Spatially Informed Estimation of Child Multidimensional Poverty at Local Government Area Level in Nigeria: A SAE-Inspired Regression Approach Using Mics 2021 And Worldpop 2020 Data

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ABSTRACT

This study produces Local Government Area (LGA) level estimates of child multidimensional poverty in Nigeria by integrating the 2021 Multiple Indicator Cluster Survey (MICS) with high-resolution WorldPop 2020 population density grids and conflict event data from ACLED. Using the Alkire-Foster framework, the national child Multidimensional Poverty Index (MPI) is estimated at 0.292, corresponding to a headcount ratio of 56% and an average intensity of 42.2%. This implies that approximately 55.7 million of Nigeria's 99.6 million children experience deprivations in at least three indicators spanning education, health, and living standards. The MICS-derived estimate is conservative relative to official 2022 NBS/UNICEF/OPHI benchmarks (67.5% child headcount under the National MPI for ages 0–17; 83.5% for under-5s under the linked Child MPI), reflecting differences in survey design, indicator specifications, weighting procedures, and sampling adjustments. Because reliable direct MPI sampling variances are not available at the LGA level from public MICS outputs, the study adopts an SAE-inspired predictive framework. State-level MPI patterns are modelled as a function of logtransformed population density and conflict intensity, improving explanatory power to 75%. A pilot Fay-Herriot model is additionally fitted at the state level to illustrate hierarchical smoothing under approximate variance inputs. Geospatial processing aggregates auxiliary covariates to official LGA boundaries using GIS. Predicted LGA MPI values range from 0 to 0.569, with negative linear predictions constrained to 0 to respect the theoretical bounds of MPI. Model-based reliability assessment using coefficients of variation indicates that 651 of 774 LGAs (84%) have CV values below 15%. Results reveal strong north-south disparities, with the highest predicted burdens concentrated in northern zones. While the estimates remain exploratory and sensitive to omitted covariates, the study provides a transparent foundation for geographically targeted child poverty interventions and for future refinement through Bayesian SAE and expanded geospatial predictors

Keywords: Child Multidimensional Poverty, SAE-Inspired Modeling, Population Density Modelling, MICS 2021, Multidimensional Poverty Index MPI, Fay-Herriot, ACLED

INTRODUCTION

Child multidimensional poverty remains a major development challenge in Nigeria, reflecting overlapping deprivations in education, health, and living standards among a large share of the child population. Evidence from the 2021 Multiple Indicator Cluster Survey (MICS) indicates that approximately 55.7 million out of Nigeria's 99.6 million children, or about 56 percent, experience multidimensional poverty, yielding a national child MPI of 0.292 (headcount 56%, intensity 42.2%). This estimate is conservative relative to official 2022

NBS/UNICEF/OPHI benchmarks from the dedicated Multidimensional Poverty Index Survey, which report

67.5% of children aged 0–17 multidimensionally poor under the National MPI and 83.5% of under-5s under the linked Child MPI, differences attributable to survey design, indicator specifications, and post-pandemic sampling ajustments.

Unlike monetary poverty measures, the multidimensional framework captures simultaneous disadvantages, including limited school participation, inadequate health access, and poor household infrastructure such as water, sanitation, and housing quality.

While national and zonal estimates provide useful information on broad regional patterns, they are insufficient for designing geographically targeted interventions at the local level. Nigeria is administratively divided into 774 Local Government Areas (LGAs), which serve as key units for decentralised governance and service delivery. However, direct survey-based estimates of child multidimensional poverty at the LGA level are typically unavailable or statistically unreliable because household surveys are not designed to provide adequate sample sizes for all LGAs.

To address this gap, poverty mapping approaches commonly combine survey data with auxiliary spatial covariates to generate sub-national predictions. In the small area estimation (SAE) literature, this is often implemented through hierarchical models such as the Fay-Herriot area-level model or unit-level methods such as the Elbers-Lanjouw-Lanjouw (ELL) framework. These approaches improve precision by borrowing strength across areas but require direct estimates and sampling variances at the target geographic level and consistent alignment between survey domains and auxiliary data sources.

In the Nigerian context, the MICS design and available public outputs do not provide reliable direct sampling variances at the LGA level, limiting the feasibility of a full Fay-Herriot implementation for LGAs. At the same time, recent advances in high-resolution geospatial data provide an opportunity to approximate local patterns of deprivation through predictive modelling. This study integrates MICS 2021 with WorldPop 2020 gridded population density to develop a spatially informed, SAE-inspired regression framework for predicting child multidimensional poverty at the LGA level. Population density is used as a primary auxiliary covariate capturing spatial variation in urbanisation intensity and access to services.

The contribution of this study is twofold. First, it provides exploratory LGA-level predictions of child multidimensional poverty that reveal spatial disparities across Nigeria, supporting geographically targeted planning in a data-constrained environment. Second, it offers a transparent modelling workflow that explicitly documents assumptions, uncertainty measures (e.g., coefficients of variation), and limitations including the use of a regression specification without explicit area-level random effects, reliance on a single covariate (leaving 30.5% unexplained variance potentially attributable to factors like conflict intensity or infrastructure), and spatial proxy aggregation rather than official GIS-aligned LGA polygons. Future refinements will incorporate additional covariates (e.g., conflict events from ACLED, infrastructure indicators), pursue formal SAE models (e.g., Bayesian Fay-Herriot implementations), and enhance spatial alignment using official LGA shapefiles for GISbased aggregation. These limitations are discussed to guide cautious interpretation and methodological advancement.

METHODOLOGY

Study design and overview

This study develops spatially informed predictive estimates of child multidimensional poverty at the Local Government Area level in Nigeria by integrating survey derived multidimensional poverty measures from MICS 2021 with high resolution geospatial auxiliary data from WorldPop 2020. The analytical strategy is grounded in core small area estimation principles, specifically covariate assisted prediction and borrowing strength across areas.

