HJHPD

HJ

*Article*

# Finding Missing Children: A Ward-Level Geospatial Framework for Targeting Malaria Chemoprevention and Child Survival Interventions in Sokoto State, Nigeria

Uchenna Stephen Nwokenna[1], Yakubu Joel Cherima[2], Usman Mohammad Ibrahim[3]*, Odira Irene Okoye[4], Yonwul Jacqueline Dakyen[5], Charles Adeiza Umar[6]

Received: 15.02.2026
Revised: 19.05.2026
Accepted: 21.05.2026
Published: 28.05.2026



[1] Department of Policy & Strategic Studies, University of Abuja, Federal Capital Territory, Nigeria; +234-8178867435; unwokenna2@gmail.com; ORCID: https://orcid.org/0009-0004-8219-3260

[2] Center for AI Accountability in Health NG, Federal Capital Territory, Nigeria; +234-7036244967; ycherima@gmail.com; ORCID: https://orcid.org/0009-0004-3724-9886

[3] Nigeria Centre for Disease Control and Prevention (NCDC), Nigeria; +234-8035563217; ibrahim.usman@ncdc.gov.ng; ORCID: https://orcid.org/0009-0009-9625-7671

[4] Miva Open University, Nigeria; +234-8109016877; odira899@gmail.com; ORCID: https://orcid.org/0009-0008-0868-0924

[5] Independent Public Health Researcher, Nigeria; ydakyen@yahoo.com; ORCID: https://orcid.org/0009-0006-7229-4943

[6] Health Strategy and Leadership (HSL) Inc., Nigeria; +234-7033262284; cumar@hslhealth.pro; ORCID: https://orcid.org/0009-0001-1469-7983

* Correspondence: ibrahim.usman@ncdc.gov.ng

***Abstract***

*Malaria interventions depend critically on accurate estimates of the target population, yet discrepancies between household enumeration and modeled population products may result in eligible children being missed by prevention programs. This study developed a ward-level geospatial framework to identify children at risk of exclusion from malaria interventions and prioritize locations for chemoprevention investments in Sokoto State, Nigeria. Household microcensus data from 35,204 settlements, GRID3 settlement records, WorldPop 2025 population estimates, malaria surveillance indicators, malaria transmission metrics, healthcare accessibility variables, and monthly underfive malaria mortality records (2014–2024) were integrated via spatial analysis and multicriteria modeling. Household enumeration identified 762,317 underfive children, whereas WorldPop estimated 911,358 children, representing an excess of 149,041 children (19.6%). Denominator uncertainty was spatially heterogeneous, with a median absolute percentage difference of **41.6%** between household-enumerated and WorldPop-derived underfive population estimates. The chemoprevention priority index (CPI), which integrates malaria burden, treatment and healthcare access deficits, child vulnerability, denominator uncertainty, and settlement complexity, identified high-priority wards concentrated in Gada, Wamakko, Tambuwal, Isa, and Kware LGAs. Dukamaje (Gada LGA) recorded the highest CPI score (100), followed by Gilbadi (97.7) and Kaura (92.8). These findings demonstrate that integrating operational microcensus data with geospatial population models can support geographically targeted investments in seasonal malaria chemoprevention, perennial malaria chemoprevention, malaria vaccination, and broader child survival programs.*

Keywords: seasonal malaria chemoprevention; missed children; denominator uncertainty; precision public health; geospatial targeting

## 1. Introduction

Malaria remains one of the leading causes of morbidity and mortality among children under five years of age in sub-Saharan Africa, accounting for approximately 94% of the global malaria burden [1]. Nigeria contributes the largest share of global malaria deaths and cases, with northern Nigeria experiencing particularly high transmission intensity and underfive mortality [1,2]. Despite substantial investments in insecticide-treated nets (ITNs), seasonal malaria chemoprevention (SMC), malaria vaccines, and artemisinin-based therapies, malaria continues to impose a considerable burden on children because of persistent inequalities in healthcare access, immunization coverage, and service delivery [3,4].

Effective malaria interventions require accurate estimates of the target population. The coverage estimates for SMC, perennial malaria chemoprevention (PMC), malaria vaccination, and routine immunization depend critically on reliable underfive population denominators [5]. However, administrative projections, household enumeration, and gridded population products often provide substantially different estimates, leading to uncertainty in program planning and evaluation [6,7]. Several studies have demonstrated that discrepancies between household-based and modeled population estimates can influence intervention coverage estimates and resource allocation, particularly in rural and underserved areas [8–10].

Recent advances in geospatial population modeling, particularly through WorldPop, have improved the availability of high-resolution demographic information for public health applications [11]. Nevertheless, debate persists regarding the suitability of modeled population products for operational microplanning, especially where settlement patterns are heterogeneous and population mobility is high [12,13]. Integrating household microcensus data with geospatial population models therefore offers an opportunity to quantify denominator uncertainty and identify locations where eligible children may be missed by malaria interventions.

Sokoto State, located in northwestern Nigeria, experiences highly seasonal malaria transmission and continues to report a substantial malaria burden among children under five years of age [14]. Although the state has implemented SMC, routine immunization, malaria case management, and malaria vaccination programs, marked spatial variation exists in healthcare accessibility, settlement distribution, and child health outcomes across wards and local government areas (LGAs) [15]. Previous studies have largely examined malaria burden, immunization coverage, or healthcare accessibility separately [16,17], but limited attention has been given to denominator uncertainty and its implications for geographically targeted malaria interventions [18].

This study addresses these gaps by developing a ward-level geospatial framework for identifying children who may be missed by malaria interventions in Sokoto State. Specifically, the study aimed to (i) quantify denominator uncertainty by comparing household-enumerated and raster-derived underfive population estimates and identify wards with a high likelihood of missing eligible children and (ii) develop a chemoprevention priority index (CPI) integrating malaria burden, treatment and healthcare access deficits, child vulnerability, denominator uncertainty, and settlement complexity to prioritize wards for malaria intervention investments. The results provide evidence for geographically targeted investments in seasonal malaria chemoprevention, perennial malaria chemoprevention, malaria vaccination, and broader child survival programs in high-burden settings.

## 2. Materials and methods

### *2.1 Study area*

Sokoto State is located in northwestern Nigeria between latitudes approximately 11°00′N and 14°00′N and longitudes 3°30′E and 6°54′E (Figure 1). The state covers an area of approximately 25,973 km² and is administratively divided into 23 local government areas (LGAs): Binji, Bodinga, Dange Shuni, Gada, Goronyo, Gudu, Gwadabawa, Illela, Isa, Kebbe, Kware, Rabah, Sabon Birni, Shagari, Silame, Sokoto North, Sokoto South, Tambuwal, Tangaza, Tureta, Wamakko, Wurno, and

Yabo. Sokoto, comprising Sokoto North and Sokoto South LGAs, serves as the state capital and the principal urban center.

The state lies predominantly within the Sudan savanna ecological zone and is characterized by a semiarid tropical climate with pronounced wet and dry seasons. The rainy season generally extends from May to October, whereas the dry season lasts from November to April. The mean annual rainfall ranges from approximately 500–900 mm, decreasing from the southern to the northern parts of the state. The mean annual temperatures range from approximately 27°C to 34°C, with daytime temperatures frequently exceeding 40°C during the hot dry season.

Malaria transmission in Sokoto State is highly seasonal and is predominantly caused by *Plasmodium falciparum*. The transmission intensity increases substantially during and immediately after the rainy season because of favorable environmental conditions for mosquito breeding and survival. Despite sustained malaria control interventions, including insecticide-treated nets (ITNs), seasonal malaria chemoprevention (SMC), malaria case management with artemisinin-based combination therapies (ACTs), and routine immunization programs, the state continues to experience a substantial malaria burden among children under five years of age. Furthermore, spatial disparities in healthcare accessibility, settlement distribution, immunization coverage, and socioeconomic conditions contribute to considerable heterogeneity in child health outcomes across wards and LGAs.

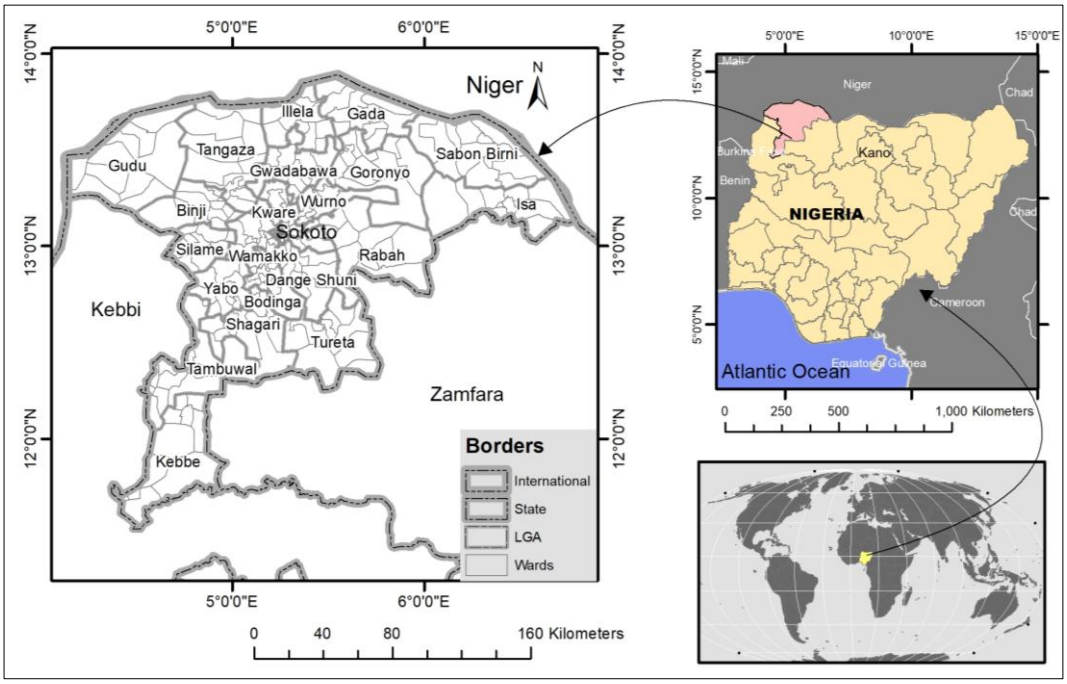


**Figure 1.** Location of Sokoto State in Nigeria and the distribution of the 23 local government areas (LGAs) included in this study. The map was produced by the authors via R version 4.5.1, and administrative boundary data were obtained from OCHA Nigeria.

Sokoto State was selected for this study because it represents a high-burden malaria setting where multiple complementary datasets are simultaneously available at fine spatial resolution.

