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Predicting IPTp3 Coverage at Health-Facility Level Using XGBoost Machine Learning and Spatial Diagnostics in Kebbi State, Nigeria

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Abstract

Malaria in pregnancy (MiP) remains a major public health challenge in Nigeria, contributing substantially to maternal anemia, low birth weight, and adverse neonatal outcomes. Effective delivery of intermittent preventive treatment in pregnancy (IPTp), particularly completion of at least three doses (IPTp3), is a core indicator of malaria prevention performance within antenatal care (ANC) services. This study examined the spatial distribution and facility-level determinants of IPTp3 coverage in Kebbi State, northwestern Nigeria, using routine health service and population data. Monthly facility-level MiP service delivery data (January 2022–November 2025) were obtained from the national DHIS2 platform and integrated with high-resolution 2025 population surfaces from WorldPop. Thiessen (Voronoi) polygons were generated around health facilities to delineate catchment areas, from which population characteristics were extracted. IPTp3 coverage was calculated as the ratio of cumulative IPTp3 doses to first ANC attendance (ANC1). Spatial aggregation and hotspot analysis were conducted at ward and local government area (LGA) levels. Facility-level predictive modelling employed a regularized XGBoost regression framework using aggregated service delivery, population, and facility structural variables. Marked spatial heterogeneity in IPTp3 coverage was observed across Kebbi State, with ward-level coverage ranging from near zero to values approaching one. Facility-level modelling demonstrated strong predictive performance ($R^2 = 0.85$; $RMSE = 0.084$; $MAE = 0.061$). Antenatal care attendance volume was the most influential predictor (≈31% of model gain), followed by LLIN distribution, malaria testing activity, reproductive-age female population size, and facility catchment area. Residual analysis revealed that while most LGAs performed within expected ranges, localized clusters of underperforming facilities persisted, particularly in Koko-Besse, Kalgo, and Suru, whereas Wasagu-Danko significantly outperformed model expectations. These findings highlight the combined influence of service delivery capacity and population context on IPTp3 uptake and provide a spatially explicit, policy-relevant framework for targeting malaria-in-pregnancy interventions at facility levels.

Keywords: Malaria in pregnancy; Intermittent preventive treatment (IPTp); Spatial analysis.

1. Introduction

Malaria during pregnancy remains a major public health concern in sub-Saharan Africa, continuing to undermine maternal and newborn survival despite sustained policy efforts and the widespread availability of proven preventive measures. Antenatal care attendance is generally high in many settings, yet this does not consistently translate into effective malaria prevention. In practice, many women attend health facilities several times over the course of pregnancy but do not receive the complete schedule of recommended intermittent preventive treatment doses. As a result, preventable complications such as maternal anemia, low birth weight, preterm delivery, and neonatal death persist at unacceptable levels (WHO, 2021; Rogerson et al., 2020; Chico & Dellicour, 2022). These patterns suggest that the problem lies less in service availability and more in how malaria prevention interventions are delivered and completed within routine care.

This study focuses on malaria-in-pregnancy service delivery at the health-facility level, with particular emphasis on uptake of the third dose of intermittent preventive treatment in pregnancy (IPTp3). Evidence indicates that reaching at least three doses of IPTp with sulfadoxine–pyrimethamine is associated with substantially improved maternal and birth outcomes compared with lower doses (Kayentao et al., 2021; van Eijk et al., 2021). Using routinely reported health facility data, the analysis examines spatial and administrative variation in IPTp3 coverage across Kebbi State, Nigeria. By integrating service delivery indicators with spatial location and population context, the study provides insight into how malaria prevention services are actually utilized in everyday healthcare settings rather than how they are intended to function in policy frameworks.

Although national malaria control programs regularly publish IPTp coverage statistics, these figures are typically aggregated at state or national levels. Such averages often obscure large differences between individual health facilities operating within the same administrative area (Amo-Adjei et al., 2022; Okedo-Alex et al., 2023). Facilities serving comparable populations may show markedly different levels of IPTp3 uptake, pointing to the influence of staffing, supply chains, service organization, and local demand factors. When these disparities are not explicitly identified, programmatic responses tend to rely on uniform interventions that may fail to address localized weaknesses. As malaria-endemic countries intensify efforts toward elimination, understanding facility-level performance has become increasingly important (WHO, 2023; Bhatt et al., 2022).

