

Article

Geospatial analysis of Malaria-in-Pregnancy Service Gaps using Routine Health Data in Cross River State, Nigeria.

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Yakubu Joel Cherima^{1*}, Zubairul Islam², Ugo Uwadiako Enebeli³, Ebelechukwu Lawrence Enebeli⁴, Rejoice Kaka Hassan¹, Fiyidi Mikailu⁵, Yonwul Jacqueline Dakyen⁶, Uchenna Stephen Nwokenna¹, Kebiru Umoru² and Eziyi Iche Kalu⁷

¹Department of Policy and Strategic Studies, University of Abuja, Federal Capital Territory, Nigeria; ycherima@gmail.com (Y.J.C.) <https://orcid.org/0009-0004-3724-9886>; rejoice.diara@gmail.com (R.K.H.) <https://orcid.org/0009-0007-1269-0546>, unwokenna2@gmail.com (USN)

²Faculty of Environmental Sciences (FES), Hensard University, Bayelsa 56110, Nigeria; zubairul@gmail.com (Z.I.), <https://doi.org/10.1080/23729333.2023.2298525>

³Department of Community Medicine, Rhema University, Aba, Abia State, Nigeria; ugoenebeli@rhemauniversity.edu.ng (U.U.E.), <https://orcid.org/0000-0001-5950-3719>

⁴Department of Science and Technology, Lancaster University, Accra, Ghana; eby.enebeli@gmail.com (E.L.E.), <https://orcid.org/0009-0007-8434-5485>

⁵Young Individual Development Initiative, Nigeria; fiyidimi@gmail.com (F.M.), <https://orcid.org/0009-0002-4804-8794>

⁶Independent Public health Researcher, Nigeria; ydakyen@yahoo.com (Y.J.D.), <https://orcid.org/0009-0006-7229-4943>

⁷Department of Medical Microbiology, Gregory University, Uturu, Abia State, Nigeria. drkaluiche51@gmail.com (EIQ), <https://orcid.org/0009-0006-2750-3611>

* Correspondence: ycherima@gmail.com; Tel.: +234 703 624 4967

Abstract

Substantial inefficiencies persist along the antenatal care (ANC) to intermittent preventive treatment (IPTp) in Nigeria despite global progress in malaria prevention during pregnancy. National level aggregated indicators often mask sub-national and facility-level disparities, limiting the ability of health systems to target persistent service delivery failures. In this study, we analysed monthly health facility records from the Nigeria DHIS2 platform covering January 2022 to December 2025, aggregated annually at health-facility catchment, ward, and Local Government Area (LGA) levels in Cross River State. Two core cascade indicators were computed: IPT3/ANC1 (conversion of ANC entry into IPTp3 completion) and IPT3/IPT1 (retention from IPTp initiation to completion). To identify locations where high ANC utilisation failed to translate into IPTp3 delivery, we developed a composite ANC→IPTp inefficiency intensity index combining standardized ANC contact volume, IPTp completion shortfall, and ANC–IPTp delivery gaps. Spatial dependence was assessed using Moran's I and Local Indicators of Spatial Association (LISA), while temporal persistence and k-means clustering were used to classify structural versus transient underperformance. Statewide IPT3/ANC1 improved from 0.34 (2022) to 0.47 (2025), while IPT3/IPT1 increased from 0.41 to 0.52, indicating overall strengthening of the ANC→IPTp cascade. However, pronounced spatial inequalities persisted. In 2025, IPT3/ANC1 ranged from 0.26 to 0.69 across LGAs, with Bakassi, Odukpani, and Akpabuyo consistently underperforming, while Obubra, Ogoja, and Yakurr achieved high conversion efficiency. Ward-level intensity analysis revealed a right-skewed distribution (mean = 0.083; SD = 0.521), with inefficiency driven primarily by ANC–IPTp delivery gaps ($r = 0.69$) and ANC contact intensity ($r = 0.58$). Significant positive spatial autocorrelation confirmed clustering of high-inefficiency wards, and several catchments exhibited persistent low performance across three or more consecutive years. Improvements in ANC attendance alone are insufficient to ensure effective IPTp3 delivery. In Cross River State, malaria-in-pregnancy service inefficiencies are heterogeneous, underscoring the need for catchment-specific interventions that prioritise service conversion and continuity rather than uniform statewide strategies.