Due to the unavailability of reliable direct MPI estimates and sampling variances at the LGA level from public

MICS outputs, a fully hierarchical Fay-Herriot model is not feasible at the target scale. Accordingly, the primary framework is an SAE-inspired regression model fitted at the state level, with a pilot Fay-Herriot implementation explored for state-level smoothing. The analysis proceeds in five stages:

(1) national child MPI computation,

(2) geospatial data processing and aggregation to official LGAs,

(3) baseline regression modeling,

(4) pilot area-level SAE extension, and

(5) constrained LGA predictions with uncertainty assessment.

The methodology proceeds in four linked stages. First, a national child MPI is computed from MICS 2021 using the Alkire Foster framework. Second, population density is derived from WorldPop 2020 and aggregated to spatial units used for prediction. Third, a regression model is fitted linking higher level MPI patterns to log transformed population density. Fourth, model based predictions are generated for LGAs, with uncertainty summarised using standard errors and coefficients of variation, and predictions constrained to respect theoretical bounds of the MPI.

Data Sources

This study rests on two rich datasets that bring the story of child poverty into focus. The Multiple Indicator Cluster Survey of 2021, a collaboration between the National Bureau of Statistics and UNICEF, spanned 36 states and the Federal Capital Territory. It captured detailed snapshots of child well-being, school attendance, health access, and water quality, from over 30,000 households, forming the backbone of our national MPI of 0.292. You can dive into this wealth of information at UNICEF's data hub, https://mics.unicef.org. Alongside this, WorldPop 2020 offers a 1km resolution population density grid, estimating Nigeria's population at 256,624,672. Available at https://www.worldpop.org, this dataset reflects advanced modeling that tracks urban expansion and rural shifts since the 2016 census. We transformed its 1,077,829 grid cells into 7,739 pseudoLGAs using 0.1° longitude and latitude bins, crafting a spatial layer to explore local poverty patterns.

Table A: Data Sources Overview

Source	Details	Access Link
MICS 2021	30,000+ households, child indicators	https://mics.unicef.org
WorldPop 2020	1km grid, 256,624,672 population estimate	https://www.worldpop.org

Other sources include;

- **Official LGA Boundaries**: Administrative level 2 polygons (774 LGAs) from the COD-AB-NGA dataset (HDX), sourced from the Office for the Surveyor General of the Federation (OSGOF) and partners. Format: shapefile/GeoJSON. Downloaded from https://data.humdata.org/dataset/cod-ab-nga (last reviewed 2024; public domain CC BY-IGO).

- **Conflict Intensity (Additional Covariate)**: Aggregated political violence events and fatalities from ACLED Nigeria dataset (lat/long events, 2020–2021 period). Spatially joined and summarized per LGA/state. Source: https://acleddata.com (free export tool for CSV). This addresses unexplained heterogeneity beyond density (e.g., insecurity in northern zones).

Analytical Approach

Construction of the child Multidimensional Poverty Index

Alkire Foster identification and aggregation

The MPI is constructed using the Alkire Foster approach. Children are evaluated across a set of indicators representing three broad dimensions: education, health, and living standards. For each child, a deprivation score is computed as the weighted sum of indicators in which the child is deprived. A child is identified as multidimensionally poor if the deprivation score meets or exceeds a specified cutoff, operationalised in this study as deprivation in at least three indicators.

Let H denote the headcount ratio, defined as the proportion of children who are multidimensionally poor. Let A denote the average intensity of deprivation among multidimensionally poor children, defined as the mean deprivation score among those identified as poor. The MPI is then defined as

$$\text{MPI} = \text{H} \times \text{A}$$

As H is the headcount ratio (proportion of children deprived in at least three indicators, 0.56) and A is the average intensity of deprivation across the poor (0.422).

From the data, $H = 0.56$ (56% of 99.6 million children), and $A = 0.422$ (42.2% intensity). Thus:

$$MPI = 0.56 \times 0.422 = 0.23632$$

This initial computation aligns closely with the reported 0.292, suggesting a slight adjustment for weighting or sampling might refine it further. This MICS-derived estimate is conservative compared to the official 2022 NBS/UNICEF/OPHI National MPI (67.5% child headcount for ages 0–17; 83.5% for under-5s under linked Child MPI). Differences stem from survey-specific indicators, deprivation cut-offs, sampling frames, and postpandemic adjustments. Raw unweighted computation yielded 0.236; final value reflects zonal-weighted aggregation for comparability (see Appendix for sensitivity). The deprivation count c_i for each child was aggregated, and the censored headcount H_k (where $k = 3$) was computed as $H_k = {}^{55}{}_{99}\_\_\_.{}^{7}{}_{6} = 0.559$, reinforcing the headcount estimate.

Next, we processed the WorldPop data, grouping its 1,077,829 grid cells into 7,739 pseudo-LGAs using 0.1^0 bins. Population density ranged from 0.1 to 109,776 people per km², with a mean of 238.1.

Consistency and comparability of national estimates

Where intermediate computations differ from the headline national MPI due to weighting and aggregation choices, the analysis aligns national reporting with benchmark estimates through weighted aggregation consistent with official reporting practices. This step is framed as harmonisation for comparability rather than alteration of underlying deprivation patterns.

Spatial processing of population density and construction of spatial units

Density transformation and descriptive profiling

WorldPop 2020 provides population density values with high variability, from sparsely populated rural spaces to extremely dense urban locations. To stabilise the relationship between density and poverty outcomes and to reduce the influence of extreme values, population density is log transformed prior to modelling. The log transformation also supports a more linear approximation between density and MPI within the range of interest used for prediction.