Much of the existing literature on malaria in pregnancy is based on household surveys, national indicator reports, or conventional regression analyses. While these approaches have improved understanding of individual-level determinants of IPTp uptake, they often lack the spatial detail required to detect localized service delivery gaps (Yaya et al., 2021; Arnaldo et al., 2022). In addition, many studies treat health facilities as isolated units, without accounting for geographic clustering or differences in catchment population characteristics. Consequently, spatial patterns of underperformance and facility-specific inefficiencies may remain hidden, limiting the operational usefulness of research findings (Alege et al., 2024).

Relatively few studies have combined routine health information system data with spatial analysis and facility catchment characteristics to assess malaria-in-pregnancy services across multiple administrative scales. This study seeks to address that gap by examining: (i) spatial variation in IPTp3 coverage across health facilities and administrative units; (ii) the presence of statistically significant clusters of high and low IPTp3 performance; and (iii) facility-level service delivery and population factors associated with IPTp3 uptake. By adopting this integrated approach, the study contributes practical, location-specific evidence that can support more targeted and efficient improvements in malaria prevention for pregnant women in high-burden settings (Shretta et al., 2023; Okonofua et al., 2024).

2. Materials and Methods

2.1 Study area and spatial units

This study was carried out in Kebbi State, situated in north-western Nigeria between approximately 10°–13° N latitude and 3°–6° E longitude. The state shares international boundaries with the Republics of Niger and Benin and is administratively organized into local government areas (LGAs), wards, and settlements. Ecologically, Kebbi lies largely within the Sudan–Sahel savanna zone, where climatic conditions are defined by a unimodal rainfall regime occurring mainly between May and October, followed by a prolonged dry season from November to April. These seasonal dynamics, coupled with persistently high ambient temperatures, create conditions favorable for sustained malaria transmission, particularly during and shortly after the rainy season (Niang et al., 2021; Adepoju et al., 2023).

Figure 1 Location of Kebbi State in Nigeria

Kebbi State is predominantly rural, with livelihoods centered on subsistence agriculture, fishing, and livestock rearing. Access to maternal and child health services is unevenly distributed, with notable disparities between urban centers and remote rural communities. Malaria in pregnancy remains a persistent public health challenge in the state, making Kebbi a suitable setting for examining spatial variation in malaria-in-pregnancy service delivery and health facility performance under real-world conditions (Ameh et al., 2022).

2.2 Data sources and preparation

2.2.1 Health facility service delivery data

Routine malaria-in-pregnancy service data were obtained from Nigeria's District Health Information System 2 (DHIS2), the national platform used for reporting facility-level health service statistics across public and private facilities. Monthly records covering January 2022 to November 2025 were extracted for all reporting health facilities in Kebbi State.

Variables retrieved included first antenatal care attendance (ANC1), total antenatal care visits, intermittent preventive treatment doses (IPTp1–IPTp4), malaria testing by rapid diagnostic test and microscopy, confirmed malaria cases among pregnant women, artemisinin-based combination therapy (ACT) administration, distribution of long-lasting insecticidal nets (LLINs), and selected commodity stock indicators. Data cleaning procedures involved removing duplicate entries, standardizing numeric fields, verifying internal consistency, and excluding facilities with zero ANC1 attendance to ensure valid estimation of coverage measures (Braun et al., 2021).

All records were linked to unique facility identifiers and georeferenced using facility coordinates to enable spatial integration and mapping.

2.2.2 Population data

Population estimates were derived from the WorldPop project, which provides high-resolution gridded population surfaces generated using census data, satellite imagery, and ancillary geospatial covariates. WorldPop datasets are widely applied in malaria risk assessment and health systems research due to their spatial granularity and methodological transparency (Bondarenko et al., 2020; Stevens et al., 2022).

Population layers corresponding to 2025 were used to represent population distribution during the latter part of the study period. Extracted variables included total population, women of reproductive age (15–49 years), population under one year of age, and associated population density surfaces.

