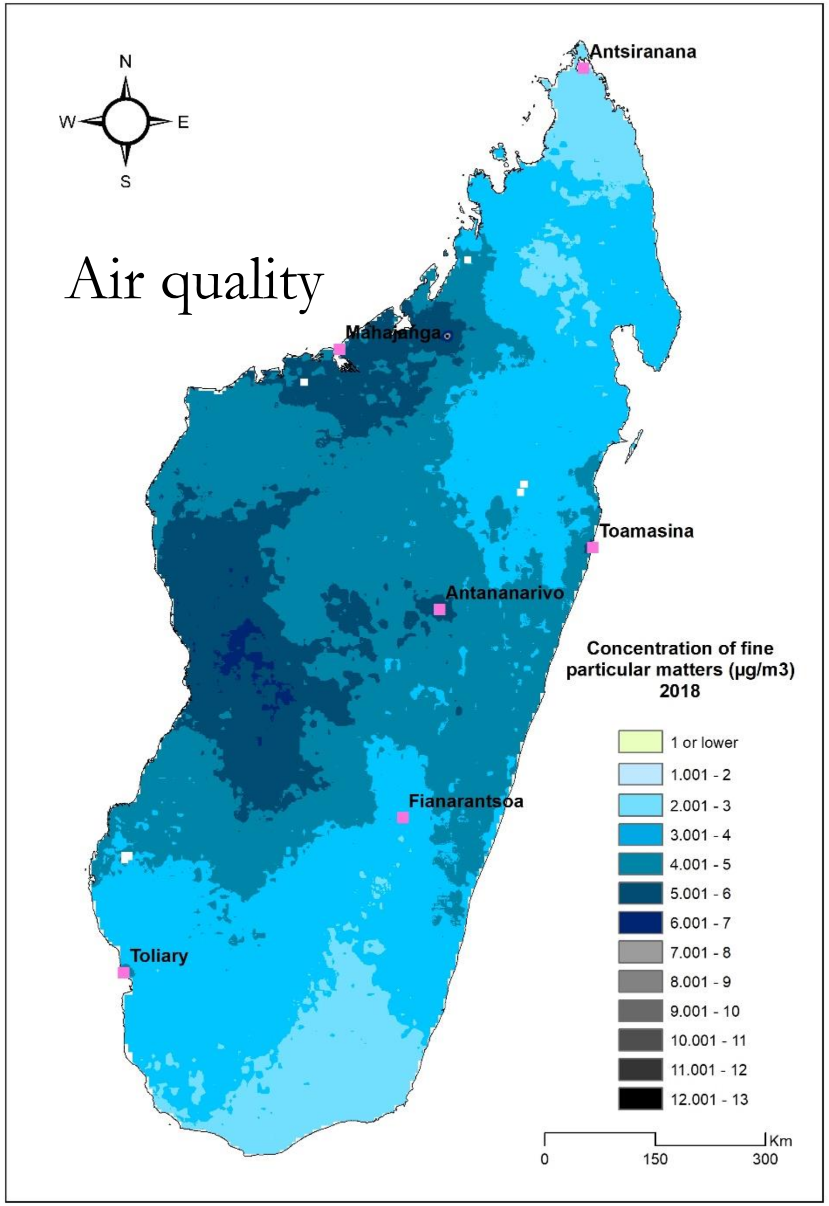