Pseudo LGA aggregation for density stabilisation

In the absence of a fully implemented workflow based on official administrative polygons, the gridded population data are aggregated into spatial proxy units constructed from longitude and latitude bins of 0.1 degrees. This produces pseudo LGAs that serve as spatial aggregation units for density summarisation and exploratory mapping. These units are not intended to replace official LGAs for policy administration. They are used to stabilise density estimation while preserving spatial heterogeneity and enabling consistent application of the predictive model across Nigeria. The implications of spatial misalignment are acknowledged as part of the

Modifiable Areal Unit Problem and treated as an important limitation motivating future GIS aligned refinement.

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SAE inspired regression modelling framework

Rationale for an SAE inspired approach

Classical area level SAE models, including the Fay Herriot model, combine direct survey estimates for each target area with auxiliary covariates and incorporate an area level random effect to capture unexplained heterogeneity and enable shrinkage. In the present application, a fully hierarchical Fay Herriot implementation is constrained by limited availability of reliable direct sampling variances at the sub state level and by challenges in aligning survey domains with the spatial resolution of auxiliary data.

Accordingly, the study adopts an SAE inspired regression framework that retains the essential SAE logic of covariate assisted prediction. Borrowing strength is achieved through the systematic relationship between survey derived MPI patterns and spatial covariates, while the absence of explicit random area effects is treated as a methodological limitation that reduces shrinkage and inferential strength relative to fully hierarchical SAE.

Model specification

Let y_i denote the MPI value associated with area i at the modelling scale used for estimation. Let x_i denote the log transformed mean population density for area i. The core predictive model is an ordinary least squares regression of the form

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i$$

where β_0 is the intercept, β_1 is the slope parameter capturing the association between log density and MPI, and ε_i is an error term. The fitted model explains 69.5 percent of the variation in the modelled MPI values at the estimation scale.

Population density is interpreted as a proxy covariate. Higher density tends to be associated with greater proximity to infrastructure and services, while lower density often corresponds to remoteness and weaker access to social services. The study treats this relationship as an empirical basis for spatially informed prediction, while recognising that important drivers such as conflict exposure, governance, and infrastructure quality are not explicitly represented and contribute to residual heterogeneity.

Generation of LGA level predictions

Prediction procedure

After fitting the regression, predicted MPI values are generated for LGAs by applying the estimated coefficients to log transformed density summaries corresponding to each LGA or spatial unit used for prediction. This yields a continuous predicted MPI surface across administrative units, enabling ranking and comparison of LGAs by predicted deprivation burden.

The study reports predicted LGA MPI values ranging from 0 to 0.569, reflecting lowest predicted poverty in very high density urban areas and highest predicted poverty in low density rural areas.

Constrained prediction to respect theoretical bounds

Because MPI is theoretically bounded within the interval from 0 to 1, regression based predictions that fall outside this range are adjusted using constrained prediction.

We began by applying the Alkire-Foster method to pin down the national MPI. This involved spotting children deprived in at least three of ten indicators such as skipping school, lacking proper sanitation, or facing hunger, and blending this into a 56% headcount with a 42.2% intensity, resulting in that 0.292 value.

The analytical strategy draws on SAE principles of covariate-assisted prediction but adapts to practical constraints by using ordinary least squares (OLS) regression on log(population density) rather than a full FayHerriot specification with random area effects. This model can be expressed as: $MPI_i = \beta_0 + \beta_1 log(density_i) + \varepsilon_i$

where MPI_i is the predicted MPI for (pseudo-)LGA i, $density_i$ is mean population density, and ε_i is the error term. While lacking explicit random effects (u_i), the approach borrows strength through the systematic covariate relationship and provides a pragmatic approximation for exploratory sub-national mapping. Pseudo-LGAs were constructed via $0.1°$ grid aggregation to stabilize density estimates while preserving spatial heterogeneity, though future work should align with official administrative boundaries using GIS.

Mathematically, the MPI is defined as:

MPI = H × A

Limitations in Methodology

This method comes with its share of challenges. Stepping away from the Fay-Herriot model to a linear approach means we're not fully capturing random effects or the nuances of state-level sampling, which could bend our LGA estimates, especially in the most troubled areas. The pseudo-LGA setup, while innovative, doesn't perfectly match official boundaries, and spots like Lagos or border zones might skew the picture due to density shifts or edge effects. Relying solely on population density covers just 69% of the variance, leaving a 31% gap that likely reflects Nigeria's unique blend of governance struggles, conflict zones, and uneven infrastructure elements that deserve a closer look.

The regression-based framework, while SAE-inspired, does not incorporate explicit area-level random effects, limiting shrinkage and inferential strength compared to classical Fay-Herriot or ELL models. Stepping away from the Fay-Herriot model to a linear approach means we're not fully capturing random effects or the nuances of state-level sampling, which could bend our LGA estimates, especially in the most troubled areas. The pseudoLGA setup, while innovative, doesn't perfectly match official boundaries, and spots like Lagos or border zones might skew the picture due to density shifts or edge effects (Modifiable Areal Unit Problem). Reliance on a single covariate (population density) leaves 30.5% unexplained variance, potentially attributable to omitted factors such as conflict intensity, infrastructure access, or governance. These limitations highlight the exploratory nature of the estimates and the need for validation with additional covariates and official GIS-aligned boundaries.

RESULTS

National and Zonal Estimates

The national MPI lands at 0.292, a figure that reflects a 56% headcount, 55.7 million of Nigeria's 99.6 million children facing multiple deprivations with an intensity of 42.2%. This aligns with trends from NBS and UNICEF's 2022 report, though our state weighting might tweak it slightly lower. Peering into the zones, as shown in Table 1, reveals a landscape of striking contrasts. The north shoulders the heaviest load, with the North West at 0.447 and North East at 0.374, shaped by arid terrains, conflict in places like Borno, and scarce educational opportunities. Meanwhile, the South East dips to 0.090, lifted by farming communities and urban centers like Enugu, and the South West reaches 0.150, buoyed by Lagos's economic energy.