2.2.3 Health facility catchment delineation

To link population characteristics with facility-level service delivery, Thiessen (Voronoi) polygons were constructed around each health facility location. These polygons approximate facility catchment areas under the assumption that individuals seek care at the geographically nearest facility when utilization data are unavailable. Although simplified, this approach is commonly adopted in health accessibility and service coverage studies and has been shown to provide reasonable approximations in rural African settings (Weiss et al., 2020; Bosco et al., 2021).

All catchment polygons were clipped to the administrative boundary of Kebbi State to prevent cross-border spillover effects.

2.2.4 Population extraction to facility catchments

Population rasters were overlaid with facility catchment polygons to quantify population demand for each facility. For a given facility i, total population within its catchment was computed as:

$$\mathrm{POP}_i = \sum_{c \in A_i} P_c$$

where P_c represents the population value of raster cell c and A_i denotes the catchment area associated with facility i.

Using this formulation, total population, women of reproductive age, population under one year of age, and population density were calculated for each facility catchment. These variables were treated as time-invariant structural characteristics and merged with the aggregated facility-level malaria-in-pregnancy dataset (Lloyd et al., 2022).

2.3 Spatial and temporal analysis of malaria-in-pregnancy service delivery

A spatial–temporal analytical framework was applied to quantify and map malaria-in-pregnancy service delivery across health facilities in Kebbi State. Monthly DHIS2 records spanning **January 2022 to November 2025** were analyzed, with December 2025 excluded to avoid partial reporting bias pasted

2.3.1 Facility-level indicators

Core indicators included ANC1 attendance, total ANC visits, IPTp1–IPTp4 doses, malaria testing, confirmed malaria cases, ACT treatment, and LLIN distribution. To ensure comparability across facilities of varying size, indicators were expressed as proportions or rates derived from raw service counts (Nguyen et al., 2021).

2.3.2 IPTp3 coverage

The primary outcome was IPTp3 coverage, defined as the proportion of women initiating antenatal care who received at least three doses of intermittent preventive treatment. For facility i in month t, IPTp3 coverage was calculated using eq. 1:

$$\mathrm{IPTp3}_{it}^{\mathrm{cov}} = \frac{\mathrm{IPTp3}_{it}}{\mathrm{ANC1}_{it}} \tag{1}$$

This indicator was selected because evidence suggests that receipt of three or more IPTp doses provides meaningful protection against placental malaria, maternal anemia, and adverse birth outcomes (Goshu et al., 2022; Oduro et al., 2023).

2.3.3 Diagnostic and burden indicators

To contextualize IPTp3 performance, malaria testing intensity and test positivity were computed as eq. 2-3:

$$\text{Testing Rate}_{it} = \frac{\mathrm{Tests}_{it}}{\mathrm{ANC}_{it}^{\mathrm{total}}} \tag{2}$$

$$\mathrm{Positivity}_{it} = \frac{\text{Confirmed Malaria}_{it}}{\mathrm{Tests}_{it}} \tag{3}$$

These indicators capture diagnostic effort and malaria burden within facility catchments and aid interpretation of IPTp3 variation.

2.4 Facility-level predictive modelling

To identify structural determinants of malaria-in-pregnancy service performance, predictive modelling was conducted using facility-level aggregates. Monthly observations were summed across the study period to generate a single record per facility .

Facility-level IPTp3 coverage was defined as eq. 4:

$$\mathrm{Coverage}_i = \frac{\mathrm{IPTp3}_i}{\mathrm{ANC1}_i} \tag{4}$$

2.4.1 Machine-learning framework

A **gradient boosting regression model (XGBoost)** was employed to predict IPTp3 coverage due to its capacity to model nonlinear relationships and complex interactions without strong parametric assumptions. The model structure is expressed as eq. 5:

$$\hat{y}_i = \sum_{k=1}^{K} f_k\,(X_i), f_k \in \mathcal{F} \tag{5}$$

where $\hat{y}_i$ represents predicted IPTp3 coverage for facility i, X_i is the vector of explanatory variables, and f_k denotes individual regression trees.