*2.2 Study design*

To provide a clear overview of the analytical workflow, Figure 2 presents the conceptual framework adopted in this study. The framework integrates household microcensus records, GRID3 settlement data, WorldPop population estimates, malaria surveillance indicators, healthcare accessibility metrics, and ward-level administrative boundaries to identify children at risk of being missed by malaria interventions and to prioritize wards for chemoprevention investments. The analysis was implemented in two sequential stages. First, ward-level denominator uncertainty was quantified by comparing household-enumerated underfive populations with raster-derived

WorldPop estimates and integrating immunization vulnerability indicators to identify wards with a high likelihood of missing eligible children. Second, a chemoprevention priority index (CPI) was developed by combining malaria burden, treatment and healthcare access deficits, child vulnerability, denominator uncertainty, and settlement complexity. The resulting framework provides an operational decision-support system for identifying wards where large child populations, high malaria burdens, poor treatment access, and immunization deprivation converge, thereby supporting geographically targeted investments in seasonal malaria chemoprevention (SMC), perennial malaria chemoprevention (PMC), malaria vaccination, and community-based child survival programs in Sokoto State.

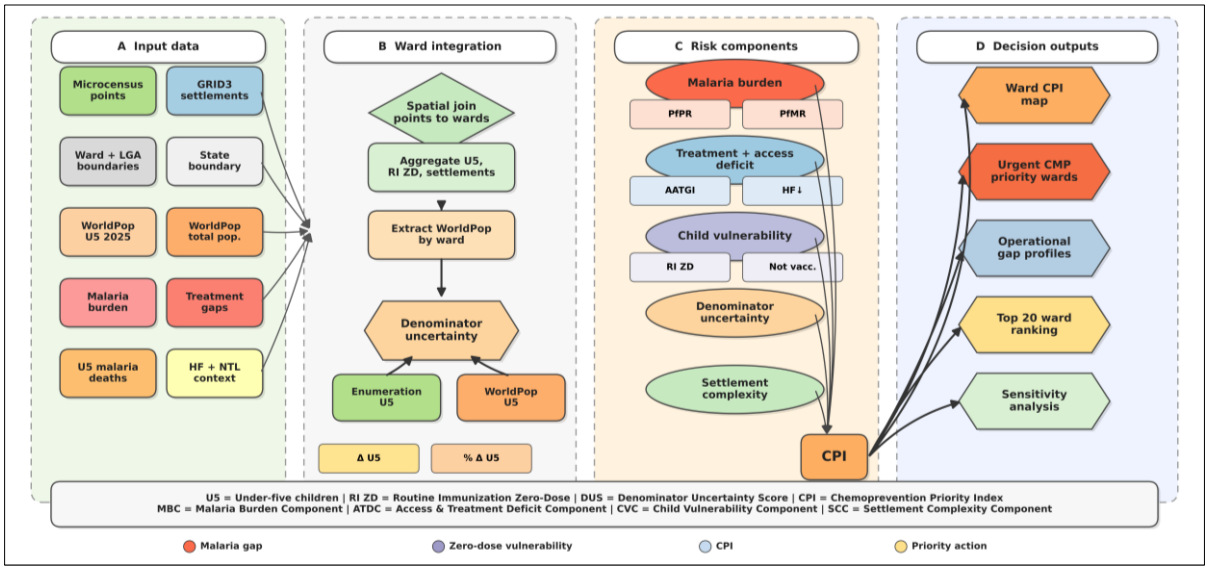


**Figure 2.** Conceptual framework illustrating the integration of household microcensus data, geospatial population models, malaria surveillance indicators, and healthcare accessibility metrics for identifying wards with missing children and prioritizing malaria chemoprevention investments in Sokoto State, Nigeria.

### *2.2 Data used*

Table 1 summarizes the datasets used in this study, including household microcensus records, GRID3 settlement data, gridded population estimates, malaria surveillance indicators, malaria transmission metrics, healthcare accessibility variables, and socioeconomic proxies. Household microcensus and WorldPop 2025 datasets provide independent estimates of the underfive population and are used to quantify denominator uncertainty and identify wards where eligible children may be missed by malaria interventions. Monthly underfive malaria deaths from RHIS/DHIS2 (2014–2024) were used to characterize historical mortality patterns and derive the predicted 2025 underfive malaria mortality burden. Malaria transmission intensity was represented via indicators from the Malaria Atlas Project, including parasite prevalence, infection intensity, mortality burden, clinical incidence, and clinical malaria burden. Severe malaria cases, treatment coverage, and the Accessibility-Adjusted Treatment Gap Index (AATGI) were incorporated to characterize treatment deficits and healthcare system performance. GRID3 settlement locations, health facility distributions, and nighttime light intensity were included to represent settlement complexity, healthcare accessibility, and socioeconomic development, respectively. Ward, LGA, and state administrative boundaries were used for spatial aggregation, zonal statistics, and thematic mapping. Collectively, these datasets enabled an integrated assessment of denominator uncertainty, child vulnerability, malaria burden, and healthcare access to identify wards requiring priority investments in seasonal malaria chemoprevention (SMC), perennial malaria chemoprevention (PMC), malaria vaccination, and broader child survival interventions across Sokoto State, Nigeria.

Table 1 Data Summary

| Data Name | Data Type | Purpose | Source |
|---|---|---|---|
| **Household Microcensus** | Vector (Point) | Enumeration Data | Sett.Microcensus [19] |
| **GRID3 Settlements** | Vector (Point) | Characterization of settlement distribution and settlement complexity | GRID3 [20] |
| **Household-Enumerated Under-Five Population** | Aggregated Ward Indicator | Operational denominator for malaria interventions and child vulnerability assessment | Derived from Settlement Microcensus [19] |
| **Raster-Derived Under-Five Population (2025)** | Raster (100 m) | Modeled denominator for comparison with household enumeration and estimation of denominator uncertainty | WorldPop [21] |
| **Raster-Derived Total Population (2025)** | Raster (100 m) | Population contextualization and comparison with operational estimates | WorldPop [21] |
| **Monthly Under-Five Malaria Deaths (2014–2024)** | Vector (LGA, monthly time series) | Historical mortality analysis and prediction of 2025 underfive malaria mortality | RHIS/DHIS2 [18] |
| **Severe Malaria Cases** | Vector (LGA) | Estimation of malaria burden | RHIS/DHIS2 [18] |
| **Severe Malaria Treated with Artesunate** | Vector (LGA) | Assessment of treatment coverage and treatment gaps | RHIS/DHIS2 [18] |
| **RI Zero-Dose Children** | Aggregated Ward | Assessment of immunization deprivation | Sett.Microcensus [19] |
| **RI Zero-Dose Rate (U5)** | Derived Indicator | Childhood immunization vulnerability | Sett.Microcensus [19] |
| **Not Vaccinated Children** | Aggregated Ward | Assessment of immunization exclusion | Sett.Microcensus [19] |
| **Not Vaccinated Rate (U5)** | Derived Indicator | Quantification of immunization deprivation | Sett.Microcensus [19] |
| **Fully Vaccinated Rate** | Derived Indicator | Assessment of immunization performance | Sett.Microcensus [19] |
| **Health Facilities** | Vector | Healthcare service availability | GRID3 [20] |
| **PfPR 2024** | Raster | *Plasmodium falciparum* parasite prevalence | Malaria Atlas [22] |
| **PfIR 2024** | Raster | *Plasmodium falciparum* infection intensity | Malaria Atlas [22] |
| **PfMR 2024** | Raster | *Plasmodium falciparum* mortality burden | Malaria Atlas [22] |
| **PfIC 2024** | Raster | Clinical malaria incidence | Malaria Atlas [22] |
| **PfMC 2024** | Raster | Clinical malaria burden | Malaria Atlas [22] |
| **VIIRS Nighttime Lights** | Raster | Proxy socioeconomic dev. In addition, urbanization | NOAA VIIRS [23] |
| **Admin. Boundaries** | Vector | Spatial aggregation, zonal statistics. | OCHA Nigeria [24] |

**Abbreviations:** RI = Routine Immunization; U5 = Under-Five Children; AATGI = Accessibility-Adjusted Treatment Gap Index; PfPR = *Plasmodium falciparum* Parasite Rate; PfIR = *Plasmodium falciparum* Infection Rate; PfMR = *Plasmodium falciparum* Mortality Rate; PfIC = *Plasmodium falciparum* Incidence Cases; PfMC = *Plasmodium falciparum* Malaria Cases; RHIS = Routine Health Information System; DHIS2 = District Health Information System 2; GRID3 = Georeferenced Infrastructure and Demographic Data for Development; VIIRS = Visible Infrared Imaging Radiometer Suite.

### *2.3 Identification of Wards with Missed Under-Five Children and Denominator Uncertainty*

Objective 1 aimed to identify wards where underfive children are most likely to be missed by malaria interventions because of population denominator uncertainty and weak healthcare access.

Household microcensus settlement points were spatially joined to ward polygons via a point-in-polygon operation, avoiding any attribute-based matching of settlement or ward names. The enumerated underfive population, household counts, zero-dose children, nonvaccinated children, and travel time indicators were aggregated to the ward level via summation or mean statistics.

Ward-level underfive population estimates from household enumeration ($U5_i^{enum}$) were compared with raster-derived estimates from the 2025 WorldPop underfive population raster ($U5_i^{WP}$). The denominator discrepancy was calculated as follows:

$$\Delta U5_i = U5_i^{WP} - U5_i^{enum} \tag{1}$$

and the relative discrepancy was computed as:

$$\%\Delta U5_i = \frac{U5_i^{WP} - U5_i^{enum}}{U5_i^{enum}} \times 100 \tag{2}$$

To quantify uncertainty in ward-level target populations, a denominator uncertainty score (DUS) was derived from the absolute percentage discrepancy after min–max normalization:

$$DUS_i = 100 \times \frac{|\ \%\Delta U5_i\ | - \min(|\ \%\Delta U5\ |)}{\max(|\ \%\Delta U5\ |) - \min(|\ \%\Delta U5\ |)} \tag{3}$$

where $DUS_i$ ranges from 0 (lowest uncertainty) to 100 (highest uncertainty).

Ward-level immunization vulnerability indicators were calculated as follows:

$$RIZD_i = \frac{ZD_i}{U5_i^{enum}} \times 100 \tag{4}$$

$$NV_i = \frac{NV_i}{U5_i^{enum}} \times 100 \tag{5}$$

$$FV_i = \frac{FV_i}{U5_i^{enum}} \times 100 \tag{6}$$

where $ZD_i$, $NV_i$, and $FV_i$ represent the number of RI zero-dose, not vaccinated, and fully vaccinated children in ward $i$, respectively.