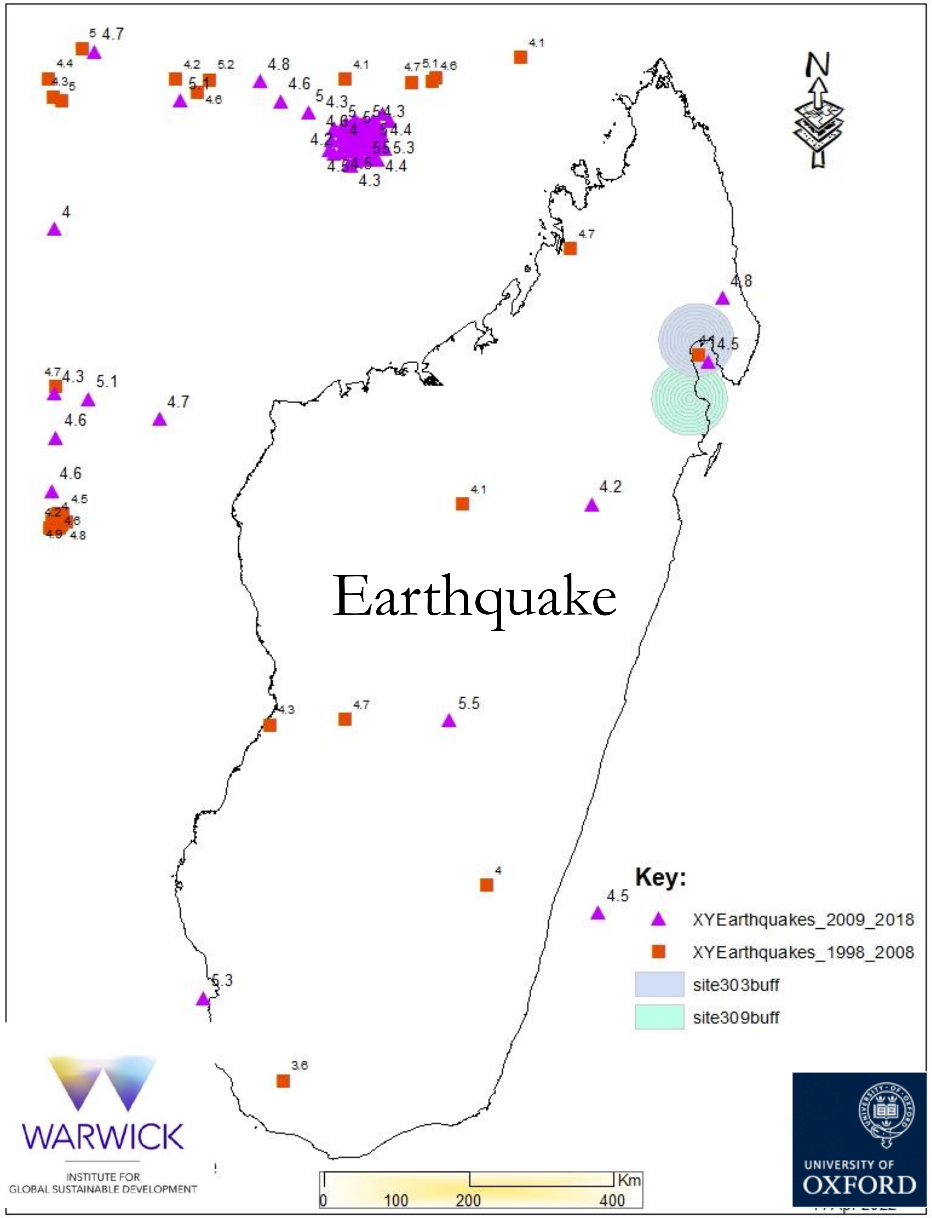
Choosing spatial extraction method