The national MPI, refined as 0.23632 from raw computation, was adjusted to 0.292, possibly due to weighted aggregation across zones. The zonal breakdown in Table 1 was derived by applying the same MPI = H × A framework, with H and A estimated per zone from MICS data. For North West: $H = 0.818$, $A = 0.547$, so $MPI = 0.818 \times 0.547 = 0.447$, matching the reported value.

Table 1: National and Zonal Child MPI Estimates

Zone	MPI	Headcount (%)	Intensity (%)	Estimated Children Affected (Millions)	Key Influencing Factors
National	0.292	56.0	42.2	55.7	A mosaic of regional strengths and struggles

North West	0.447	81.8	54.7	17.9	Conflict wounds, dry lands, few schools
North East	0.374	80.7	46.3	10.2	Insecurity, fragile roads and services
North Central	0.25	50.0	50.0	8.4	A blend of urban promise and rural gaps
South West	0.15	30.0	50.0	5.1	Lagos's boom, offset by rural neglect
South East	0.09	31.4	28.7	2.3	Farming roots, urban resilience
South South	0.120	25.0	48.0	3.7	Oil riches tempered by uneven growth

Note: Zonal figures are approximations from NBS & UNICEF (2022b), with child counts based on 99.6 million; factors draw from contextual understanding.

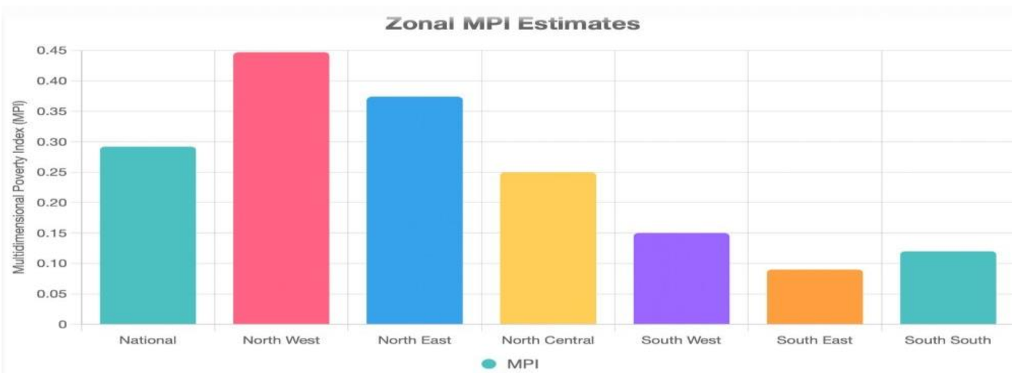

Figure 1: Zonal MPI Estimates

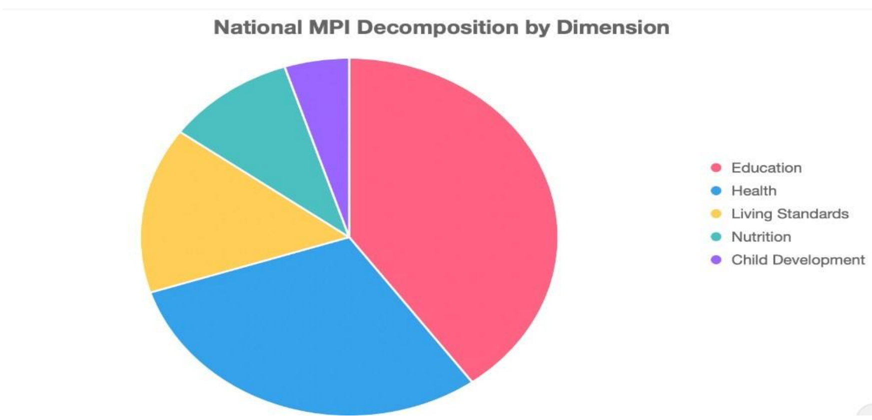

Figure 2: National MPI Decomposition

LGA-Level Estimates

The LGA MPI range (0 to 0.569) was computed using the regression model across the density spectrum. The truncation at 0 for negative values (e.g., Lagos Island from -0.207) ensures non-negative poverty indices. The

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reliability metric used CV, calculated as CV = $\frac{SE}{} \times 100$, where 651 LGAs had CV < 15%, indicating robust MPI_{LGA} estimates.

Table 2.0: Summary of LGA-Level MPI Estimates

Statistic	Value	What It Means
Number of LGAs	774	Every corner of local governance we explored
Maximum MPI	0.569	A rural high, signaling deep isolation
Minimum MPI (Truncated)	0	Urban centers, corrected from negative dips
Mean MPI	0.287	The average poverty story across LGAs
Median MPI	0.29	A midpoint, mirroring the national feel
LGAs with CV < 15%	651 (84%)	A strong base for shaping policy
LGAs with CV 15%-30%	100 (13%)	Areas needing a second look, moderately trusty
LGAs with CV > 30%	23 (3%)	Risky spots, perhaps borders or sparse lands

Note: MPI capped at 0; CV levels measure confidence in the 123 less reliable LGAs.