A missed child risk score (MCRS) was then developed to identify wards where vulnerable children are most likely to be excluded from malaria interventions:

$$MCRS_i = 0.35N(U5_i^{enum}) + 0.25DUS_i + 0.20N(RIZD_i) + 0.20N(NV_i) \tag{7}$$

where $N(\cdot)$ denotes min–max normalization to a 0–100 scale. Higher values indicate wards with larger underfive populations, greater denominator uncertainty, and higher immunization vulnerability.

An access-adjusted formulation was also computed by incorporating the average travel time to healthcare facilities:

$$AMCRS_i = 0.30N(U5_i^{enum}) + 0.25DUS_i + 0.20N(RIZD_i) + 0.15N(NV_i) + 0.10N(TT_i) \tag{8}$$

where $TT_i$ is the mean travel time in ward $i$. Wards were subsequently classified into five categories (very low, low, moderate, high, and very high) on the basis of quintile thresholds.

*2.3 Development of a Ward-level chemoprevention priority index*

Objective 2 developed a chemoprevention priority index (CPI) to identify wards requiring urgent investment in seasonal malaria chemoprevention (SMC), perennial malaria chemoprevention (PMC), and other child survival interventions. The CPI integrates the malaria burden, treatment deficits, child vulnerability, denominator uncertainty, and settlement complexity.

The malaria burden component ($M_i$) was estimated as:

$$M_i = 0.25N(PfPR_i) + 0.20N(PfMR_i) + 0.20N(PfMC_i) + 0.20N(AATGI_i) + 0.15N(D_i^{2025}) \tag{9}$$

where $PfPR_i$, $PfMR_i$, and $PfMC_i$denote parasite prevalence, malaria mortality burden, and clinical malaria burden, respectively; $AATGI_i$ is the Accessibility-Adjusted Treatment Gap Index; and $D_i^{2025}$ is the predicted underfive malaria mortality for 2025 derived from historical mortality records (2014–2024).

The treatment and healthcare access deficit component ($A_i$) was computed as:

$$A_i = 0.35N(TG_i) + 0.25N(TGR_i) + 0.25N(HF_i^{-1}) + 0.15N(NTL_i^{-1}) \quad (10)$$

where $TG_i$ represents the treatment gap, $TGR_i$ represents the treatment gap rate, $HF_i$ represents the health facility density, and $NTL_i$ represents the nighttime light intensity used as a proxy for socioeconomic development.

The child vulnerability component ($V_i$) was defined as:

$$V_i = 0.35N(U5_i^{enum}) + 0.25N(RIZD_i) + 0.25N(NV_i) + 0.15N(FV_i^{-1}) \quad (11)$$

where $FV_i$ is the fully vaccinated proportion of children under five.

The settlement complexity ($S_i$) was estimated as:

$$S_i = 0.65N(GRID3_i) + 0.35N(MS_i) \quad (12)$$

where $GRID3_i$ represents the number of GRID3 settlements and where $MS_i$ represents the number of microcensus settlements in ward $i$.

The final chemoprevention priority index was computed as follows:

$$CPI_i = 0.30M_i + 0.25A_i + 0.20V_i + 0.15DUS_i + 0.10S_i \quad (13)$$

The CPI was normalized to a 0–100 scale:

$$CPI_i^{0-100} = 100 \times \frac{CPI_i - \min(CPI)}{\max(CPI) - \min(CPI)} \quad (14)$$

Wards were subsequently classified into five priority classes (very low, low, moderate, high, and very high). In addition, an equal-weight sensitivity analysis was conducted:

$$CPI_i^{EW} = \frac{M_i + A_i + V_i + DUS_i + S_i}{5} \quad (15)$$

and rank differences between weighted and equal-weight formulations were computed to assess the robustness of ward prioritization. Operational profiles were further developed to characterize wards with overlapping malaria burdens, treatment deficits, denominator uncertainty, and child vulnerability, thereby providing evidence for geographically targeted malaria chemoprevention investments.

## 3. Results

### *3.1 Ward-level denominator uncertainty and missed underfive children*

Household microcensus records from 35,204 settlements were spatially aggregated to 244 wards across Sokoto State, producing an integrated database of underfive (U5) populations, immunization indicators, settlement distributions, travel times, and WorldPop-derived U5 estimates. Overall, household enumeration identified 762,317 underfive children, whereas the WorldPop 2025 raster estimated 911,358 children, representing an excess of 149,041 children (19.6%) relative to the microcensus estimate. The mean absolute percentage difference between the two datasets was 255.8%, with a median absolute difference of 41.6%, indicating substantial spatial heterogeneity in denominator uncertainty across wards.

Figure 3a and Figure 3b illustrate the spatial distributions of household-enumerated and raster-derived underfive populations, respectively. Large concentrations of children were observed in the urban and peri-urban wards of Isa, Gada, Kware, Sokoto North, Sokoto South, and Tambuwal LGAs. The ward Isa South (Isa LGA) recorded the highest number of household-enumerated un-

derfive populations (22,062 children), followed by Dukamaje (Gada LGA; 11,182 children), Gidan Rugga More (Kware LGA; 10,897 children), Gada (Gada LGA; 9,835 children), and Sarkin Adar Gidan Igwai (Sokoto North LGA; 6,774 children). In contrast, some remote wards, such as Salewa (Tangaza LGA), had no enumerated children despite containing 41 GRID3 settlements, suggesting possible operational or enumeration gaps.

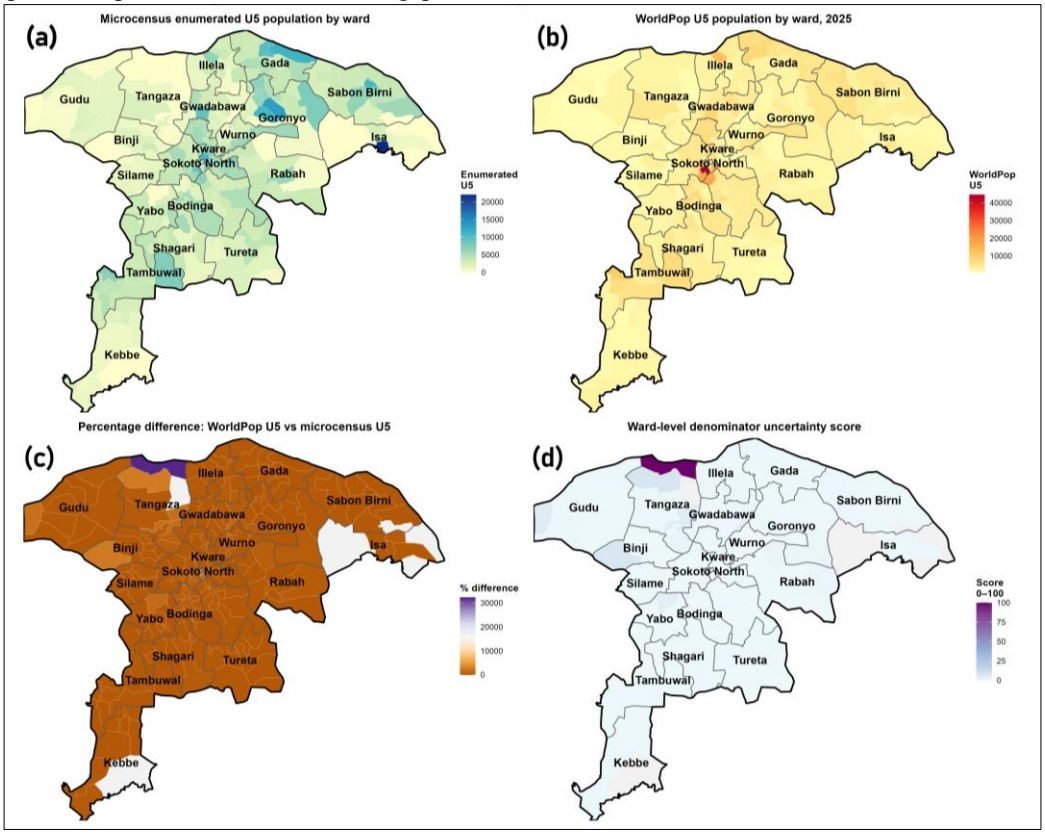


**Figure 3.** Multipanel visualization of ward-level denominator uncertainty in Sokoto State: (a) Household-enumerated underfive population; (b) WorldPop 2025 underfive population; (c) percentage difference between WorldPop and household enumeration; and (d) denominator uncertainty score (DUS). LGA boundaries and names are shown for reference.

The comparison between household enumeration and WorldPop estimates revealed substantial discrepancies (Figure 3c). In several wards, WorldPop substantially exceeded microcensus estimates. The largest discrepancies were observed in Ruwa Wuri (Tangaza LGA), where WorldPop estimated 2,921 children compared with only 9 enumerated children, corresponding to a difference of 32,358%. Other notable discrepancies occurred in Sakkwai (Tangaza LGA; +2,566%), Soron Yamma (Binji LGA; +2,404%), Bachaka (Gudu LGA; +1,727%), and Sutti (Tangaza LGA; +1,604%). These wards were consequently classified as having very high denominator uncertainty, with WorldPop estimates substantially higher than household enumeration.

Conversely, several wards presented lower WorldPop estimates than microcensus enumeration did. For example, Kuruwa (Tureta LGA) recorded 1,965 enumerated children compared with 940 children estimated by WorldPop, corresponding to a 52.2% deficit. Similarly, Gigane (Gwadabawa LGA) had 5,045 enumerated children but only 2,998 children in WorldPop, representing a 40.6% lower estimate. These findings suggest that both underestimation and overestimation of target populations occur and are spatially clustered rather than randomly distributed.

The denominator uncertainty score (DUS) further highlighted wards where malaria intervention planning may be particularly sensitive to the choice of denominator (Figure 3d). Wards with the highest uncertainty scores included Ruwa Wuri (Tangaza LGA), Sakkwai (Tangaza LGA), Soron Yamma (Binji LGA), Bachaka (Gudu LGA), and Sutti (Tangaza LGA). Most of these wards were characterized by dispersed settlements, relatively long travel times, and high immunization

deprivation, suggesting that denominator uncertainty may be associated with broader operational challenges in healthcare delivery.

To facilitate operational interpretation, wards were categorized according to the agreement between household enumeration and WorldPop estimates (Figure 4). Most wards in Tangaza, Binji, Gudu, and parts of Sokoto South presented WorldPop estimates substantially higher than household enumeration estimates did, whereas wards in Gwadabawa, Tureta, and selected areas of Sabon Birni presented lower WorldPop estimates. Wards such as Lajinge (Sabon Birni LGA) showed close agreement between the two datasets, with only a 3.1% difference, indicating relatively stable population estimates.