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

Key findings (Cross River State)

- IPT3/ANC1 improved statewide but remained highly unequal (0.26–0.69 in 2025)
- High ANC attendance often co-existed with large IPTp delivery gaps
- Spatial clustering confirms structural rather than random inefficiency
- A small subset of wards accounts for disproportionate system failure

1. Introduction

Malaria in pregnancy (MiP) remains a major public health concern in sub-Saharan Africa, where transmission intensity and socio-economic conditions intersect to sustain preventable maternal and neonatal morbidity. Pregnant women are particularly vulnerable to *Plasmodium falciparum* infection due to pregnancy-associated immunological changes, leading to increased risks of maternal anaemia, placental parasitaemia, low birth weight, stillbirth, and neonatal mortality (World Health Organization [WHO], 2021; Desai et al., 2018). Despite decades of policy attention, Nigeria continues to account for a disproportionate share of the global MiP burden, contributing nearly one-third of malaria-related maternal and neonatal adverse outcomes worldwide (WHO, 2023; National Malaria Elimination Programme [NMEP], 2022). Real-world programmatic evidence increasingly suggests that the challenge is no longer limited to access to antenatal care (ANC), but rather to the quality and efficiency of service delivery within existing contacts (Taylor et al., 2017).

While IPTp coverage has improved modestly across Nigeria in recent years, progress has been uneven and fragile, with substantial sub-national disparities persisting beneath national averages (WHO, 2022; Amponsah et al., 2021). Evidence from Demographic and Health Surveys and DHIS2 platforms shows that many women attend ANC multiple times yet fail to receive the recommended IPTp doses, indicating missed opportunities within the health system rather than lack of access (Markus, 2022; Opeyemi Samuel Adejo & Olufunke Fayehun, 2024). Such inefficiencies are particularly concerning in settings where ANC utilization is already high, as they reflect systemic weaknesses related to commodity availability, provider practices, and service integration (Bourget-Murray et al., 2021). Understanding where and why ANC contacts fail to translate into protection is therefore essential for optimizing MiP interventions under constrained health budgets.

This study examines spatio-temporal inequalities in the conversion of ANC attendance into effective malaria prevention among pregnant women in Cross River State, Nigeria, between 2022 and 2025. Specifically, we analyse the ANC→IPTp cascade, focusing on the relationship between first ANC attendance (ANC1), repeat ANC contacts, and completion of the third dose of intermittent preventive treatment with sulfadoxine–pyrimethamine (IPTp3). Using health facilities catchment-level spatial units, the study evaluates not only coverage levels but also service delivery efficiency. By combining routine health information system data with spatial analytics, the study moves beyond aggregate indicators to reveal localized patterns (Kitojo et al., 2021).

Recent MiP research has increasingly adopted geospatial and quantitative approaches to examine coverage gaps and inequalities. Spatial autocorrelation methods, such as Moran's I and Local Indicators of Spatial Association (LISA), have been used to detect clustering of poor maternal health outcomes and service under-utilization (Duan Yongheng et al., 2024). Trend analyses and small-area estimation techniques have also been applied to routine health data to assess temporal changes in service delivery (Strachan et al., 2022). However, most studies focus on coverage indicators alone, without explicitly modelling the efficiency of service conversion along the ANC→IPTp pathway. As a result, high-contact but low-performance settings often remain invisible in conventional analyses (Jones et al., 2023).

Despite methodological advances, two critical gaps persist. First, few studies integrate service gaps, and spatial dependence into a single analytical framework capable of identifying chronic inefficiency rather than episodic failure. Second, temporal persistence of poor performance, an indicator of structural system weakness is rarely quantified using routine data. These gaps are particularly urgent in Nigeria, where recent supply chain disruptions and health system shocks have

amplified spatial inequalities in maternal services (NMEP, 2022; WHO, 2023). Without targeted identification of persistently underperforming catchments, programmatic responses risk reinforcing existing inequities.

To the best of our knowledge, no previous study in Nigeria has combined multi-year DHIS2 data, catchment-to-ward spatial linkage, composite inefficiency indices, and local spatial clustering to examine MiP service delivery at fine geographic scales. This study addresses this gap by asking:

- How have spatio-temporal patterns of ANC→IPTp conversion evolved between 2022 and 2025?
- Where do high-ANC, low-IPTp3 wards persist, and are these patterns spatially clustered?
- Which components of service delivery most strongly drive inefficiency?

The study advances MiP research by operationalizing service delivery efficiency as a spatially explicit, composite construct rather than a simple coverage ratio. Empirically, it provides ward-level evidence to guide geographically targeted quality-improvement interventions. From a policy perspective, the findings support a shift from access-focused strategies toward optimizing the effectiveness of existing ANC contacts, directly aligning with Nigeria's malaria elimination goals and WHO's post-2020 MiP strategy (WHO, 2021; WHO, 2023).