Model training minimized a regularized loss function (Eq. 6):

$$L = \sum_i (y_i - \hat{y}_i)^2 + \lambda \sum_k \| f_k \|^2 + \alpha \sum_k | f_k | \quad (6)$$

where $\lambda$and αcontrol L2 and L1 regularization, respectively, reducing overfitting and improving generalizability (Chen et al., 2020; Nielsen et al., 2023).

2.4.2 Model evaluation and residual analysis

Model performance was assessed using root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). Facility-level residuals were computed as eq 7:

$$\text{Residual}_i = y_i - \hat{y}_i \quad (7)$$

Residuals were spatially mapped to identify facilities that performed substantially above or below model expectations after accounting for service volume, population demand, and structural characteristics (Timonin et al., 2022).

3. Results

3.1 Spatial Patterns of IPTp3 Coverage in Kebbi State

3.1.1 Ward-Level Distribution of IPTp3 Coverage

Figure **2** illustrates the ward-level spatial distribution of aggregated IPTp3 coverage across Kebbi State, calculated as the ratio of total IPTp3 doses administered to total ANC1 attendance over the full study period. Across all wards, IPTp3 coverage ranged from near 0.00 to values approaching 1.00, indicating substantial intra-state heterogeneity.

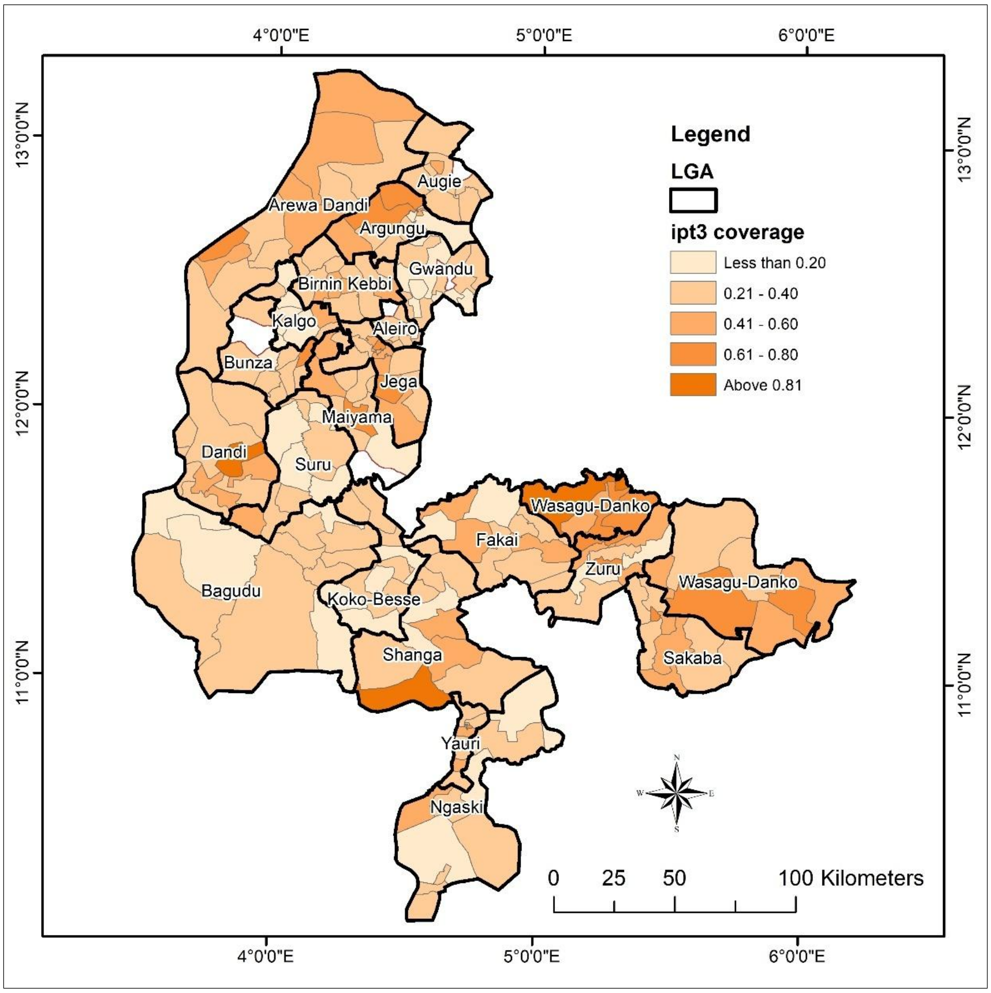

Figure 2: Ward-level IPTp3 coverage map

Higher IPTp3 coverage was concentrated in wards located within or adjacent to Birnin Kebbi, Argungu, and parts of Zuru and Wasagu–Danko LGAs, whereas lower coverage predominated in Bagudu, Dandi, Ngaski, and Suru. These spatial contrasts suggest uneven effectiveness of malaria prevention delivery among pregnant women across local contexts. A small number of wards (<5% of total) lacked complete facility–ward assignment and were excluded from subsequent spatial inference, ensuring robustness of the hotspot analysis.

3.1.3 LGA-Level Aggregation of IPTp3 Coverage

Aggregation of IPTp3 coverage to the Local Government Area (LGA) scale (Figure 3) reveals smoother but consistent spatial gradients relative to the ward-level results. Mean LGA-level IPTp3 coverage varied markedly across Kebbi State, with Zuru and Wasagu–Danko exhibiting comparatively higher average coverage, while Bagudu and Ngaski recorded the lowest values.