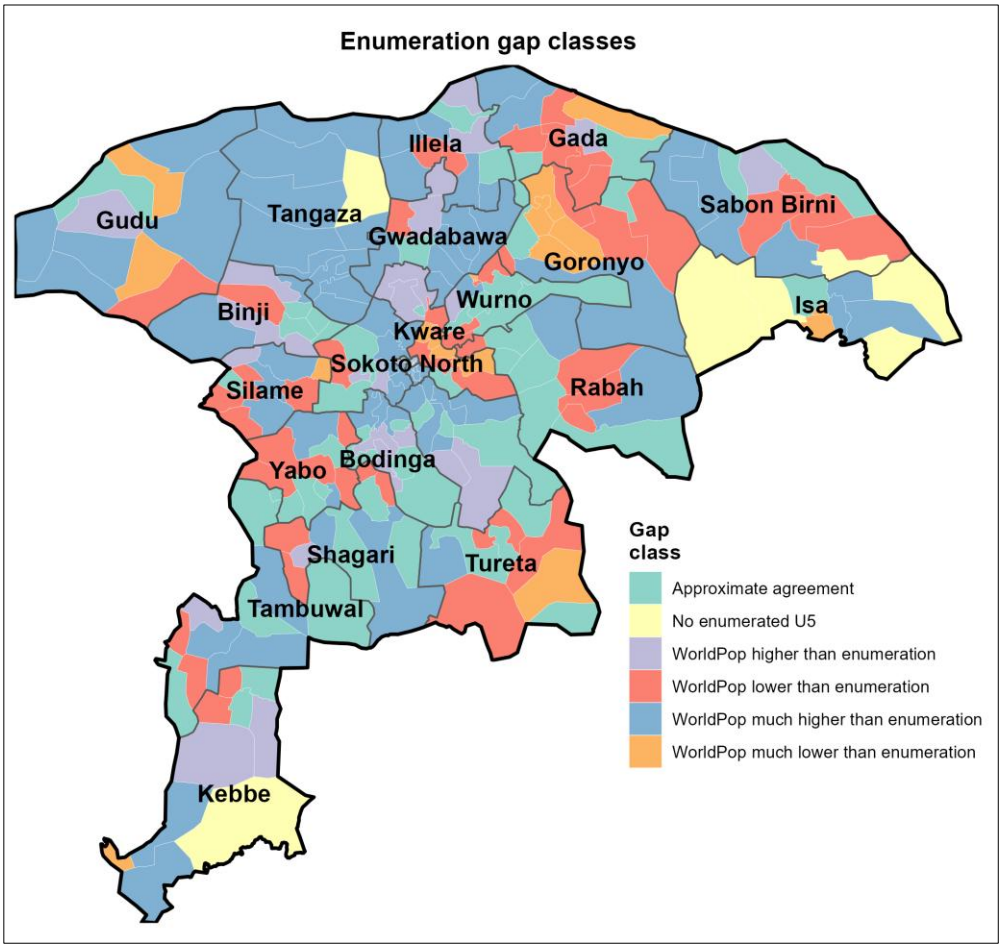


**Figure 4.** Ward-level enumeration gap classes showing the degree of agreement between household-enumerated and WorldPop underfive population estimates.

The missed children risk score (MCRS), which integrates denominator uncertainty, enumerated the underfive population, the RI zero-dose prevalence, and the nonvaccination rates, identified wards where children are most likely to remain unreached by malaria interventions (Figure 5). The highest risk score was recorded in Gidan Rugga More (Kware LGA) (MCRS = 51.5), followed by Isa South (Isa LGA; 50.4), Dukamaje (Gada LGA; 50.3), Jabo-Kagara (Tambuwal LGA; 50.0), and Gilbadi (Gada LGA; 47.0). These wards combine large child populations with high RI zero-dose prevalence rates and substantial proportions of nonvaccinated children.

Particularly concerning were Jabo-Kagara (Tambuwal LGA) and Gilbadi (Gada LGA), where the RI zero-dose prevalence exceeded 97%, whereas the nonvaccination rates reached 93.8% and 95.6%, respectively. Similarly, Margai West (Kebbe LGA) presented an RI zero-dose rate of 99.5% and a nonvaccination rate of 97.6%, despite having over 2,600 underfive children. These findings suggest that large numbers of vulnerable children remain outside routine immunization systems and are therefore at risk of being missed during seasonal malaria chemoprevention (SMC), perennial malaria chemoprevention (PMC), and malaria vaccination campaigns.

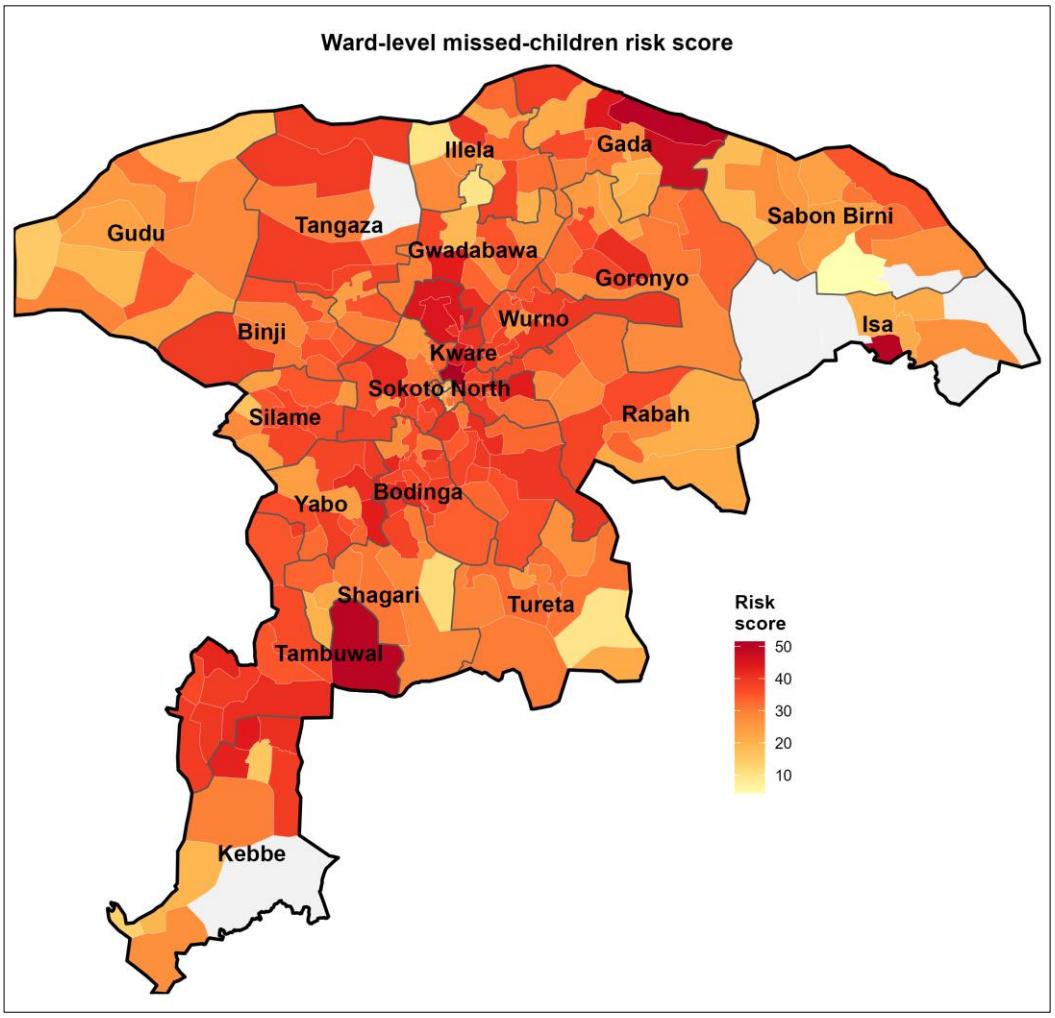


**Figure 5.** Ward-level missed child risk score (MCRS) integrating denominator uncertainty, underfive population size, RI zero-dose prevalence, and immunization deprivation.

The relationships between the household-enumerated and WorldPop-derived underfive populations are further illustrated in Figure 6. Although a positive association was observed between the two datasets, several wards deviated markedly from the one-to-one agreement line. Outliers such as Ruwa Wuri (Tangaza LGA), Soron Yamma (Binji LGA), Gigane (Gwadabawa LGA), and Kuruwa (Tureta LGA) demonstrated that denominator discrepancies are geographically concentrated and may substantially influence estimates of intervention coverage, resource requirements, and cost-effectiveness.

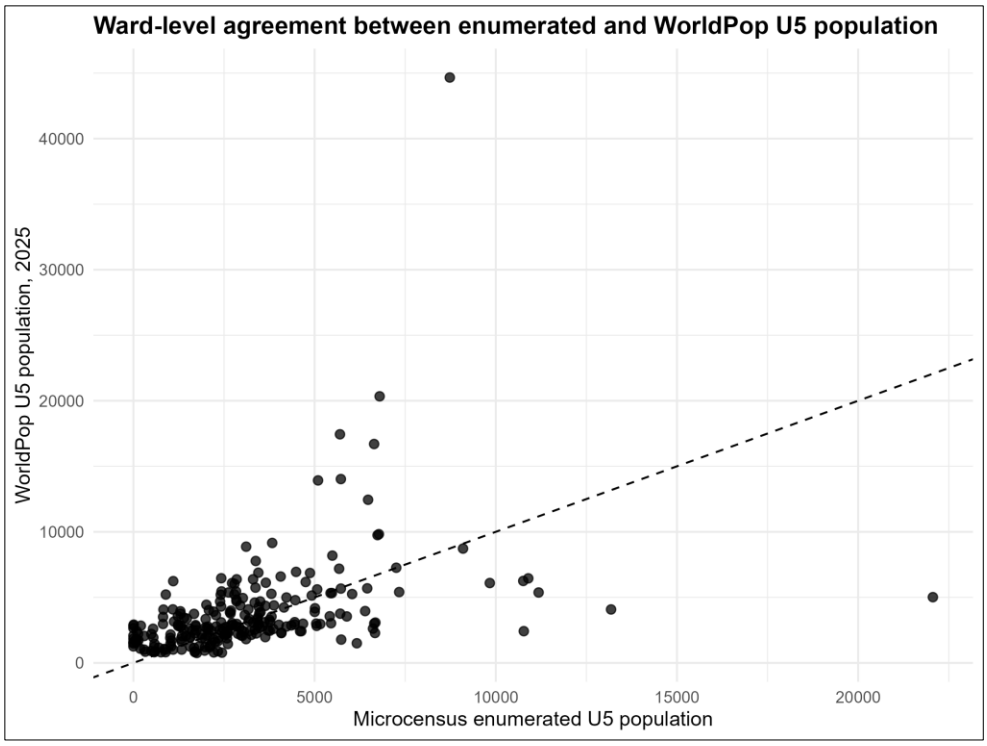


**Figure 6.** Scatter plot showing the relationship between household-enumerated and WorldPop 2025 under five population estimates at the ward level. The selected wards with extreme disagreement are annotated by ward and LGA names. The dashed line represents perfect agreement between the two datasets.