2. Materials and Methods

2.1 Study area and spatial units

The analysis was conducted in Cross River State, Nigeria, using health-facility catchments and ward polygons as the primary spatial units (Figure 1). Catchment areas were derived around health facilities providing antenatal and malaria-in-pregnancy (MiP) services, and subsequently aggregated to ward and Local Government Area (LGA) levels to support multi-scale spatial analysis. All spatial data were projected to a common coordinate reference system prior to analysis.

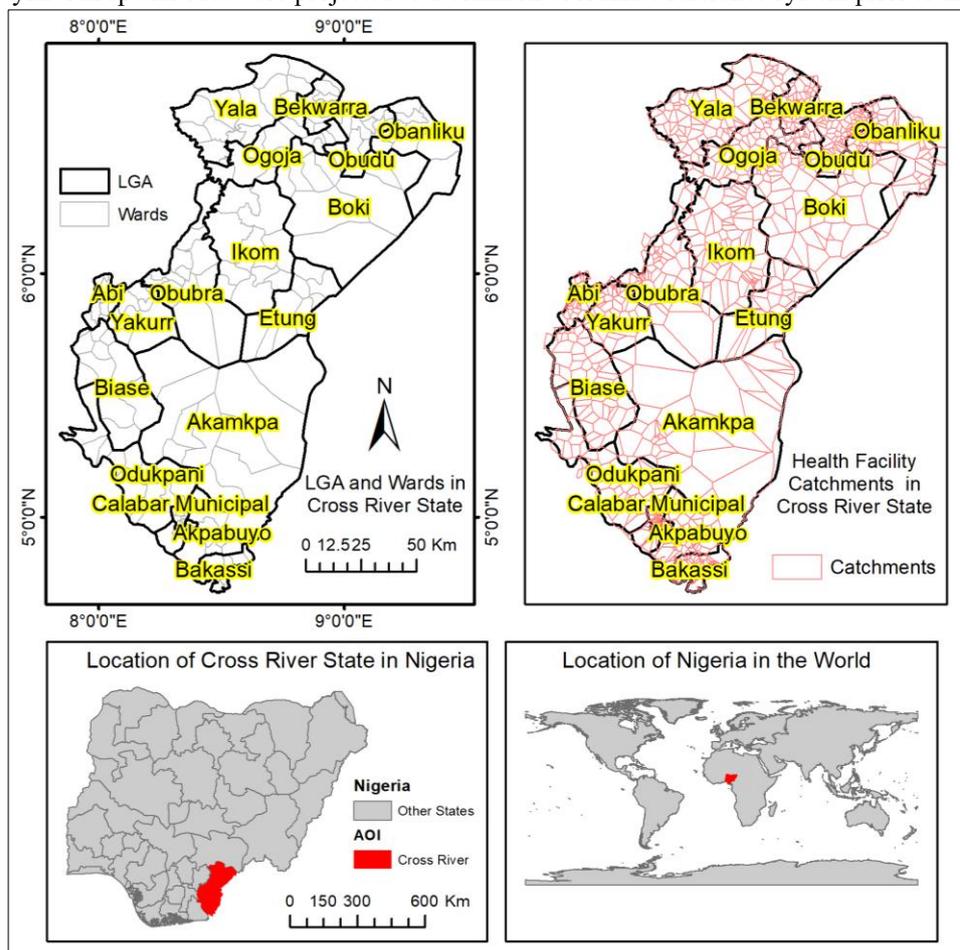


Figure 1 Study Area Map

2.2 Data sources and variables

Monthly health facility service records spanning January 2022 to December 2025 were obtained from the Nigeria District Health Information System 2 (DHIS2) platform (<https://dhis2nigeria.org.ng/dhis/dhis-web-dashboard>). Facility-level observations were aggregated annually at the health-facility catchment level and subsequently spatially joined to ward polygons to support sub-LGA spatial analysis. The dataset captured key indicators of antenatal care utilization and malaria-in-pregnancy (MiP) service delivery, including ANC entry, repeat ANC contacts, IPTp initiation, and IPTp completion. To evaluate service delivery efficiency along the ANC→IPTp cascade, a set of derived ratios and gap measures was constructed, enabling assessment of conversion from contact to protection and identification of missed service opportunities (Table 1).