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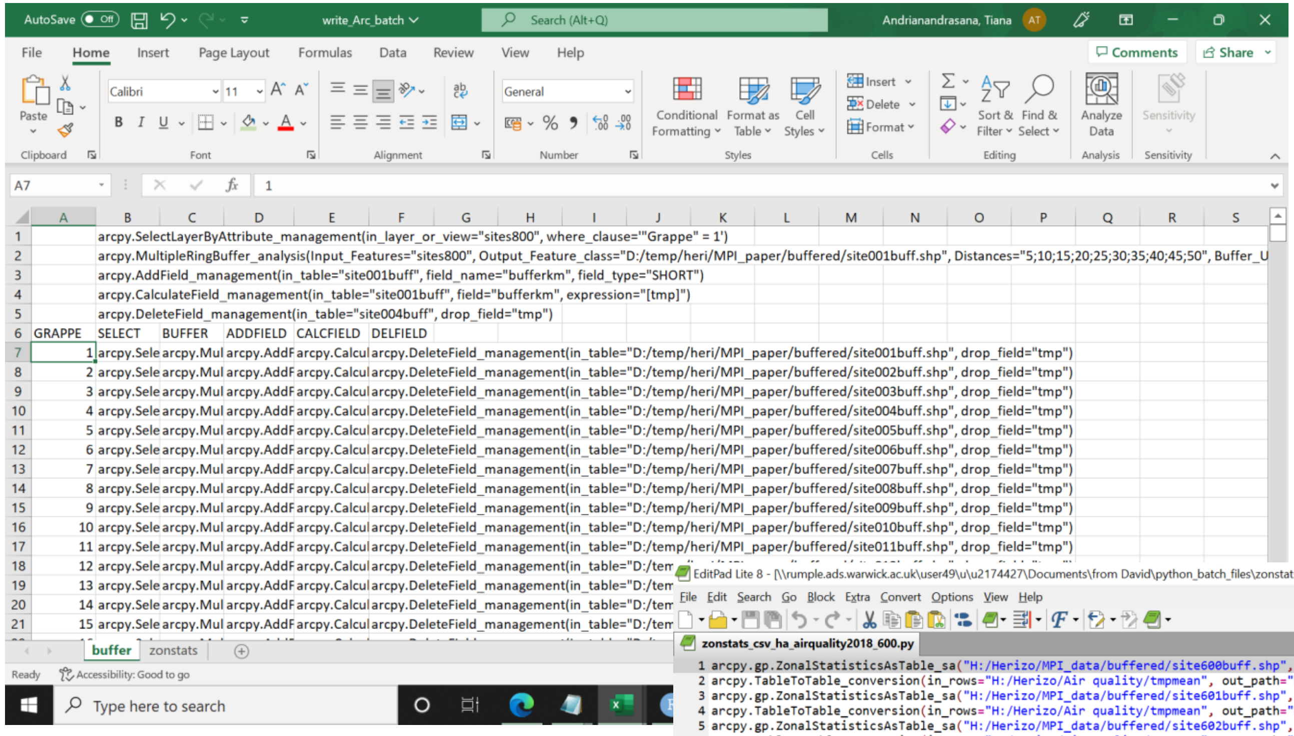
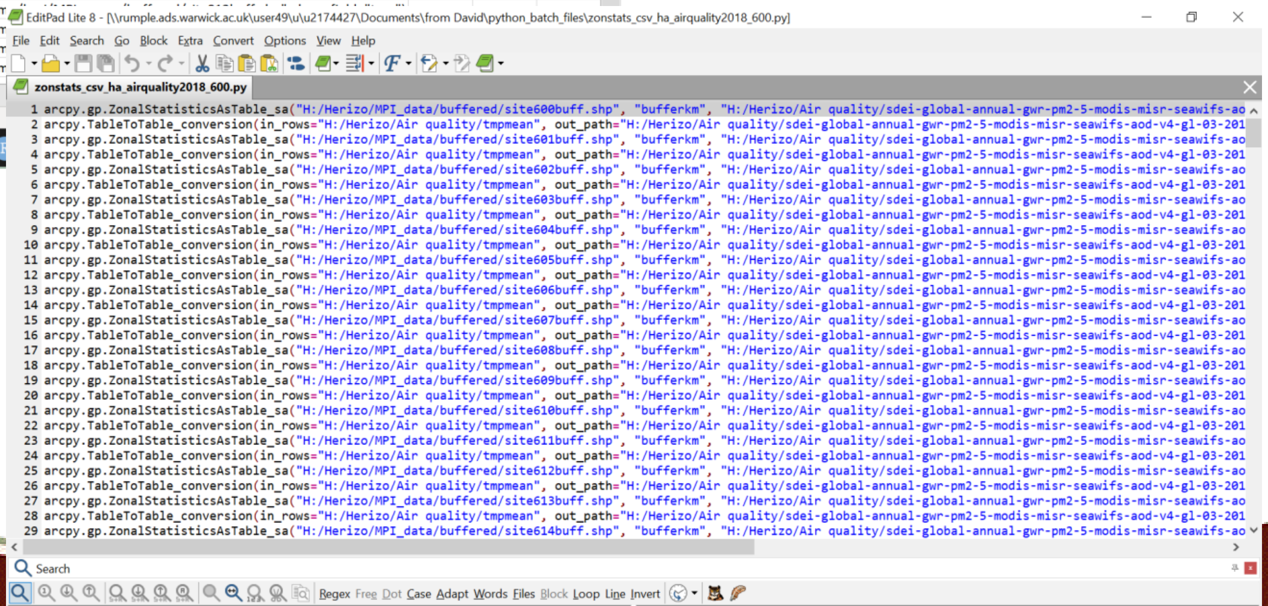
Buffer zones: draw circles around each cluster, compile, and extract them.