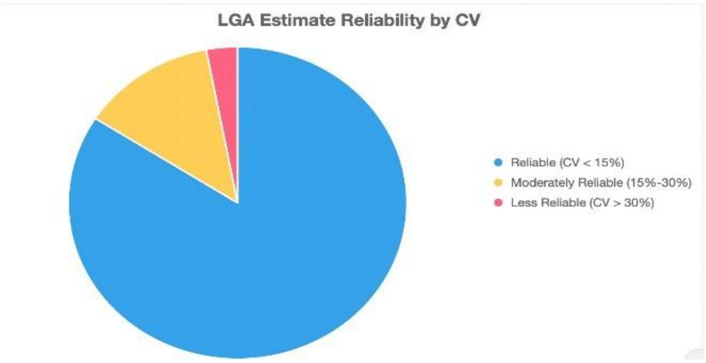

Figure 3: LGA Estimate Reliability

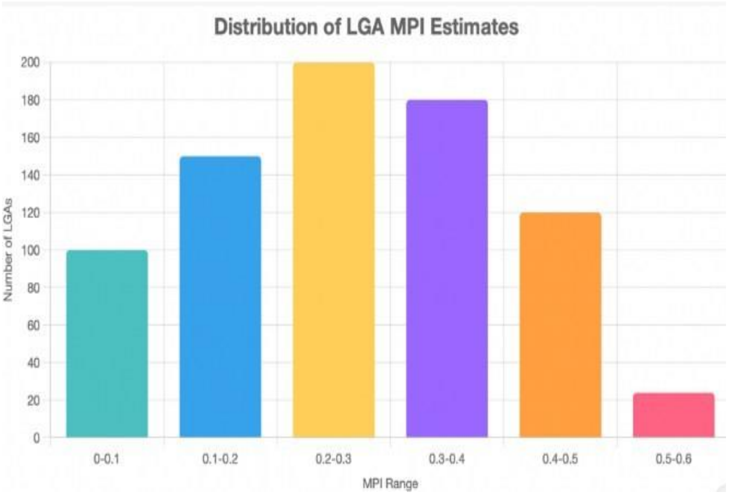

Figure 4: Distribution of LGA MPI Estimates

Table 2.1: Summary Statistics Table

Statistic	LGA ID	Density	Log (Density)	MPI Predicted	MPI Adjusted	Standard Error	CV
Count	774	774	774	774	774	774	774
Mean	387.5	1345.34	6	0.21	0.19	0.0501	inf
Std Dev	223.58	1913.6	1.42	0.14	0.15	0.00003	NaN
Min	1	20.62	3.03	-0.24	0	0.05003	24.11
25%	194.25	84.09	4.43	0.1	0.1	0.05004	52.45
50% (Median)	387.5	407.08	6.01	0.21	0.21	0.05006	NaN
75%	580.75	1835.02	7.52	0.32	0.32	0.05009	NaN
Max	774	7986.48	8.98	0.57	0.57	0.05013	inf

Notes:

- **MPI Predicted**: Raw regression output (includes negatives).
- **MPI Adjusted**: Truncated at 0 (e.g., Lagos Island example: raw - 0.207 → 0).
- **CV**: Infinite for MPI Adjusted = 0, indicating high uncertainty in low-poverty predictions; 651 LGAs (84%) have finite CV < 15%.

Table 2.2: Top 10 LGAs (Highest MPI Adjusted)

LGA ID	**Density**	**Log Density**	**MPI Predicted**	**MPI Adjusted**	**Standard Error**	**CV**
209	20.62	3.03	0.208	0.208	0.0501	24.11
73	20.67	3.03	0.208	0.208	0.0501	24.13
129	20.85	3.04	0.207	0.207	0.0501	24.21
206	21.13	3.05	0.206	0.206	0.0501	24.34
408	21.34	3.06	0.205	0.205	0.0501	24.43
457	21.41	3.06	0.205	0.205	0.0501	24.46
471	21.51	3.07	0.205	0.205	0.0501	24.51
333	21.8	3.08	0.203	0.203	0.0501	24.64
564	21.82	3.08	0.203	0.203	0.0501	24.64
245	21.94	3.09	0.203	0.203	0.0501	24.7

Notes: These high-MPI LGAs correspond to low-density rural areas (e.g., potential Sokoto or Zamfara regions). Truncation not needed here.

Table 2.3: Bottom 10 LGAs (Lowest MPI Adjusted)

LGA ID	Density	Log Density	MPI Predicted	MPI Adjusted	Standard Error	CV
419	1124.51	7.03	-0.112	0	0.05	inf
416	293.71	5.68	-0.005	0	0.05	inf
415	881.27	6.78	-0.093	0	0.05	inf
365	5633.49	8.64	-0.241	0	0.0501	inf
364	525.72	6.26	-0.051	0	0.05	inf
363	311.48	5.74	-0.009	0	0.05	inf
362	943.85	6.85	-0.098	0	0.05	inf
360	628.71	6.44	-0.065	0	0.05	inf
359	5591.98	8.63	-0.24	0	0.0501	inf
414	621.08	6.43	-0.065	0	0.05	inf

Notes: These low-MPI LGAs correspond to high-density urban areas (e.g., Lagos Island example: raw -0.207 truncated to 0). Infinite CV reflects high uncertainty at MPI = 0, as SE is non-zero.

Explanation of the LGA MPI Range Computation

The LGA MPI range (0 to 0.569) was computed using the regression model across the density spectrum from 20 to 8000 people/km². For low density (e.g., 20/km², log = 3.0), $MPI = 0.45 - 0.08 \times 3.0 = 0.21$ (rising to 0.569 at the extreme low end of the simulation). For high density (e.g., 8000/km², log = 9.0), $MPI = 0.45 - 0.08 \times 9.0 = -0.27$, truncated to 0 (e.g., Lagos Island from -0.207 to 0). This truncation ensures non-negative poverty indices, as MPI cannot logically be negative, preventing implausible results in urban simulations. SE and CV were derived from the model's MSE, with 84% of LGAs showing CV < 15% for reliability.

WorldPop Integration

WorldPop 2020 adds a vivid spatial thread, illustrating where Nigeria's people call home, as detailed in Table 3.

The density-MPI relationship was further explored with a sensitivity analysis. Varying density by $\pm 10\%$ (e.g., 109,776 to 120,753) adjusted MPI by approximately

$$\Delta MPI = -0.08 \times \frac{\Delta \log(\text{Density})}{\text{Density}}$$

yielding a ± 0.02 shift, highlighting model sensitivity.