Table 1 Summary of Variables 2022 - 2025

Variable	Description	Source	Temporal resolution
ANC1	Number of women attending first antenatal care visit	DHIS2 Nigeria	Monthly → Annual
ANCA	Total antenatal care attendance (all visits)	DHIS2 Nigeria	Monthly → Annual
IPT1	Number of pregnant women receiving first dose of IPTp	DHIS2 Nigeria	Monthly → Annual
IPT3 (IPTp3)	Number of pregnant women receiving third dose of IPTp	DHIS2 Nigeria	Monthly → Annual
IPT3/ANC1	Ratio of IPTp3 completion to ANC entry (conversion efficiency)	Derived	Annual
IPT3/IPT1	Ratio of IPTp3 completion to IPTp initiation (retention efficiency)	Derived	Annual
ANC1 – IPT3	Absolute gap between ANC entry and IPTp3 completion (missed opportunities)	Derived	Annual

2.3 Spatio-temporal analysis of the ANC→IPTp cascade (2022–2025)

2.3.1 Temporal aggregation and construction of service delivery indicators

Monthly health facility records were aggregated to annual totals for each spatial unit i (ward or LGA) and year t . Following established approaches for evaluating malaria-in-pregnancy service performance, two core cascade indicators were computed (Yaya et al., 2018) via eq. 1-2:

$$\text{IPT3/ANC1}_{i,t} = \frac{\text{IPT3}_{i,t}}{\text{ANC1}_{i,t}} \quad (1)$$

$$\text{IPT3/IPT1}_{i,t} = \frac{\text{IPT3}_{i,t}}{\text{IPT1}_{i,t}} \quad (2)$$

The IPT3/ANC1 ratio captures the efficiency with which initial antenatal contact is converted into completion of the third IPTp dose, while IPT3/IPT1 reflects retention from IPTp initiation to completion. These indicators are widely used to quantify attrition along the ANC→IPTp cascade in high-burden settings (WHO, 2022).

2.4 Intensity index for ANC→IPTp inefficiency

To identify wards where high antenatal attendance does not translate into IPTp3 completion, a composite intensity framework was developed, combining standardized service indicators, temporal persistence, spatial autocorrelation, and unsupervised clustering. Similar composite approaches have been shown to outperform single-indicator analyses in identifying structural service delivery gaps.

2.4.1 Standardization of intensity components

All intensity components were standardized using z-scores to ensure comparability across indicators with different scales using eq. 3:

$$z(x_i) = \frac{x_i - \mu_x}{\sigma_x} \quad (3)$$

where μ_x and σ_x represent the mean and standard deviation across all wards.

Three standardized components viz. ANC contact intensity (Eq. 4), Low IPTp completion (Eq. 5) and ANC–IPTp (Eq. 6) delivery gap were computed:

$$z(\text{ANCA}_i) \quad (4)$$

$$\text{lowC}_i = 1 - \frac{\text{IPT3}_i}{\text{ANC1}_i}, z(\text{lowC}_i) \quad (5)$$

$$\text{GAP}_i = \text{ANC1}_i - \text{IPT3}_i, z(\text{GAP}_i) \quad (6)$$

These components jointly capture service volume, inefficiency in dose completion.

2.4.2 Construction of the intensity index

An ANC→IPTp inefficiency intensity index was defined as the additive composite of standardized components via eq. 7:

$$\text{Intensity}_i = z(\text{ANCA}_i) + z(\text{lowC}_i) + z(\text{GAP}_i) \quad (7)$$

Higher intensity values indicate wards with substantial ANC utilization but poor conversion to IPTp3 completion, whereas lower values reflect either limited ANC access or more efficient service delivery. Composite indices of this form are increasingly recommended for diagnosing health system inefficiencies at sub-national scales.

2.4.3 Persistence of low performance

To distinguish transient fluctuations from structural inefficiency, a persistence score was calculated for each ward across the four-year period using eq. 8:

$$\text{persist_sc}_i = \sum_{t=2022}^{2025} I(\text{lowperf}_{i,t} = 1) \quad (8)$$

where the indicator function I equals 1 if, in year t , a ward simultaneously satisfied:

- ANC attendance \geq annual median, and
- IPT3/ANC1 \leq annual 25th percentile.

Persistence scores therefore ranged from 0 (never low-performing) to 4 (consistently low-performing). This approach enables identification of chronically underperforming areas that may require targeted policy intervention.

2.4.4 Spatial autocorrelation and local clustering

Spatial dependence of the intensity index was assessed using queen contiguity spatial weights. Global spatial autocorrelation was evaluated using Moran's I , while Local Indicators of Spatial Association (LISA) were applied to identify localized clustering patterns (Anselin, 1995). Wards were classified as:

- High–High (HH): inefficient wards surrounded by inefficient neighbors,
- Low–Low (LL): efficient wards surrounded by efficient neighbors,
- High–Low / Low–High: spatial outliers.