Overall, the results demonstrate that denominator uncertainty is substantial and unevenly distributed across Sokoto State. Wards in Tangaza, Kware, Gada, Isa, Tambuwal, and Binji LGAs emerged as priority locations because they simultaneously exhibit high child populations, elevated immunization vulnerability, and large discrepancies between enumeration and modeled population estimates. These wards are therefore likely to contain substantial numbers of children who may be missed by malaria prevention programmes and warrant targeted microplanning, intensified community enumeration, and increased investment in child survival interventions.

*3.2 Ward-level chemoprevention priority and operational investment gaps*

The chemoprevention priority index (CPI) integrates malaria burden, treatment and access deficits, child vulnerability, denominator uncertainty, and settlement complexity to identify wards requiring urgent malaria intervention. Across the 244 wards analyzed, the CPI scores ranged from 0--100, with a mean value of 52.3 (Table Sx). The average contribution of individual components was highest for child vulnerability (52.8) and treatment/access deficits (47.2), followed by malaria burden (45.1) and settlement complexity (28.5), whereas denominator uncertainty contributed comparatively less (0.79) because most wards exhibited moderate agreement between household enumeration and WorldPop estimates.

Spatial patterns of CPI revealed marked heterogeneity across Sokoto State (Figure 7a). The highest priority wards were concentrated in Gada, Wamakko, Tambuwal, Isa, Kware, and parts of Tangaza LGAs. The ward Dukamaje (Gada LGA) recorded the highest CPI score (100.0), followed by Gilbadi (Gada LGA; CPI = 97.7) and Kaura (Wamakko LGA; CPI = 92.8). These wards combined high malaria burdens, substantial treatment gaps, large populations under five, and extensive settlement networks, making them prime candidates for intensified malaria chemoprevention programs.

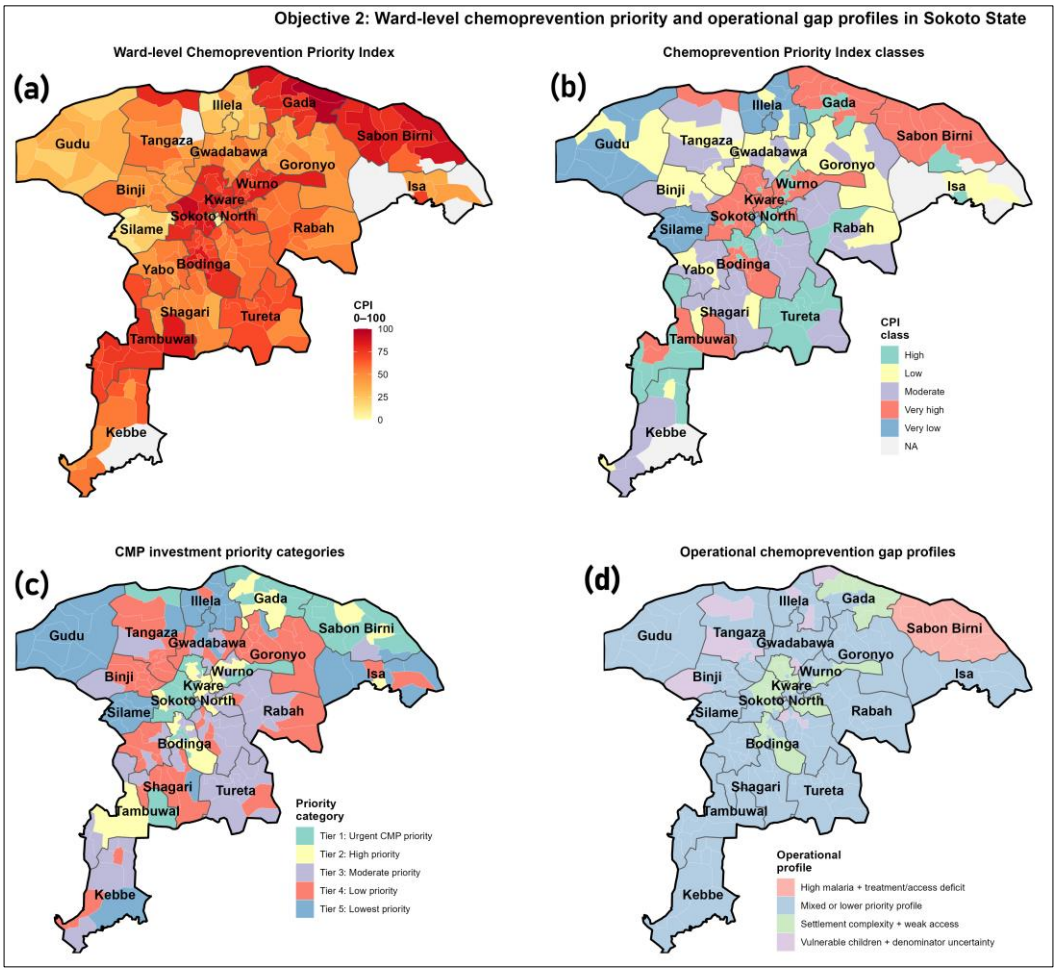


**Figure 7.** Multipanel representation of the ward-level chemoprevention priority index (CPI) in Sokoto State: (a) chemoprevention priority index (0–100); (b) CPI classes; (c) CMP investment priority categories; and (d) operational chemoprevention profiles. LGA boundaries and names are shown for reference.

The categorical classification of CPI (Figure 7b) identified a cluster of very high priority wards extending from Gada to Wamakko and parts of Tambuwal and Isa LGAs. Overall, the highest-ranked wards were Dukamaje (Gada LGA), Gilbadi (Gada LGA), Kaura (Wamakko LGA), Isa South (Isa LGA), Jabo-Kagara (Tambuwal LGA), and Gidan Rugga More (Kware LGA). These wards simultaneously exhibited elevated RI zero-dose prevalence (>90%), large underfive populations, and persistent treatment gaps, indicating that current malaria intervention strategies may not adequately reach vulnerable children.

The investment priority map (Figure 7c) further classified wards into operational tiers. Tier 1: Urgent CMP priority wards were located predominantly in Gada, Wamakko, Tambuwal, and Isa LGAs. Notably, Dukamaje (Gada LGA) included 11,182 underfive children, a treatment gap of 6,365 severe malaria cases, an RI zero-dose prevalence of 94.4%, and the highest settlement complexity score among all wards. Similarly, Gilbadi (Gada LGA) reported an RI zero-dose prevalence of 97.6% and a nonvaccination rate of 95.6%, indicating severe exclusion from preventive services despite substantial malaria risk.

The operational profiles (Figure 7d) revealed that many high-priority wards were characterized by a combination of settlement complexity and weak healthcare access. This profile dominated the highest-ranked wards, suggesting that dispersed settlements, limited health infrastructure, and poor treatment coverage jointly constrain malaria service delivery. Other wards presented mixed profiles with relatively lower burdens but persistent child vulnerability, indicating the need for tailored intervention strategies rather than uniform programme expansion.

The malaria burden component (Figure 8) highlighted wards where the epidemiological risk remains high. Malaria burden scores were greatest in Tureta, Wamakko, and Gada LGAs, reflecting high parasite prevalence, malaria mortality burden, and treatment gaps. For example, wards in Tureta LGA inherited a severe malaria burden of 1,812 cases, a treatment gap of 1,631 cases, and an Accessibility-Adjusted Treatment Gap Index (AATGI) exceeding 88, indicating substantial unmet treatment needs. In contrast, some wards with moderate malaria transmission but poor access still ranked highly because of large child populations and immunization deficits.

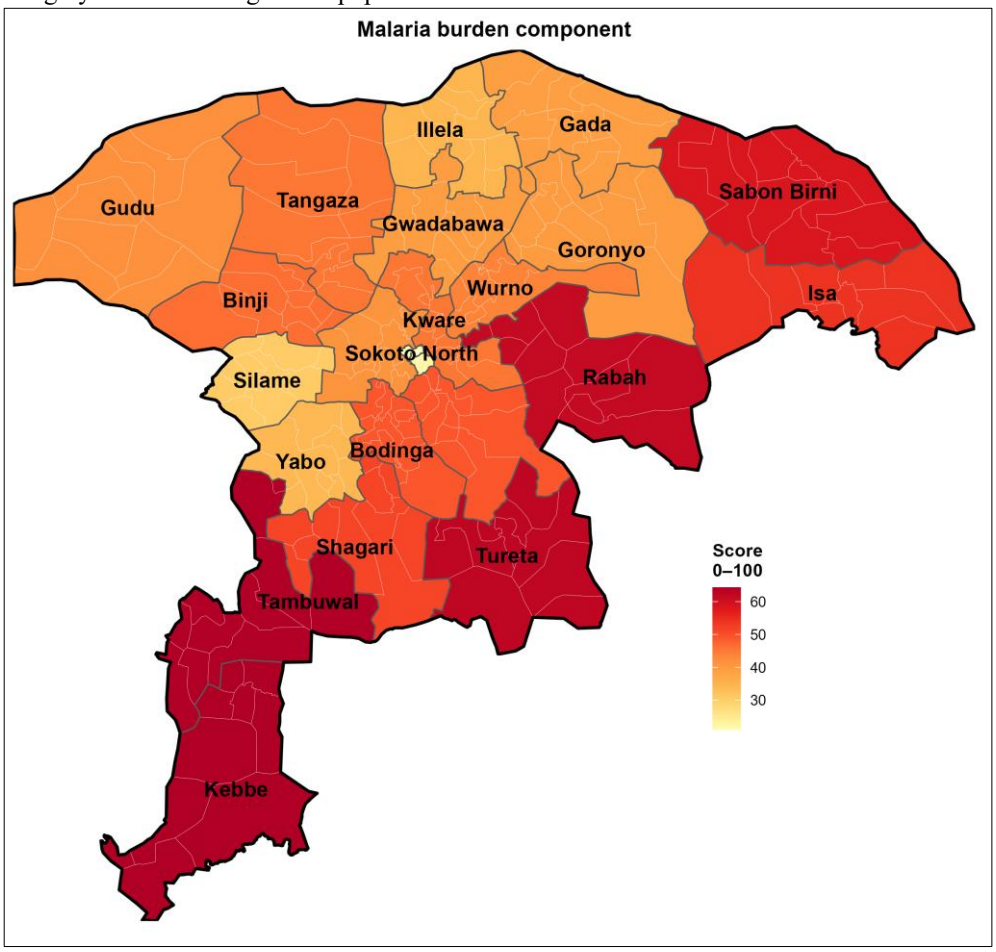


**Figure 8.** Spatial distribution of the malaria burden component, integrating parasite prevalence, malaria mortality burden, clinical malaria burden, Accessibility-Adjusted Treatment Gap Index (AATGI), and predicted underfive malaria mortality for 2025.