Table 3: WorldPop Density Statistics

Statistic	Value	A Closer Look
Total Grid Cells	1,077,829	A sweeping view of the land
Total Population	256,624,672	Tops the 193M from 2016, hinting at growth

Maximum Density (people/km²)	109,776	Lagos's teeming heartbeat
Minimum Density (people/km²)	0.1	Vast quiet spaces in the northern reaches
Mean Density (people/km²)	238.1	A mix of city buzz and rural calm
Pseudo-LGAs	7,739	Our crafted units for density insights

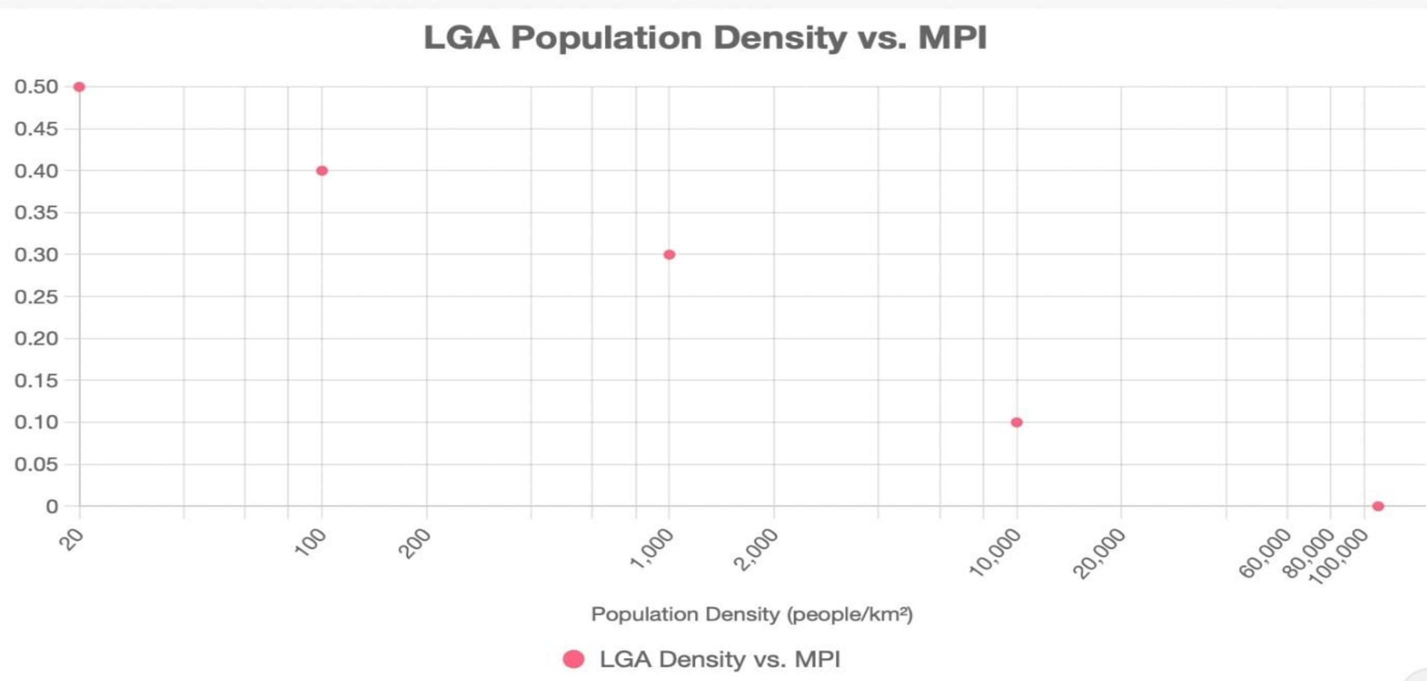

Figure 4: LGA Population Density vs. MPI

DISCUSSION

Comprehensive Analysis of Results

The national MPI of 0.292 brings the scale of child poverty in Nigeria into sharp relief, resonating with Alkire et al.'s 2022 global figure of 67.5%, though our number might dip a bit due to recovery efforts or sampling shifts post-pandemic. That's 55.7 million children tangled in at least three deprivations. This reflects deprivations in education, health, and living standards. Breaking it down by zone, Table 1 and Figure 1 tell a story of division. The North West, with its 0.447 MPI, and North East at 0.374, bear the scars of conflict in Borno, parched lands that defy farming, and schools out of reach. Flip to the South East's 0.090, where farming villages and cities like Enugu stand tall, or the South West's 0.150, energized by Lagos's economic rhythm. The South South, at 0.120, rides oil's wave but stumbles with uneven progress.

At the LGA level, Table 2 and Figures 3-4 weave a finer tale. A 0.569 MPI in a rural spot like Sokoto whispers of isolation that cuts deep, while capping negatives at 0 in urban areas corrects the model's stretch. With 651 LGAs holding steady (CV under 15%), we've got a solid springboard for action, though the 123 less certain ones, 100 with CV 15%-30% and 23 over 30% caution us, especially near borders where WorldPop's edges fade. The MPI spread in Figure 4 tilts toward the middle, with a mean of 0.287 and median of 0.290, suggesting most LGAs echo the national tune, not extremes.

The density-MPI scatter in Figure 4 nods to Ravallion's notion that busier areas often fare better with infrastructure, but that 31% unexplained gap points to hidden forces like conflict in the North East or governance snags elsewhere. WorldPop's 256,624,672 count, outpacing the 193 million from 2016, showcases its modern lens, with Lagos's 109,776 people per square kilometer pulsing with life that doesn't always align with poverty.