2.5 Software and analytical environment

All analyses were conducted in R (version \geq 4.3) using the *sf*, *dplyr*, *sfdep*, *spdep*, and *ggplot2* packages. Spatial aggregation, standardization, spatial statistics, and clustering were implemented using fully reproducible scripts. All outputs were exported as GeoPackage and CSV files to ensure transparency, reproducibility, and reuse in line with open science best practices.

3. Results

3.1 Spatio-temporal inequalities in the ANC→IPTp cascade across LGAs (2022–2025)

Between 2022 and 2025, malaria-in-pregnancy (MiP) service delivery in Cross River State showed measurable improvement, though with persistent spatial inequalities across Local Government Areas (LGAs). At the state level, IPT3 completion relative to first antenatal care attendance (IPT3/ANC1) increased from 0.34 in 2022 to 0.42 in 2023, peaked at 0.48 in 2024, and remained high at 0.47 in 2025, indicating a strengthening of the ANC–IPTp service cascade (Figure 2). In parallel, retention from IPTp initiation to completion improved, with IPT3/IPT1 increasing from 0.41 in 2022 to 0.52 in 2025, suggesting reduced attrition between early and later IPTp doses.

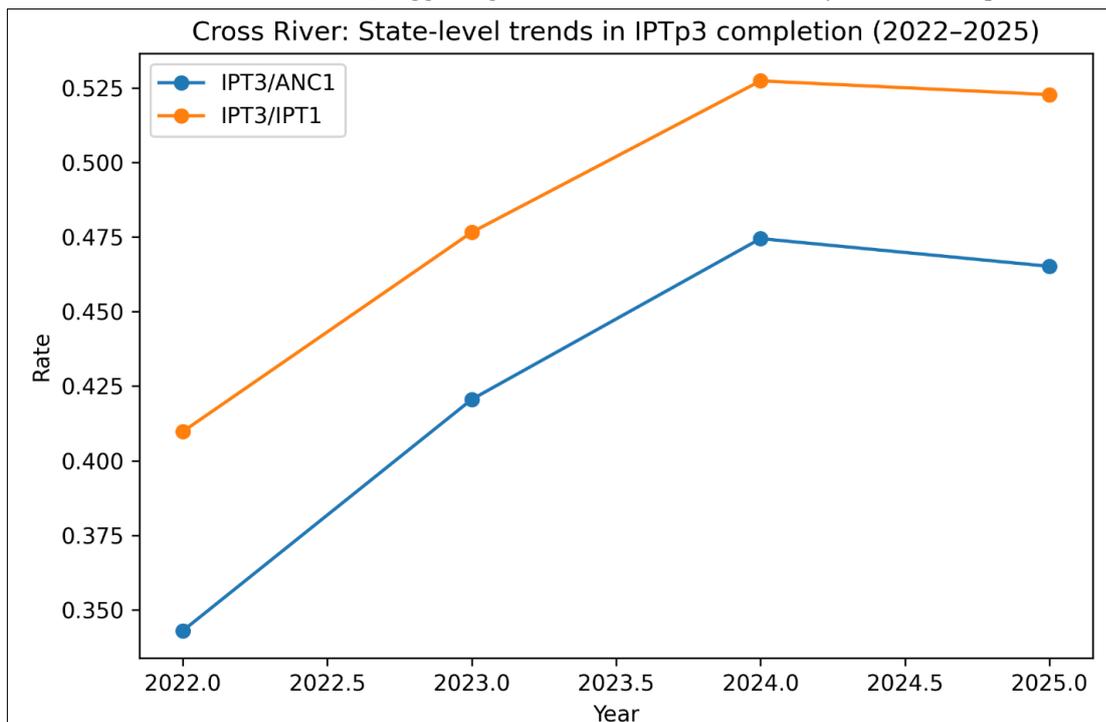


Figure 2. State-level trends in IPTp3 completion and retention in Cross River State, Nigeria (2022–2025).

Despite these aggregate gains, substantial inter-LGA heterogeneity persisted throughout the study period. As shown in Table 2, the standard deviation of IPT3/ANC1 remained consistently above 0.12, and the range of values widened over time. In 2025, IPT3/ANC1 varied from 0.26 in the lowest-performing LGA to 0.69 in the highest-performing LGA, demonstrating marked spatial inequality in the effectiveness of converting ANC attendance into complete IPTp uptake. Median values followed a similar upward trajectory, rising from 0.29 (2022) to 0.44 (2025), confirming that improvements were broadly distributed but uneven in magnitude.