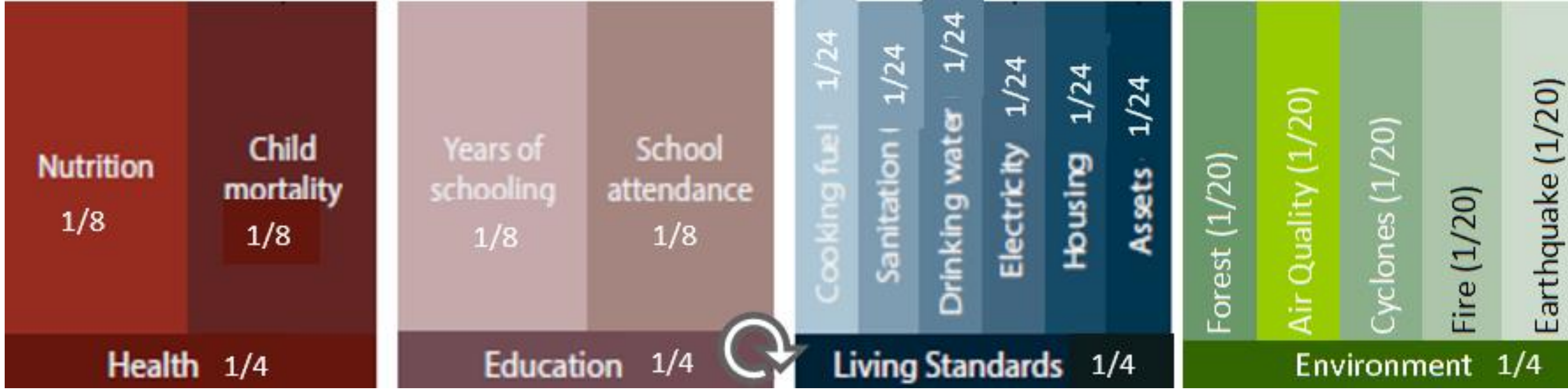


- Write python batch file
- Microsoft Excel
- Python command
- Geoprocessing Arc GIS

Environment and MPI: Geospatial merging

An environmentally augmented Multidimensional Poverty Index:
The Case of Madagascar

S Alkire, H Andrianandsana, A Fortacz, F Vollmer



- Merges global MPI data for Madagascar 2008-2018 with satellite data using GPS of the cluster
- All households in a cluster are deprived if
  - the **forest** cover is less than 10% within a 10km radius.
  - the annual concentration of fine **particulate** matter is higher than 5 μg/m3 (micrograms (one-millionth of a gram) per cubic meter air) within a 10km radius.
  - a **cyclone** was recorded within a 50km radius. Tropical depressions (wind circulation under 61.1km/h) and tropical cyclones (wind circulation of 62.7km/h - 117km/h) are considered as cyclones.
  - three or more **fires** were recorded within a 10km radius
  - an **earthquake** (with a magnitude of 4 or more) was recorded within a 10km radius.

Computes an Environmentally-Augmented MPI; also raises methodological challenges and possible ways forward.

Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford

OPHI RESEARCH IN PROGRESS SERIES 50a

Incorporating Environmental and Natural Resources within Analyses of Multidimensional Poverty

Géraldine Thiry, Sabina Alkire, and Judith Schleicher*

January 2018

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Individual Child MPI

Linked Child MPIs

MPIs address **children** and other groups using 4 strategies:

Always

1) Ensure MPI **indicators** capture key child deprivations
2) **Disaggregate** the MPI by age groups
3) Analyse **gendered and intra-household** patterns

Sometimes

4) Develop an **individual-level MPI that is linked** to the National MPI (same dimensions/indicators and linked weights and poverty cutoff), yet adds one or more additional dimensions.

India could do this using NFHS-5

82

China & World Economy / 82–105, Vol. 30, No. 1, 2022

Exploring China's Potential Child Poverty

*Yangyang Shen, Sabina Alkire**

sustainability

MDPI

Article

Children and Multidimensional Poverty: Four Measurement Strategies

Jakob Dirksen * and Sabina Alkire

Oxford Poverty and Human Development Initiative, Oxford Department of International Development, University of Oxford, Oxford OX1 3TB, UK; sabina.alkire@qeh.ox.ac.uk
* Correspondence: jakob.dirksen@qeh.ox.ac.uk