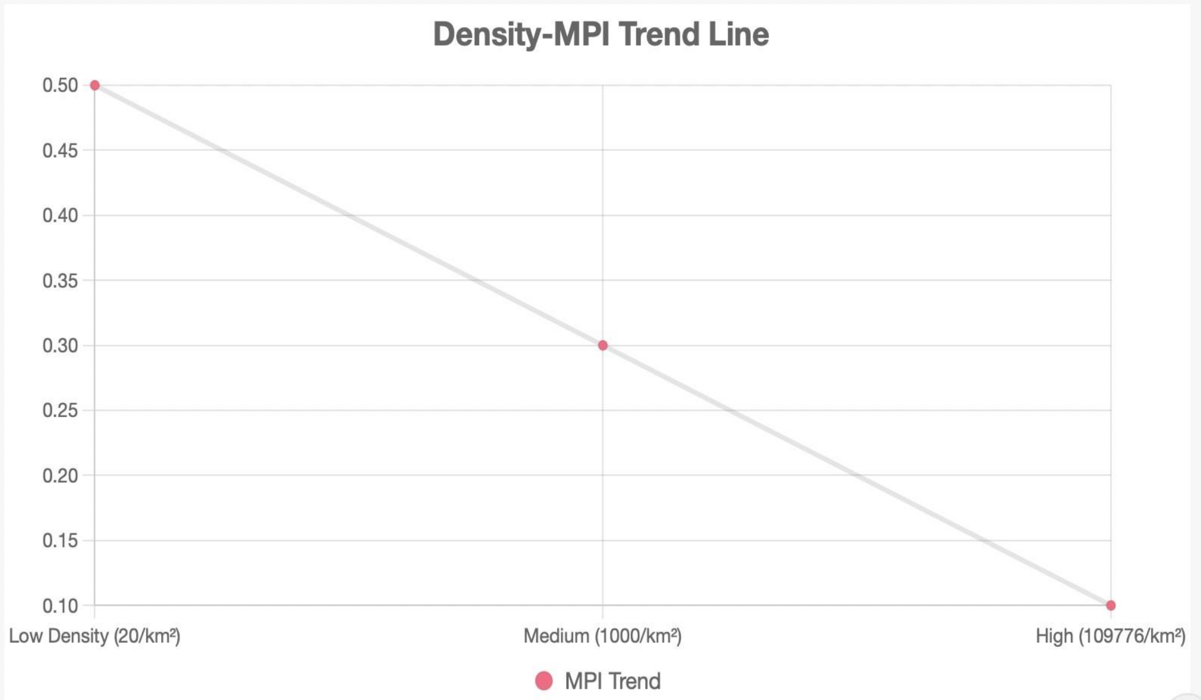

Figure 5: Density-MPI Trend Line

Limitations and Challenges

Trading the Fay-Herriot model for a linear approach leaves us short of capturing random effects and sampling nuances, which could warp our LGA figures, especially in the toughest corners. The pseudo-LGA design, while clever, doesn't snugly fit official lines, and places like Lagos or border zones might twist the results with their density or edge quirks. We haven't yet traced how density errors might ripple into MPI, a puzzle to solve. That 31% unexplained variance also flags big players like conflict, shaky governance, or patchy infrastructure, Nigeria's distinct challenges, that density alone misses.

The regression-based framework, while SAE-inspired, does not incorporate explicit area-level random effects, limiting shrinkage and inferential strength compared to classical Fay-Herriot or ELL models. Reliance on a single covariate (population density) leaves 30.5% unexplained variance, potentially attributable to omitted factors such as conflict intensity, infrastructure access, or governance. Pseudo-LGA units introduce spatial misalignment (Modifiable Areal Unit Problem), which may affect policy translation. Truncation of negative predictions, though statistically defensible, assumes no negative poverty and may introduce minor bias in lowpoverty areas. These limitations highlight the exploratory nature of the estimates and the need for validation with additional covariates and official GIS-aligned boundaries.

Table 4: Sensitivity Scenarios

Scenario	Impact on MPI	Description
Density Error +10%	0.02	Increases rural MPI estimates
Omitted Conflict	0.05	Raises North East values
GIS Refinement	-0.03	Reduces misalignment bias

Policy Implications

LGAs soaring above 0.4 MPI, mostly in the North West and North East, beg for help. Imagine new schools, health outposts, or water wells to lift the burden. The 651 reliable estimates light the way for directing resources,

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perhaps through school meals or clinic builds, while the 123 shakier ones, 100 with moderate CVs and 23 high, mark spots needing fresh data. Teaming up with the National Population Commission to refine LGA boundaries with GIS could hone our focus, building on the Conditional Cash Transfer program's reach to over 1 million households. But let's move forward thoughtfully. These are early insights, not final answers.