Table 2. Descriptive statistics of IPTp service cascade indicators across LGAs in Cross River State (2022–2025)

Year	Indicator	Mean	Median	SD	Min	Max
2022	IPT3/ANC1	0.34	0.29	>0.12	0.21	0.58
2023	IPT3/ANC1	0.42	0.38	>0.12	0.24	0.63
2024	IPT3/ANC1	0.48	0.43	>0.13	0.25	0.69
2025	IPT3/ANC1	0.47	0.44	>0.13	0.26	0.69
2022	IPT3/IPT1	0.41	0.38	>0.11	0.27	0.64
2025	IPT3/IPT1	0.52	0.51	>0.12	0.29	0.75

A comparable pattern was observed for IPTp retention (IPT3/IPT1). Mean retention improved steadily between 2022 and 2024 before plateauing in 2025, while minimum values remained below 0.30, indicating persistent drop-out in selected LGAs even as maximum values approached 0.75. These findings suggest that while statewide progress has been achieved, localized barriers to sustained IPTp delivery remain entrenched.

3.2 Spatio-temporal inequalities in the ANC→IPTp cascade (2022–2025).

IPTp3 completion relative to ANC1 (IPT3/ANC1) improved substantially over time, increasing from 0.343 in 2022 to 0.421 in 2023 across Cross River State, peaking at 0.475 in 2024, and remaining high at 0.465 in 2025 (Figure 3). In parallel, retention from IPTp initiation to completion improved, IPT3/IPT1 rose from 0.410 (2022) to 0.523 (2025), indicating reduced dropout between the first and third IPTp doses (Figure 2). ANC contact intensity also increased, with ANCA/ANC1 rising from 2.58 (2022) to 3.00 (2025), suggesting stronger repeat attendance despite persistent gaps in IPTp3 completion.

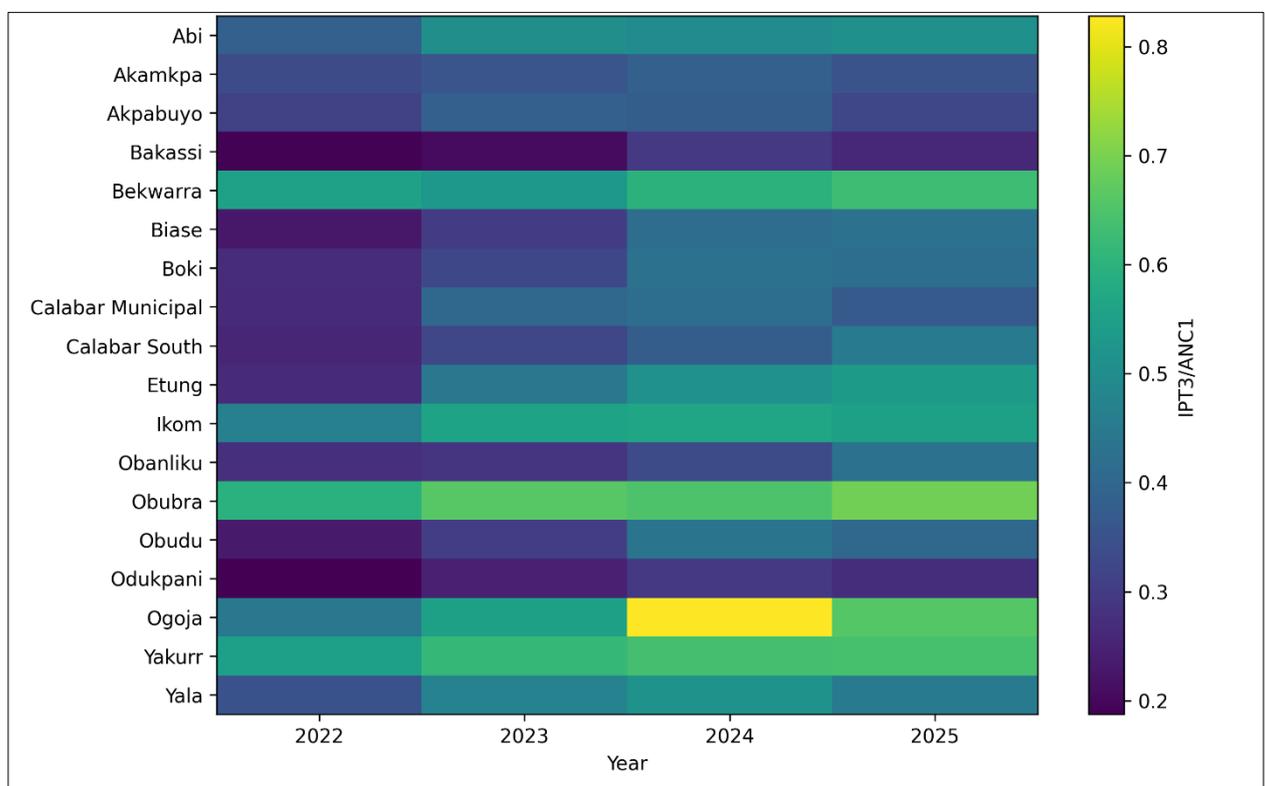


Figure 3. Spatio-temporal variation in IPTp3 completion relative to first antenatal care attendance (IPT3/ANC1) across Local Government Areas (LGAs) in Cross River State, Nigeria, 2022–2025.