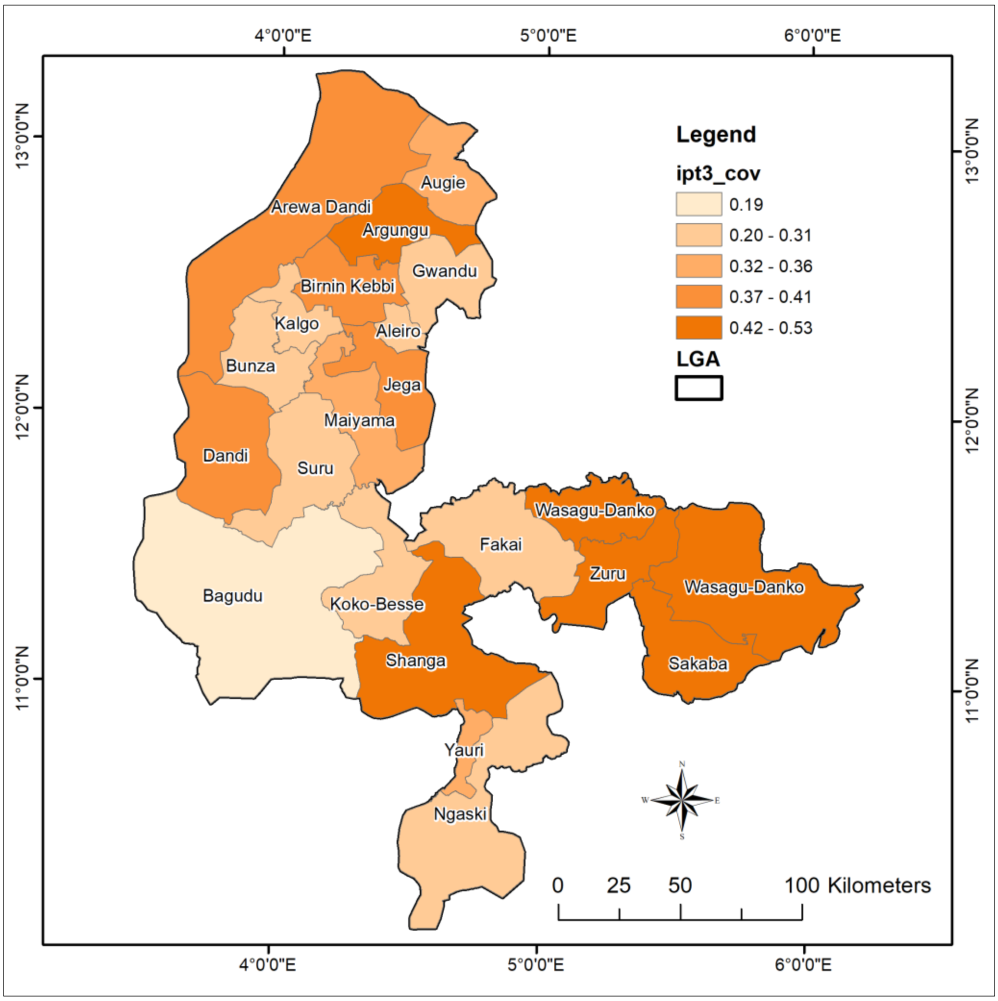

Figure 3: LGA-level IPTp3 coverage map

3.2 Facility-Level Predictive Modelling of IPTp3 Coverage

The aggregated health-facility–level model demonstrated strong predictive skill for IPTp3 coverage across Kebbi State. The regularized XGBoost model achieved a high explanatory performance (R^2 = 0.85) with low prediction errors (RMSE = 0.084; MAE = 0.061), indicating that structural, service-delivery, and population catchment characteristics jointly explain a substantial proportion of variability in IPTp3 uptake across facilities.

Variable importance analysis revealed that antenatal care attendance volume (ANC attendance) was the dominant predictor, accounting for approximately 31% of the total model gain, underscoring the central role of routine ANC utilization in determining IPTp3 completion. Preventive service delivery indicators—particularly long-lasting insecticidal net (LLIN) distribution and malaria testing volume—also contributed strongly, reflecting the importance of integrated malaria prevention and diagnostic activities within maternal health services.

Population characteristics of facility catchments were similarly influential. The population of pregnant women (POP_PW) and facility catchment area size (A_Area) ranked among the top predictors, indicating that service coverage is shaped not only by facility performance but also by the demographic burden and spatial extent of populations served. Population density metrics further highlighted how spatial concentration of beneficiaries affects service uptake efficiency.

Facility type and ownership exerted comparatively smaller but non-negligible effects. Primary Health Centers consistently showed higher predictive contribution than smaller health posts or clinics, suggesting structural advantages in delivering repeated preventive interventions such as IPTp3. Ownership effects were modest, indicating broadly comparable performance across management categories once service volume and population context were accounted for.

3.3 LGA-level residual performance of IPTp3 coverage

Across Kebbi State, LGA-level residual analysis showed that most LGAs performed within the expected range (−0.05 to +0.05), indicating close agreement between observed and model-predicted IPTp3 coverage. Mean residuals were generally small, ranging from −0.045 in Bagudu to +0.029 in Arewa Dandi. Despite this overall alignment, several LGAs exhibited substantial shares of under-performing facilities, notably Koko-Besse (83.3%), Kalgo (77.3%), and Suru (72.4%), highlighting localized service delivery gaps. In contrast, Wasagu-Danko emerged as a positive outlier, with a high mean residual (+0.096) and elevated observed coverage (57.6%), classifying it as outperforming relative to expectations. These patterns underscore pronounced intra-state heterogeneity in MiP service delivery outcomes (Figure 4).