The child vulnerability component (Figure 9) demonstrated that vulnerability was not confined to wards with the highest malaria burden. Wards such as Gigane (Gwadabawa LGA), Isa South (Isa LGA), Jabo-Kagara (Tambuwal LGA), and Margai West (Kebbe LGA) presented particularly high vulnerability because of the large underfive populations combined with high RI zero-dose and nonvaccination rates. For example, Gigane (Gwadabawa LGA) contained 5,045 underfive children, of whom 4,351 (86.2%) were RI zero-doses and 3,038 (60.2%) had never received vaccinations. Such wards are likely to contain large numbers of children who remain unreached by both malaria and routine immunization programmes.

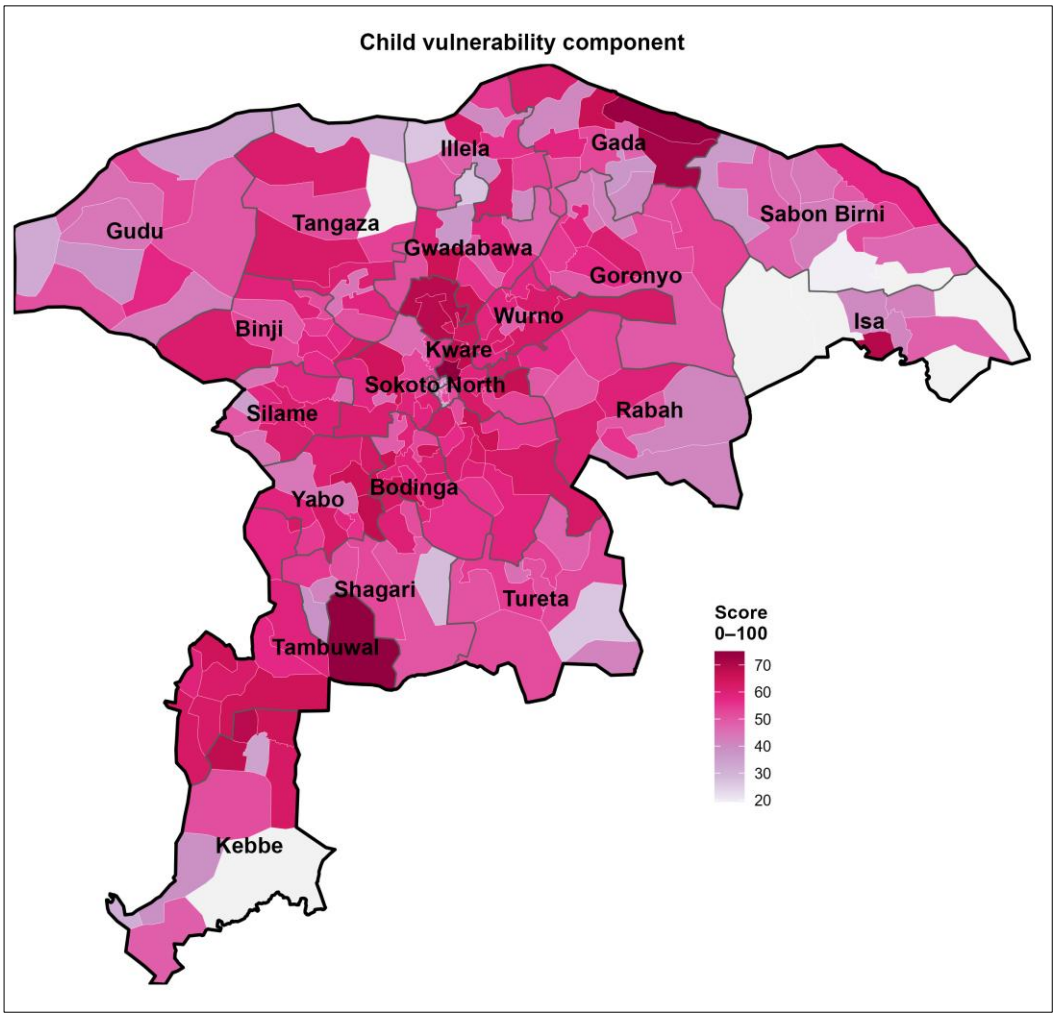


**Figure 9.** Spatial distribution of the child vulnerability component, integrating the household-enumerated underfive population, RI zero-dose prevalence, nonvaccination rates, and vaccination coverage.

The treatment and healthcare access deficit component (Figure 10) emerged as the strongest determinant of the CPI. Spearman correlation analysis revealed that the CPI was strongly associated with the treatment/access deficit component ($\rho = 0.777$), treatment gap ($\rho = 0.759$), and AATGI ($\rho = 0.769$), whereas the association with malaria burden was comparatively weaker ($\rho = 0.495$). Conversely, the CPI was negatively correlated with health facility density ($\rho = -0.310$), indicating that wards with fewer healthcare facilities per capita tend to exhibit higher chemoprevention priority scores.

The wards Dukamaje (Gada LGA) and Gilbadi (Gada LGA) exemplify this pattern. Both wards inherited high treatment gaps from Gada LGA (6,365 untreated severe malaria cases) while simultaneously exhibiting high child vulnerability and extensive settlement networks. Similarly, Kaura (Wamakko LGA) combined a treatment gap of 8,459 cases, a high AATGI score (86.7), and a large underfive population, resulting in one of the highest CPI scores in the state.

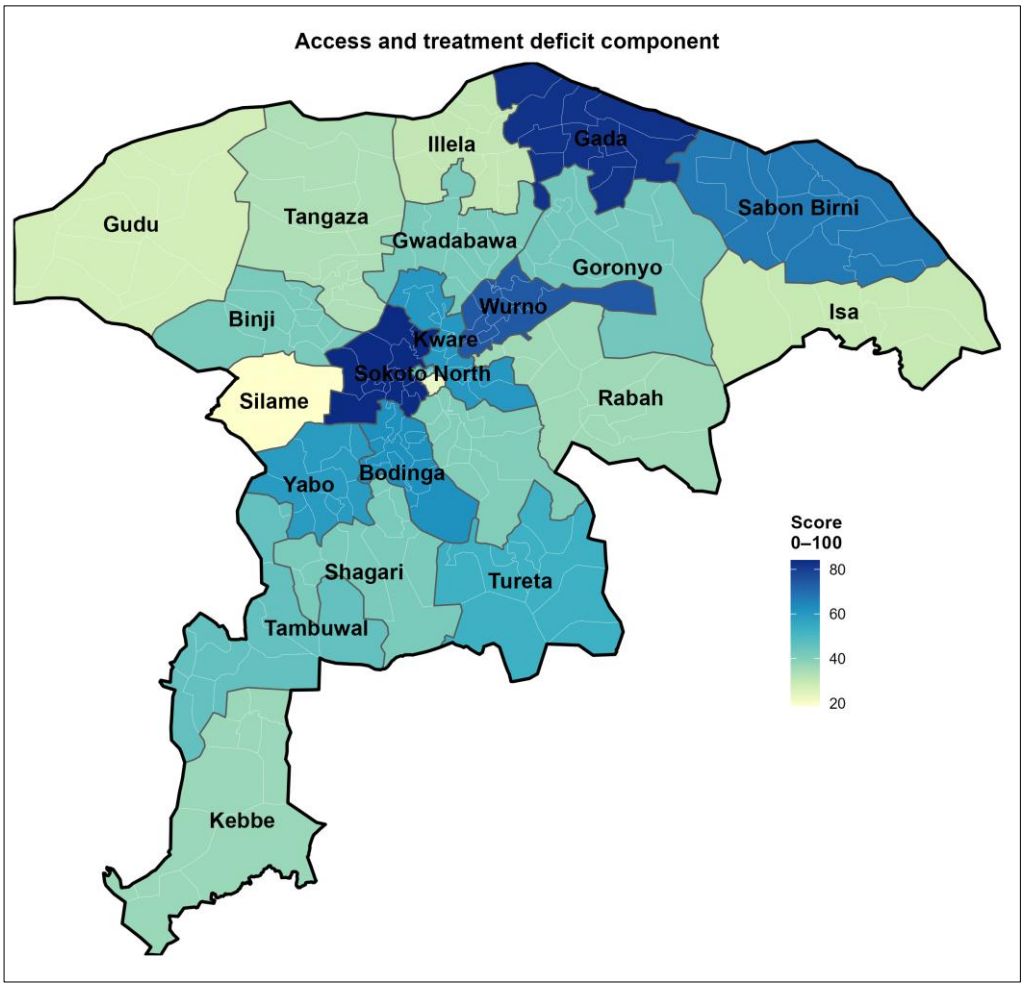


**Figure 10.** Spatial distribution of the treatment and healthcare access deficit component, integrating treatment gaps, treatment gap rates, health facility density, and nighttime light intensity.

The relative contributions of the five components to the chemoprevention priority index (CPI) are summarized in Figure 10b. The child vulnerability component had the highest average contribution (mean = 52.8), followed by the access and treatment deficit component (47.2) and the malaria burden component (45.1). In contrast, the settlement complexity component contributed moderately (28.5), whereas the denominator uncertainty component had the smallest average contribution (0.79). These results indicate that chemoprevention priorities in Sokoto State are driven primarily by child vulnerability and healthcare access constraints rather than by uncertainty in population denominators (Figure 11).