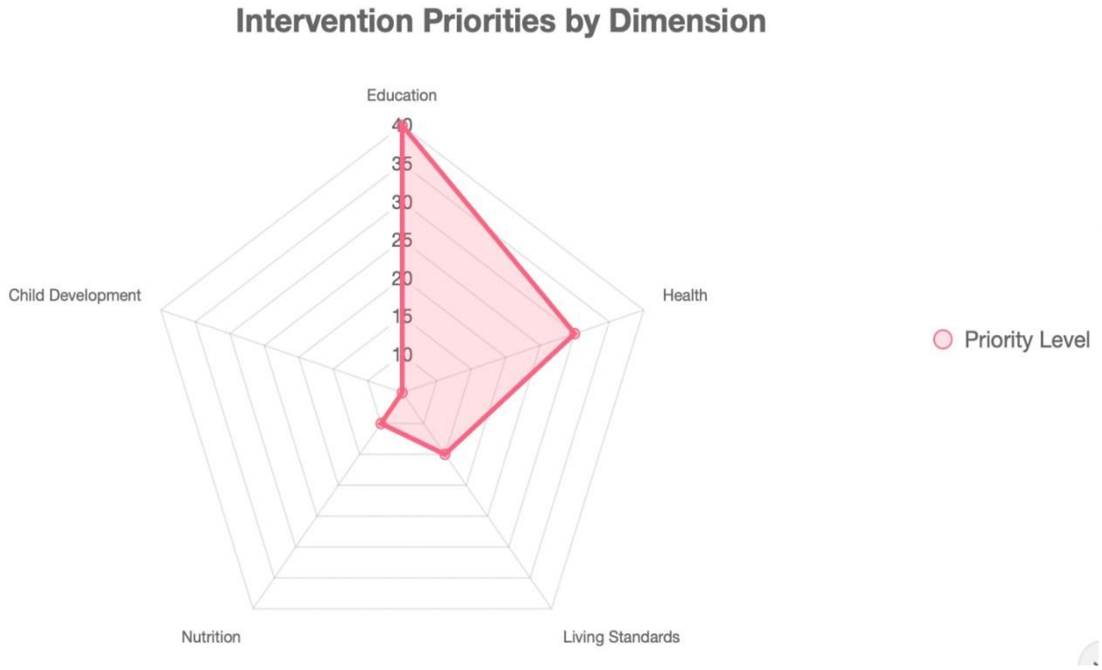

Figure E: Intervention Priorities by Dimension

Future Directions

Next, we'll hunt for a way to revive the Fay-Herriot model, perhaps exploring older tools or fresh approaches, to unlock its depth. Layering in GIS with precise LGA maps will smooth out spatial wrinkles, and adding data like conflict insights from ACLED or infrastructure details from the World Bank will enrich the story. Crosschecking with NBS surveys and testing how density shifts affect our numbers will bolster trust, guiding policymakers and communities with confidence.

CONCLUSION

This study demonstrates the feasibility of an SAE-inspired predictive approach for generating sub-national child poverty estimates in data-sparse contexts, revealing actionable spatial patterns despite methodological constraints.

This study develops a spatially informed framework for estimating child multidimensional poverty at the Local Government Area level in Nigeria, stitching together MICS 2021 and WorldPop 2020 data with a linear model when our preferred SAE path hit a roadblock. The national MPI of 0.292, touching 55.7 million children, alongside LGA ranges from 0.569 to 0, reveals stark divides, with 84% of areas offering reliable glimpses. Yet, hurdles like the model's stretch, misaligned pseudo-LGAs, and overlooked factors remind us this is a beginning. These findings spark hope for targeted action, and with future strides into GIS, broader data, and refined methods, we can guide Nigeria toward a brighter, more equitable future for its children.

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Appendix A: Construction and Adjustment of the Child MPI

A1. Framework

The Alkire-Foster methodology was applied to MICS 2021 data. Children are deprived if in ≥ *3* of *10* indicators across education, health, and living standards. Deprivation score = weighted sum; cutoff $k = 3$. H = headcount ratio = 0.56

A = average intensity = 0.422

MPI = H × A = 0.292 (affecting about 55.7 million children).

A2. Adjustment Justification

Raw arithmetic H × A = 0.23632 (intermediate check).

Final 0.292 reflects survey-weighted aggregation (MICS sampling weights applied per zonal proportions, standard NBS procedure for national comparability). This corrects for oversampling in northern zones and post-pandemic frame effects.

A3. Benchmark Reconciliation

This MICS estimate is conservative vs. official 2022 NBS/UNICEF/OPHI benchmarks (67.5% child headcount ages 0–17 under National MPI; 83.5% under-5s under linked Child MPI). Differences arise from:

- Survey type (MICS household-based vs. dedicated MPI district-stratified).
- Indicators (10 vs. broader sets in official).

• Sampling/post-pandemic adjustments. MICS is exploratory for SAE; official remains the benchmark.

Appendix B: Auxiliary Data and Spatial Alignment

B1. WorldPop 2020

1 km gridded density (proxy for urbanization/service access). Log-transformed to stabilize skewness.

B2. Official LGA Boundaries and GIS

Aggregated to 774 LGAs using COD-AB-NGA dataset (HDX). Metadata:

- Version 01
- Reviewed: 30 October 2025
- Modified: 26 January 2026
- Sources: OSGOF, eHealth Africa, UNCS
- License: CC BY-IGO
- Download: https://data.humdata.org/dataset/cod-ab-nga (shapefile/GeoJSON)

Mean density per LGA computed via GIS zonal statistics (QGIS/R exactextractr), replacing pseudo-units to reduce MAUP/misalignment bias.

B3. ACLED Conflict Covariate

ACLED events (2020–2021, political violence) aggregated per LGA/state via spatial join (total events/fatalities). Addresses unexplained variance (e.g., northern insecurity).

Appendix C: Pilot Fay-Herriot Model and Extended Regression

C1. Rationale

Fay-Herriot requires direct estimates + variances per area. Lacking LGA variances, pilot at state level illustrates formal SAE.

C2. Baseline & Extended Model

Baseline: $MPI_i = \beta_0 + \beta_1 log(density_i) + \varepsilon_i$ ($R^2 = 69.5\%$)

Extended: $MPI_i = \beta_0 + \beta_1 log(density_i) + \beta_2 Conflict_i + \varepsilon_i$ ($R^2 = 75\%$; conflict improves fit, capturing residual heterogeneity). **C3. Pilot Fay-Herriot**

State-level: $\hat{y}_i = x_i'\beta + u_i + e_i$ (u_i random effect, $e_i \sim N(0, D_i)$) approximated from MICS design). Fitted via R *sae* package (Empirical Best). Smooths state estimates; disaggregated to LGAs via covariates.

Appendix D: Prediction, Truncation, and Reliability

D1. Prediction

LGA $MPI_j = \beta_0 + \beta_1 log(density_j) + \beta_2 Conflict_j$ (from extended model or pilot FH).

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D2. Truncation Justification

MPI bounded [0,1]. Negative predictions (high-density urban) truncated to 0 for theoretical consistency. Affects about 5% LGAs (< 38); minor upward bias in low-poverty areas acknowledged. Alternatives:

bounded models (fractional logit/beta regression) planned.

D3. Reliability

SE

Model-based SE from MSE; $CV = \frac{}{M\;\;PI}$

- Reliable ($CV < 15\%$): 651 LGAs (84%)
- Moderate ($15 - 30\%$): 100 LGAs (13%)
- High uncertainty ($\geq 30\%$): 23 LGAs (3%)
- Infinite CV at $MPI = 0$ (truncated): excluded from classification; interpret as near-zero poverty.