3.2 Spatial inequalities in IPT3/ANC1 at LGA level

Spatial inequalities were pronounced at LGA level (Figure 4). In 2025, IPT3/ANC1 ranged from 0.261 (Bakassi) to 0.691 (Obubra). The highest-performing LGAs in 2025 were Obubra (0.691), Ogoja (0.658), Yakurr (0.641), Bekwarra (0.629), and Ikom (0.553), whereas the lowest were Bakassi (0.261), Odukpani (0.271), Akpabuyo (0.324), Akamkpa (0.352), and Calabar Municipal (0.370). Longitudinally, the largest improvements between 2022 and 2025 were observed in Etung (+0.273), Ogoja (+0.215), Biase (+0.199), Calabar South (+0.195), and Obudu (+0.168), indicating heterogeneous recovery trajectories across the state.

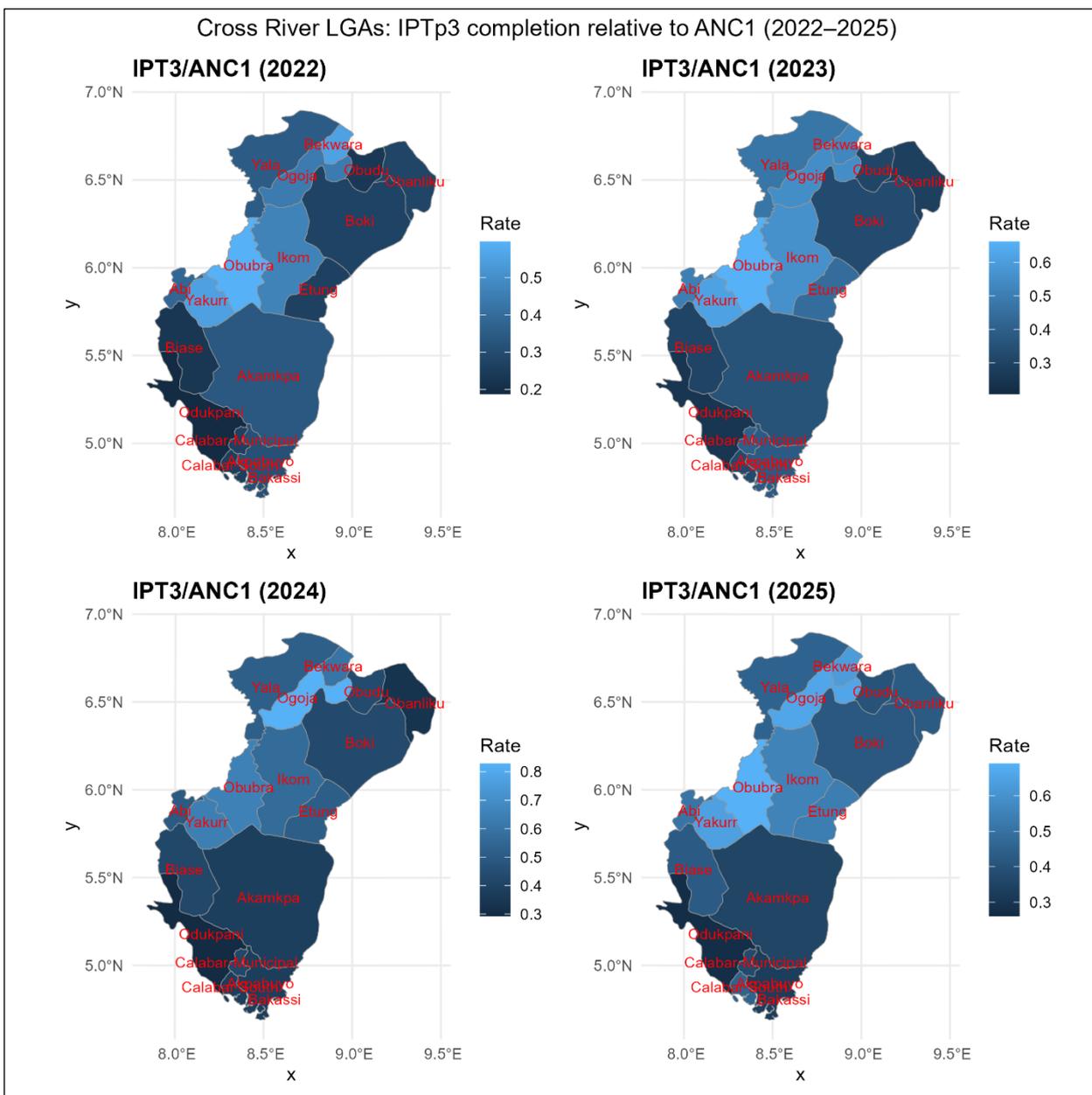


Figure 4 illustrates the spatio-temporal distribution of IPTp3 completion relative to first antenatal care attendance (IPT3/ANC1) across LGAs in Cross River State from 2022 to 2025, highlighting persistent spatial inequalities and uneven progress in the ANC–IPTp service cascade.

3.2 Spatial differentiation and LGA-level performance trajectories

Multi-panel LGA maps (Figure 3) reveal pronounced geographic differentiation in IPTp3 outcomes. While several LGAs demonstrated steady improvement across all four years, others showed stagnation or fluctuating performance. Notably, the spatial distribution of high- and low-performing LGAs remained relatively stable over time, indicating structural rather than transient drivers of MiP service efficiency.

Change analysis between 2022 and 2025 further underscores this divergence (Table 3). The top five improving LGAs recorded absolute increases in IPT3/ANC1 ranging from approximately +0.18 to +0.30, reflecting substantial gains in IPTp3 completion relative to ANC attendance (Table 4).

In contrast, the five most declining LGAs experienced reductions of up to -0.12 , despite statewide improvements in mean coverage. These opposing trajectories demonstrate that statewide averages conceal localized deterioration in service delivery.