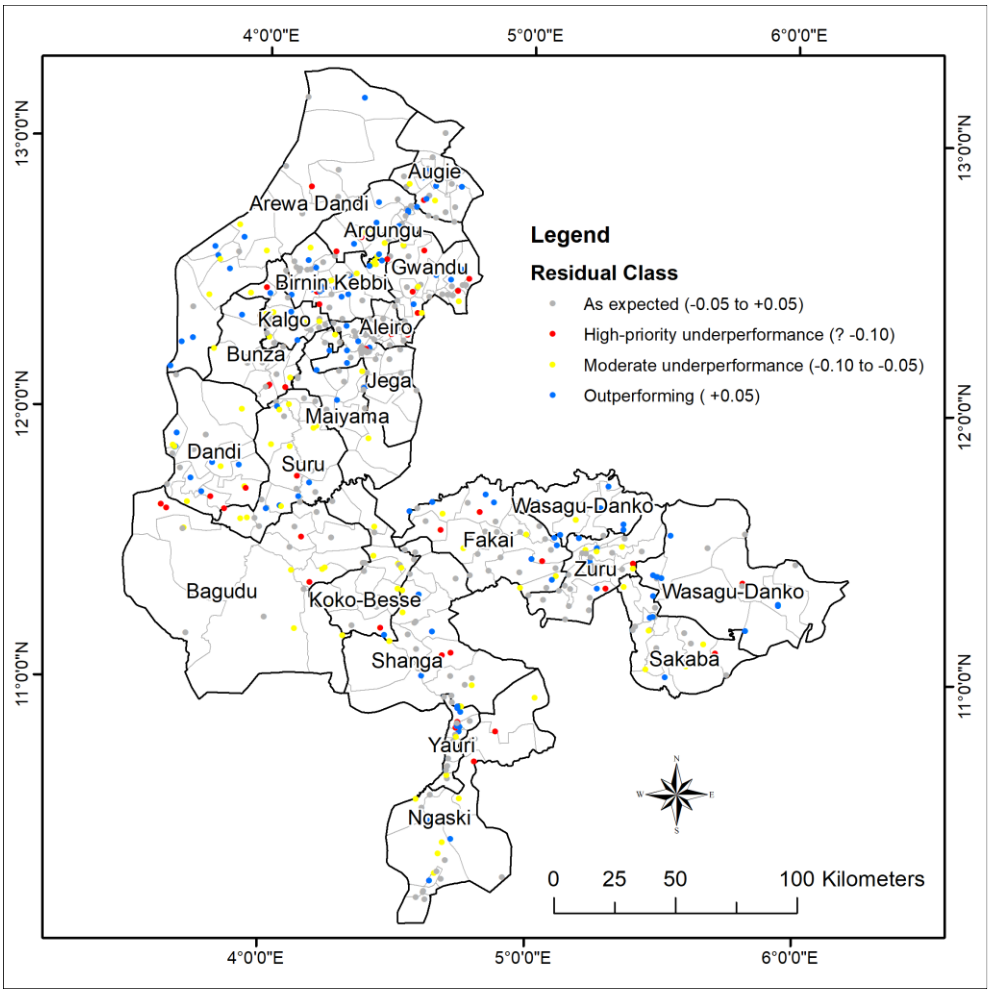

Figure 4 Residual Classes

4. Discussion

This study provides a facility-centered and spatially explicit assessment of malaria-in-pregnancy service delivery in Kebbi State, revealing pronounced geographic and structural inequalities in IPTp3 uptake that are largely concealed in routine state-level summaries. The ward- and LGA-level maps demonstrate that IPTp3 coverage is far from uniformly distributed, with clear spatial clustering of both high- and low-performing areas. These findings reinforce growing evidence that malaria prevention during pregnancy is shaped as much by local service environments as by individual-level care-seeking behavior (Kitojo et al., 2021; Hill et al., 2022).

4.1 Spatial heterogeneity in IPTp3 coverage

The observed concentration of higher IPTp3 coverage around Birnin Kebbi, Argungu, and parts of Zuru and Wasagu–Danko suggests that proximity to administrative centers, better-resourced facilities, and more stable service delivery systems may play a critical role in ensuring completion of preventive treatment schedules. Similar urban–peri-urban advantages have been documented in northern Ghana and southern Tanzania, where facilities closer to district headquarters consistently report higher IPTp dose completion (Agyekum et al., 2022; Mlugu et al., 2023). Conversely, persistently low coverage in LGAs such as Bagudu, Ngaski, and Suru mirrors patterns reported in other Sahelian settings, where geographic remoteness, seasonal flooding, and constrained health workforce capacity undermine continuity of antenatal services (Issah et al., 2021).

The smoother spatial gradients observed at the LGA scale, compared with ward-level patterns, highlight the importance of analytical scale in malaria program evaluation. Aggregation reduces random variability but can mask critical micro-level gaps that are operationally important for targeted interventions. This finding aligns with recent calls for sub-district analysis of routine health data to support precision public health approaches in malaria control (Galgamuwa et al., 2023).