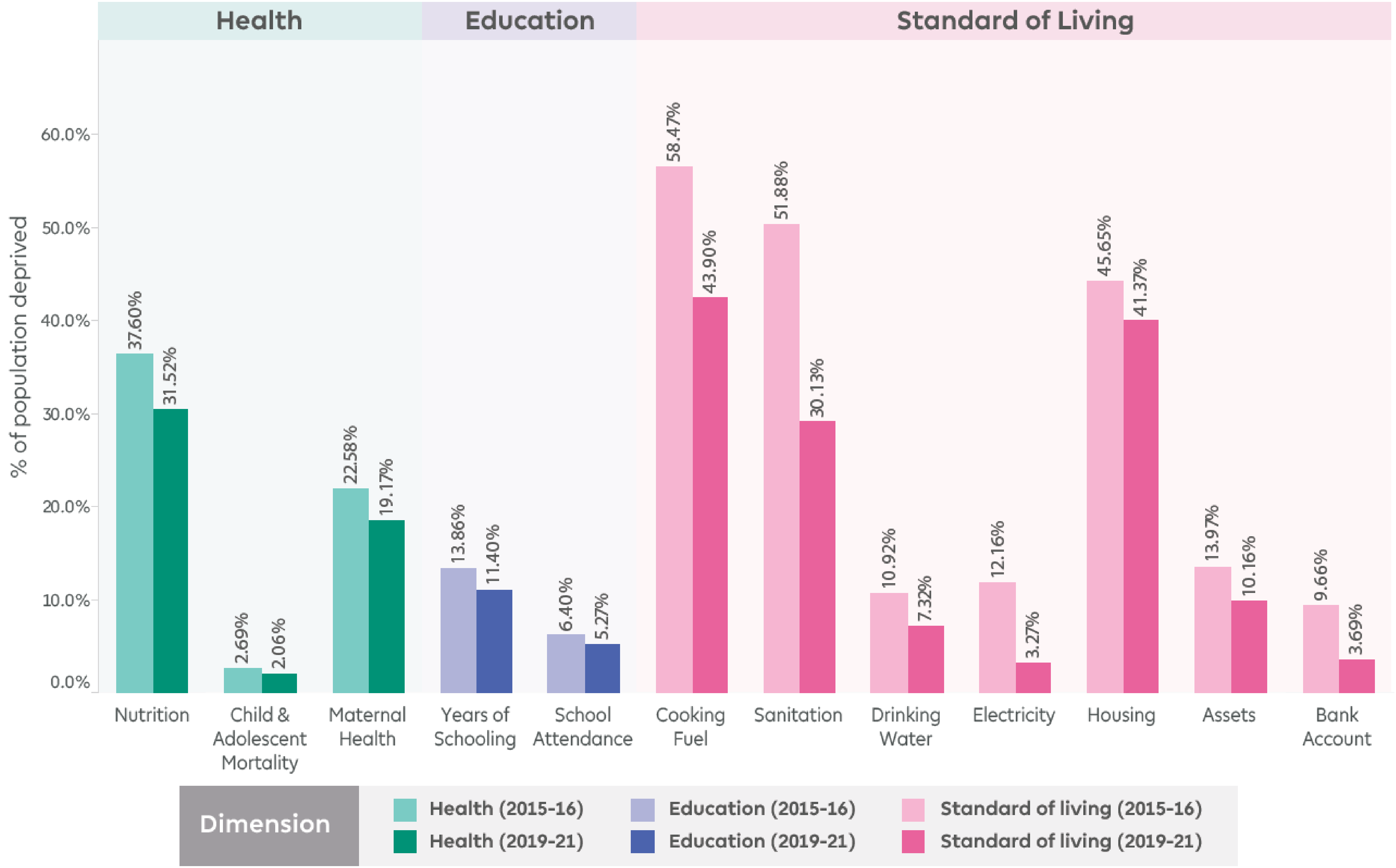
Strengthening the Policy Impact of Multidimensional Metrics Given Attention Constraints: Constructing Linked Metrics

Sabina Alkire[1] Ana Vaz[2] Christian Oldiges[3]

"The relatively recent explosion of information makes **attention**, rather than information, **the scarce resource** in organisations"

Hansen & Haas 2001

Thank you!



Health
Education
Standard of Living
% of population deprived
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
37.60%
31.52%
2.69%
2.06%
22.58%
19.17%
13.86%
11.40%
6.40%
5.27%
58.47%
43.90%
51.88%
30.13%
10.92%
7.32%
12.16%
3.27%
45.65%
41.37%
13.97%
10.16%
9.66%
3.69%
Nutrition
Child & Adolescent Mortality
Maternal Health
Years of Schooling
School Attendance
Cooking Fuel
Sanitation
Drinking Water
Electricity
Housing
Assets
Bank Account
Dimension
Health (2015-16)
Health (2019-21)
Education (2015-16)
Education (2019-21)
Standard of living (2015-16)
Standard of living (2019-21)

Snapshot of Multidimensional Poverty in India

Year	Headcount Ratio (H)	Intensity of Poverty (A)	MPI (H x A)
2019-21	14.96%	44.39%	0.066
2015-16	24.85%	47.14%	0.117