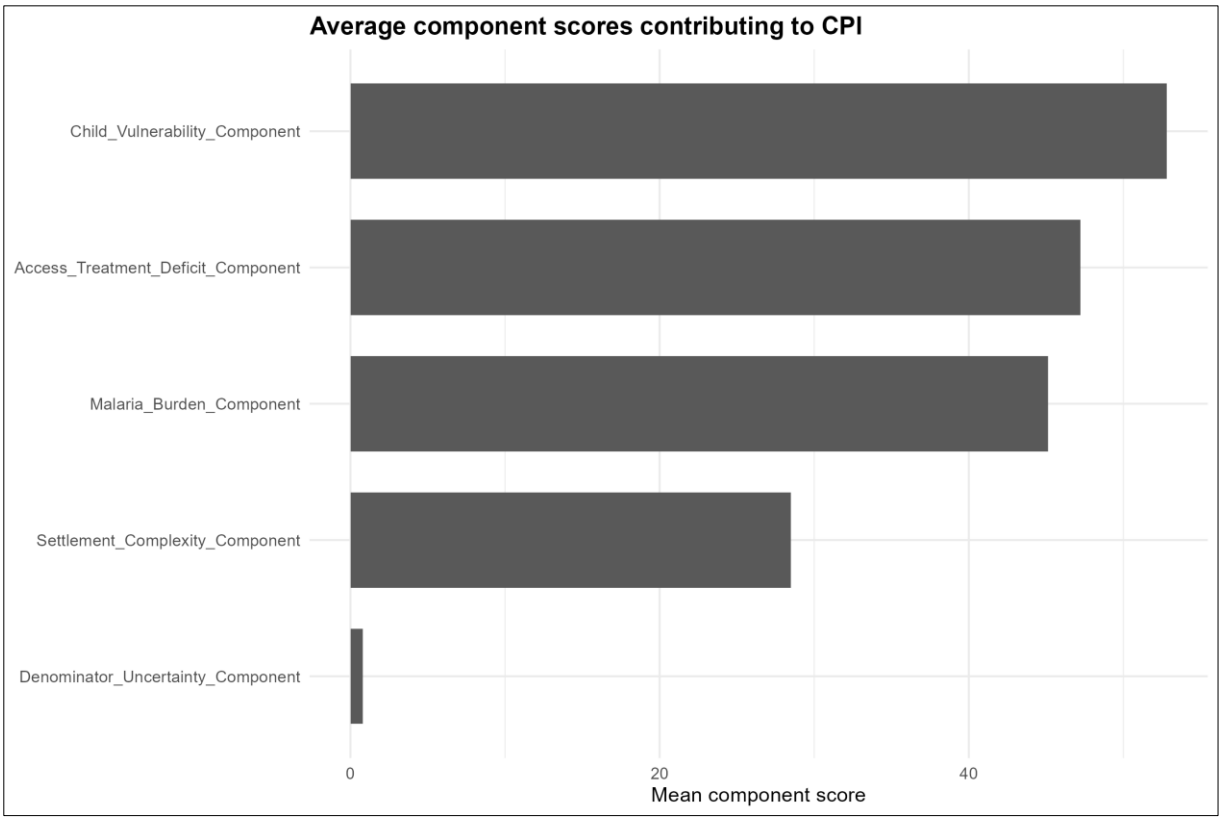


**Figure 11.** Average component scores contributing to the chemoprevention priority index (CPI). Child vulnerability and healthcare access deficits were the dominant determinants of the CPI across wards, whereas denominator uncertainty contributed relatively little to the overall priority score.

Sensitivity analysis comparing weighted and equal-weight CPI formulations demonstrated that ward rankings were generally robust (Figure 12). Nevertheless, some wards exhibited notable rank shifts. Illela (Illela LGA) improved by 78 positions under equal weighting, whereas Salame (Gwadabawa LGA) and Tangaza (Tangaza LGA) improved by 52 and 50 positions, respectively. These changes suggest that although treatment and access deficits dominate the weighted CPI, child vulnerability and settlement complexity become more influential when all the components are assigned equal importance.

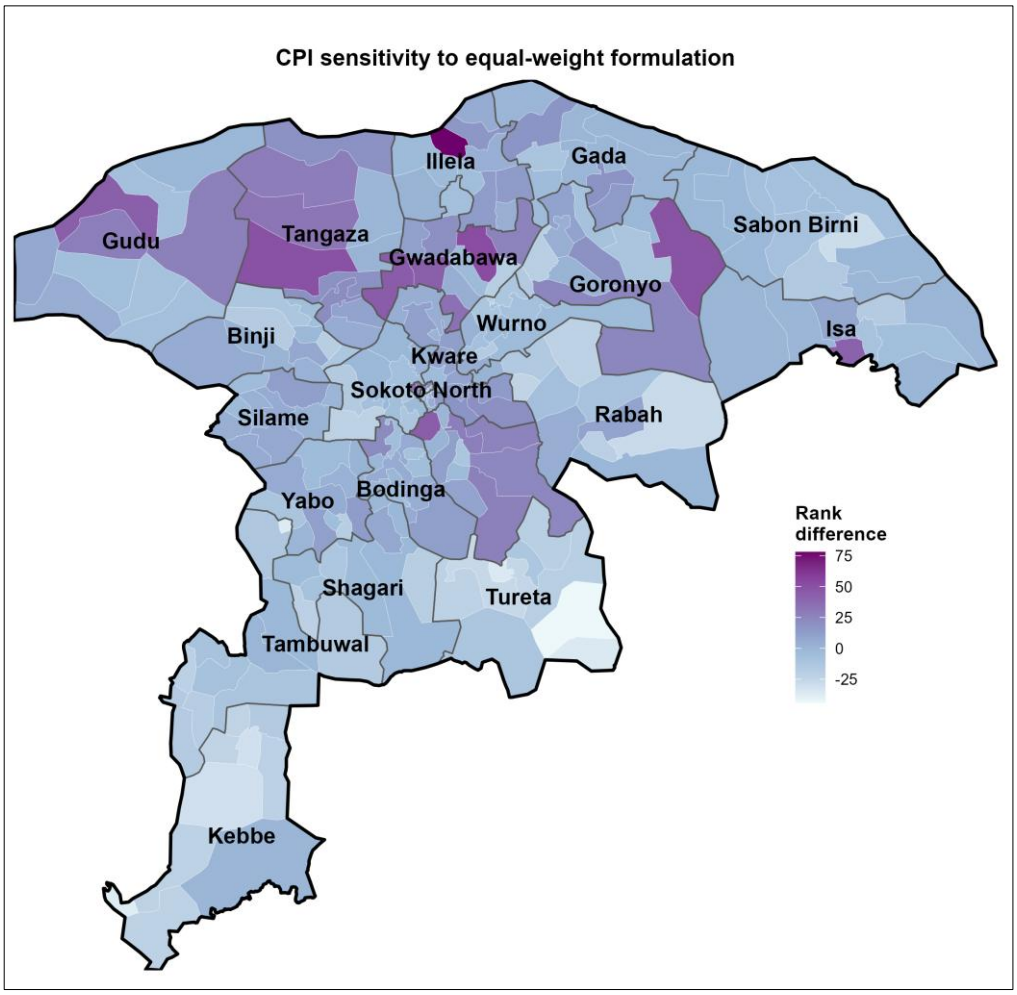


**Figure 12.** Rank differences between weighted and equal-weight chemoprevention priority index formulations. Positive values indicate wards that rank higher under equal weighting, whereas negative values indicate wards that rank lower.

Overall, the CPI framework identified a distinct set of wards requiring urgent malaria intervention and investment. The highest priority wards Dukamaje (Gada LGA), Gilbadi (Gada LGA), Kaura (Wamakko LGA), Isa South (Isa LGA), Jabo-Kagara (Tambuwal LGA), and Gidan Rugga More (Kware LGA) represent locations where large child populations, high immunization vulnerability, persistent treatment gaps, and operational complexities converge. These wards should therefore constitute the primary focus of geographically targeted seasonal malaria chemoprevention, perennial malaria chemoprevention, malaria vaccination, and community-based child survival programmes in Sokoto State.

## 4. Discussion

This study developed a ward-level geospatial framework for identifying children who may be missed by malaria interventions and prioritizing locations for chemoprevention investments in Sokoto State, Nigeria. The results demonstrate substantial spatial heterogeneity in underfive population estimates, malaria burdens, healthcare access, and child vulnerability, supporting the hypothesis that intervention needs are unevenly distributed across wards. Importantly, denominator uncertainty was not randomly distributed but was concentrated in geographically distinct areas, indicating that conventional population denominators may underestimate or overestimate the number of children eligible for malaria interventions in specific locations.

The comparison between household-enumerated and raster-derived underfive populations revealed considerable discrepancies across wards, with some areas exhibiting substantial positive or negative deviations. Similar discrepancies between household enumeration and gridded population

products have been reported in other low-resource settings, where settlement fragmentation, seasonal migration, and limitations of census-based modeling contribute to inaccuracies in population estimates [26–28]. Although WorldPop and other gridded products have greatly improved the availability of spatial demographic data, recent studies have emphasized that modeled populations should be interpreted cautiously when used for operational microplanning, particularly in sparsely populated and rapidly changing environments [29,30]. Our findings extend this evidence by demonstrating that denominator uncertainty itself can serve as a useful operational indicator for identifying wards where children may be systematically missed by malaria interventions.

The spatial patterns of malaria burden and healthcare accessibility further support the need for geographically targeted interventions. Wards with high malaria burdens often have poor treatment coverage, limited healthcare accessibility, and increased child vulnerability. This observation is consistent with previous studies showing that malaria mortality is strongly influenced not only by transmission intensity but also by access to diagnosis, treatment, and preventive services [31,32]. The inclusion of the Accessibility-Adjusted Treatment Gap Index (AATGI) enabled the identification of locations where healthcare systems are least able to respond to malaria burden, thereby providing a more comprehensive representation of operational risk than disease burden alone.

The chemoprevention priority index (CPI) developed in this study integrates five dimensions: malaria burden, treatment and healthcare access deficits, child vulnerability, denominator uncertainty, and settlement complexity. The resulting priority rankings highlighted wards where multiple disadvantages converge and where investments in seasonal malaria chemoprevention (SMC), perennial malaria chemoprevention (PMC), malaria vaccination, and community-based child health programmes are likely to yield the greatest impact. Previous prioritization frameworks have generally focused on epidemiological indicators or accessibility measures in isolation [33,34]. In contrast, the CPI provides a multidimensional approach that simultaneously accounts for disease burden, service delivery constraints, population uncertainty, and demographic vulnerability.

These findings have important implications for malaria financing and program implementation. Organizations that emphasize cost-effectiveness and evidence-based allocation of resources increasingly require fine-scale information on where interventions can achieve the greatest marginal benefit [35]. The identification of wards with high denominator uncertainty and elevated CPI scores may improve the targeting of SMC, PMC, malaria vaccination, and integrated child survival programmes by ensuring that investments are directed toward populations that are both highly vulnerable and potentially underserved. In this context, the framework developed here aligns with emerging global health strategies that prioritize precision public health and geographically targeted interventions [36].

Several limitations should be acknowledged. First, malaria mortality data were available only at the LGA level and were therefore assumed to represent ward-level conditions within each LGA. Second, the analysis relied on WorldPop 2025 population estimates, which are model-based and may contain uncertainties associated with census inputs and settlement classification. Third, temporal changes in settlement dynamics and migration were not explicitly modeled. Nevertheless, the integration of household microcensus records with gridded population products and malaria surveillance indicators provides a robust basis for operational decision-making and substantially reduces the uncertainties associated with reliance on a single data source.