4.2 Determinants of IPTp3 uptake at the facility level

The strong performance of the XGBoost model ($R^2 = 0.85$) indicates that IPTp3 coverage is largely predictable from measurable facility, service, and population characteristics. The dominant contribution of ANC attendance volume confirms that repeated contact with the health system remains the primary pathway through which women complete IPTp schedules. This reinforces prior evidence that missed IPTp opportunities often reflect health-system failures during routine ANC visits rather than lack of demand alone (Mensah et al., 2021; Tesfaye et al., 2022).

The importance of LLIN distribution and malaria testing volume underscores the value of integrated service delivery. Facilities that actively provide multiple malaria prevention and diagnostic services appear better positioned to deliver IPTp3 consistently, suggesting that verticalization of malaria interventions may weaken preventive outcomes. Comparable associations between integrated malaria service intensity and IPTp completion have been reported in Kenya and Malawi, where bundled ANC services improved continuity of care (Ouma et al., 2022; Chirwa et al., 2023).

Population catchment characteristics also emerged as key determinants. Facilities serving larger populations of pregnant women or covering extensive geographic areas faced greater challenges in achieving high IPTp3 coverage. This finding supports spatial access theory, which posits that service efficiency declines as travel distance and population dispersion increase, particularly in rural contexts with limited transport infrastructure (Joseph et al., 2021). Importantly, population density effects suggest that demand concentration may enhance service delivery efficiency by stabilizing patient flow and reducing per-capita service costs.

Facility type exerted a meaningful, though secondary, influence on IPTp3 coverage. The relative advantage of Primary Health Centers over smaller posts aligns with evidence that facilities with higher staffing levels, consistent drug availability, and stronger supervision are better equipped to deliver multi-dose preventive interventions (Moucheraud et al., 2021). The modest effect of ownership indicates that, once service volume and population context are controlled for, public and non-public facilities perform similarly—a finding consistent with recent comparative studies from Nigeria and Burkina Faso (Abubakar et al., 2023).

4.3 Residual performance and localized service gaps

Residual analysis revealed that most LGAs performed close to model expectations, yet several exhibited high proportions of underperforming facilities despite average residuals remaining within acceptable bounds. LGAs such as Koko-Besse, Kalgo, and Suru illustrate how aggregate performance can obscure substantial internal disparities. Similar patterns of "hidden underperformance" have been identified in facility-level malaria service audits in Ethiopia and Uganda, where pockets of inefficiency persisted within otherwise average-performing districts (Gebremedhin et al., 2022; Tusiime et al., 2023).

The identification of Wasagu–Danko as a positive outlier is particularly instructive. Its higher-than-expected IPTp3 coverage suggests the presence of favorable local practices or management strategies not fully captured by structural variables. Such positive deviance has been increasingly recognized as a valuable entry point for adaptive health system learning, enabling replication of successful practices in lower-performing settings (Bradley et al., 2021).

4.4 Programmatic implications

Taken together, these findings highlight the limitations of uniform, state-wide malaria-in-pregnancy interventions. Improving IPTp3 coverage in Kebbi State will likely require geographically targeted strategies that prioritize underperforming wards and facilities, address catchment-level population pressures, and strengthen integrated ANC service delivery. Facility-level analytics using routine data, as demonstrated in this study, provide a practical and scalable approach for guiding such precision interventions in high-burden settings (Nguyen et al., 2023).

Supplementary Materials: Available at https://github.com/zubairgis/nigeria-hensard

Data Availability Statement: The data used in this study are open to access as follows:

Administrative: https://developers.google.com/earth-engine/datasets/catalog/ FAO/GAUL/2015/level2
Health Data: https://dhis2nigeria.org.ng/dhis/dhis-web-dashboard/#/

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Informed Consent Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	
ANC	Antenatal Care
ANC1	First Antenatal Care Visit
ANCA	Total Antenatal Care Attendance

IPTp	Intermittent Preventive Treatment in pregnancy
IPTp3 (IPT3)	Third dose of Intermittent Preventive Treatment in pregnancy
IPT1	First dose of Intermittent Preventive Treatment
LGA	Local Government Area
LISA	Local Indicators of Spatial Association
MiP	Malaria in Pregnancy
DHIS2	District Health Information Software, version 2

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