Future studies could extend this framework by incorporating household travel time to health facilities, malaria vaccine coverage, climate variability, and longitudinal microcensus updates. Machine learning approaches may also be used to predict wards at risk of becoming future hotspots of unmet malaria intervention needs. Similar approaches could be applied in other high-burden regions of sub-Saharan Africa to support precision targeting of malaria interventions and optimize the allocation of limited public health resources.

**Data availability statement:** Household Microcensus data, including household locations, household-enumerated under-five population estimates, routine immunization zero-dose children, not vaccinated children, and related vaccination indicators, were obtained through the Nigerian Settlement Microcensus programme. These datasets are not publicly available because they contain operational and potentially sensitive geospatial information but may be accessed through the implementing agencies subject to data-sharing agreements and approval.

GRID3 settlement and health facility datasets were obtained from the GRID3 Nigeria data repository and are publicly available at https://data.grid3.org/. Settlement datasets were used to characterize settlement distribution and complexity, while health facility datasets were used to assess healthcare service availability.

Raster-derived under-five population estimates and total population estimates for 2025 were obtained from the WorldPop project and are publicly available at https://www.worldpop.org/ and through the WorldPop Open Population Repository at https://wopr.worldpop.org/.

Monthly under-five malaria mortality records (2014–2024), severe malaria cases, and severe malaria cases treated with artesunate were obtained from the Nigerian Routine Health Information System (RHIS) through the District Health Information System 2 (DHIS2) platform managed by the Federal Ministry of Health. These data are not publicly available due to national data governance and confidentiality requirements but may be available from the relevant authorities upon reasonable request and approval.

Malaria transmission and burden indicators for 2024, including *Plasmodium falciparum* Parasite Rate (PfPR), Infection Rate (PfIR), Mortality Rate (PfMR), Clinical Incidence (PfIC), and Malaria Cases (PfMC), were obtained from the Malaria Atlas Project and are publicly available at https://malariaatlas.org/explorer/.

Nighttime light intensity data were obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band products provided by the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA), available at https://eogdata.mines.edu/products/vnl/.

Administrative boundary datasets for Nigeria were obtained from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) Common Operational Datasets and are publicly available at https://data.humdata.org/dataset/cod-ab-nga.

Derived datasets and analytical outputs generated during the study are available from the corresponding author upon reasonable request.

**Author Contributions:** Author Contributions: Conceptualization, U.M.I., U.S.N., and Z.I.; methodology, Z.I., U.M.I., and U.S.N.; software, Z.I.; validation, U.M.I., U.S.N., Y.J.C., and C.A.U.; formal analysis, Z.I.; investigation, U.S.N., Y.J.C., U.M.I., O.I.O., Y.J.D., and C.A.U.; data curation, U.S.N., Y.J.C., and U.M.I.; visualization, Z.I.; writing—original draft preparation, Z.I. and U.M.I.; writing—review and editing, U.S.N., Y.J.C., O.I.O., Y.J.D., and C.A.U.; supervision, U.M.I.; project administration, U.M.I.; resources, U.S.N., Y.J.C., O.I.O., Y.J.D., and C.A.U. All authors have read and agreed to the published version of the manuscript.

**Funding**

This research received no external funding.

**Informed Consent Statement**

Not applicable.

**Conflicts of interest**

The authors declare that they have no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| Abbreviation | |
|---|---|
| CPI | Chemoprevention Priority Index |
| MCRS | Missed Child Risk Score |
| DUS | Denominator Uncertainty Score |
| AATGI | Accessibility-Adjusted Treatment Gap Index |
| SMC | Seasonal Malaria Chemoprevention |
| PMC | Perennial Malaria Chemoprevention |
| RI | Routine Immunization |
| U5 | Under-Five Children |
| LGA | Local Government Area |
| GRID3 | Geo-Referenced Infrastructure and Demographic Data for Development |

## References

1. World Health Organization. World Malaria Report 2024. Geneva: World Health Organization; 2024. Available online: WHO Malaria 2024 Country Profile: Nigeria .
2. World Health Organization. Nigeria Malaria Country Profile 2024. Geneva: WHO; 2024. Available online: Nigeria Country Profile .
3. UNICEF Nigeria: Nigeria Receives Malaria Vaccines Ahead of Roll Out. Abuja: UNICEF; 2024.
4. Shekarau E, Uzoanya M, Ogbulafor N; Severe Malaria Working Group. Severe malaria intervention status in Nigeria: workshop meeting report. Malar J. 2024 Jun 5;23(1):177. doi: 10.1186/s12936-024-05001-1. PMID: 38840162; PMCID: PMC11155025.
5. Cairns M, Roca-Feltrer A, Garske T, Wilson AL, Diallo D, Milligan PJ, Ghani AC, Greenwood BM. Estimating the potential public health impact of seasonal malaria chemoprevention in African children. Nat Commun. 2012 Jun 6;3:881. doi: 10.1038/ncomms1879. PMID: 22673908; PMCID: PMC3621394.
6. Utazi CE, Thorley J, Alegana VA, Ferrari MJ, Takahashi S, Metcalf CJE, Lessler J, Cutts FT, Tatem AJ. Mapping vaccination coverage to explore the effects of delivery mechanisms and inform vaccination strategies. Nat Commun. 2019 Apr 9;10(1):1633. doi: 10.1038/s41467-019-09611-1. PMID: 30967543; PMCID: PMC6456602.
7. Tatem AJ. Mapping the denominator: spatial demography in the measurement of progress. *Int Health.* 2014 Sep;6(3):153-5. doi: 10.1093/inthealth/ihu057. Epub 2014 Aug 14. PMID: 25125576; PMCID: PMC4161992.
8. Wardrop, N.A.; et al. Spatially disaggregated population estimates in the era of big data and machine learning. Nature Scientific Data. 2018, 5, 180063.
9. Tatem, A.J. WorldPop, open data for spatial demography. Scientific Data. 2017, 4, 170004. doi:10.1038/sdata.2017.4.
10. Stevens, F.R.; et al. Disaggregating census data for population mapping using Random Forests with remotely sensed and ancillary data. PLoS ONE. 2015, 10(2), e0107042.
11. WorldPop Population Methods. WorldPop, University of Southampton; 2025.
12. WorldPop Frequently Asked Questions. WorldPop; 2025.
13. United Nations Population Fund (UNFPA). The Value of Modeled Population Estimates for Census Planning and Development. New York: UNFPA; 2022.
14. Bhatt, S.; et al. The effect of malaria control on Plasmodium falciparum in Africa between 2000 and 2015. Nature. 2015, 526, 207–211.
15. National Malaria Elimination Programme (NMEP); National Population Commission (NPC); National Bureau of Statistics (NBS); ICF. Nigeria Malaria Indicator Survey 2021. Abuja, Nigeria; 2022.

16. Aregbeshola, B.S.; Khan, S.M. Healthcare accessibility and child health inequalities in Nigeria: a spatial perspective. BMC Public Health. 2022, 22, 1348.
17. Utazi, C.E.; Thorley, J.; Alegana, V.A.; et al. High-resolution mapping of vaccination coverage and zero-dose children in Nigeria. Lancet Global Health. 2023, 11(4), e556–e565.
18. Tatem, A.J.; Sorichetta, A.; Pezzulo, C.; et al. High-resolution gridded population datasets and their application in public health. Philosophical Transactions of the Royal Society B. 2017, 372, 20160284.
19. HISP Centre, University of Oslo. (2024). *District Health Information System 2 (DHIS2): Open-source health management information platform*. University of Oslo, Norway. https://dhis2.org
20. National Primary Health Care Development Agency (NPHCDA). (2024). *Routine immunization micro-census operational guidelines and implementation framework*. Abuja, Nigeria.
21. Center for International Earth Science Information Network (CIESIN), Columbia University, Novel-T, and Flowminder Foundation. (2024). *GRID3 Nigeria health facility database*. GRID3 Initiative. https://grid3.org
22. WorldPop. (2025). *Global high-resolution population denominators project*. School of Geography and Environmental Science, University of Southampton, United Kingdom. https://www.worldpop.org
23. Malaria Atlas Project. (2024). *Spatial malaria datasets for Nigeria: PfPR, PfIR, PfMR, PfIC and PfMC*. University of Oxford. https://malariaatlas.org
24. National Aeronautics and Space Administration (NASA), & National Oceanic and Atmospheric Administration (NOAA). (2025). *Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band nighttime lights products*. https://earthdata.nasa.gov
25. United Nations Office for the Coordination of Humanitarian Affairs (OCHA). (2024). *Nigeria administrative boundaries (Admin 0–2)*. Humanitarian Data Exchange (HDX). https://data.humdata.org
26. Wardrop, N.A.; Jochem, W.C.; Bird, T.J.; et al. Spatially disaggregated population estimates in the era of big data and machine learning. Scientific Data 2018, 5, 180063.
27. Stevens, F.R.; Gaughan, A.E.; Linard, C.; Tatem, A.J. Disaggregating census data for population mapping using Random Forests with remotely sensed and ancillary data. PLoS ONE 2015, 10, e0107042.
28. Tatem, A.J. Mapping populations at risk: improving spatial demographic data for infectious disease modeling and control. Nature Reviews Microbiology 2014, 12, 529–540.
29. Tatem, A.J. WorldPop, open data for spatial demography. Scientific Data 2017, 4, 170004.
30. Pezzulo, C.; Sorichetta, A.; Gaughan, A.E.; et al. Subnational mapping of population pyramids and dependency ratios in Africa and Asia. Scientific Data 2017, 4, 170089.
31. Weiss, D.J.; Lucas, T.C.D.; Nguyen, M.; et al. Mapping the global prevalence, incidence, and mortality of Plasmodium falciparum, 2000–2017. The Lancet 2019, 394, 322–331.
32. Ohrt, C.; et al. Access to malaria diagnosis and treatment and its relationship with mortality in sub-Saharan Africa. Malaria Journal 2021, 20, 247.
33. Noor, A.M.; Alegana, V.A.; Gething, P.W.; et al. Defining equity in physical access to clinical services using geographical information systems as part of malaria planning and monitoring. Tropical Medicine & International Health 2009, 14, 882–890.
34. Utazi, C.E.; Thorley, J.; Alegana, V.A.; et al. High-resolution mapping of vaccination coverage and zero-dose children in Nigeria. The Lancet Global Health 2023, 11, e556–e565.
35. Morton, A.; Thomas, R.; Smith, R. Cost-effectiveness analysis and geographic targeting of public health interventions. Health Policy 2020, 124, 1260–1268.
36. Dowell, S.F.; Blazes, D.; Desmond-Hellmann, S. Four steps to precision public health. Nature 2016, 540, 189–191.