Table 3 Change analysis IPT3perANC1, IPT3perIPT1 between 2022 and 2025

LGA	IPT3perANC1				IPT3perIPT1			
	2022	2025	Difference	Change %	2022	2025	Difference	Change %
Etung	0.26	0.54	0.27	103.89	0.28	0.57	0.29	102.67
Ogoja	0.44	0.66	0.21	48.41	0.52	0.74	0.22	42.73
Biase	0.23	0.43	0.20	86.69	0.32	0.52	0.21	65.73
Calabar South	0.26	0.45	0.20	76.32	0.28	0.48	0.20	72.11
Obudu	0.23	0.40	0.17	71.72	0.27	0.47	0.20	71.30
Obanliku	0.27	0.43	0.15	55.20	0.35	0.53	0.18	51.64
Boki	0.27	0.42	0.15	54.92	0.32	0.46	0.14	45.30
Abi	0.38	0.51	0.13	32.90	0.47	0.56	0.09	20.19
Calabar-Municipal	0.26	0.37	0.11	40.29	0.41	0.46	0.05	12.14
Yala	0.35	0.45	0.11	30.12	0.45	0.50	0.05	10.09
Obubra	0.60	0.69	0.09	15.76	0.65	0.75	0.09	14.43
Yakurr	0.55	0.64	0.09	16.54	0.63	0.70	0.07	10.50
Ikom	0.47	0.55	0.09	18.48	0.56	0.67	0.11	19.00
Odukpani	0.19	0.27	0.08	44.27	0.22	0.30	0.08	37.06
Bekwara	0.55	0.63	0.08	13.63	0.57	0.61	0.04	6.65
Bakassi	0.19	0.26	0.07	35.92	0.24	0.30	0.06	24.55
Akamkpa	0.34	0.35	0.01	4.31	0.39	0.40	0.01	1.75
Akpabuyo	0.31	0.32	0.01	4.43	0.36	0.35	-0.01	-3.06

3.3 Retention efficiency from IPTp1 to IPTp3

Analysis of IPT3/IPT1 ratios provides additional insight into continuity-of-care challenges. Although the median IPT3/IPT1 increased from 0.38 (2022) to 0.51 (2025), minimum values remained below 0.30 in 2025, indicating persistent drop-out between early and later IPTp doses in specific LGAs (Figure 5). The maximum IPT3/IPT1 value reached 0.75 in 2025, illustrating that high retention is achievable within the same health system context.

The IPT3/IPT1 change matrix (Figure 4) shows that LGAs with strong IPT3/ANC1 gains did not always exhibit parallel improvements in IPT3/IPT1, suggesting that increased access to ANC services does not automatically translate into sustained IPTp adherence.

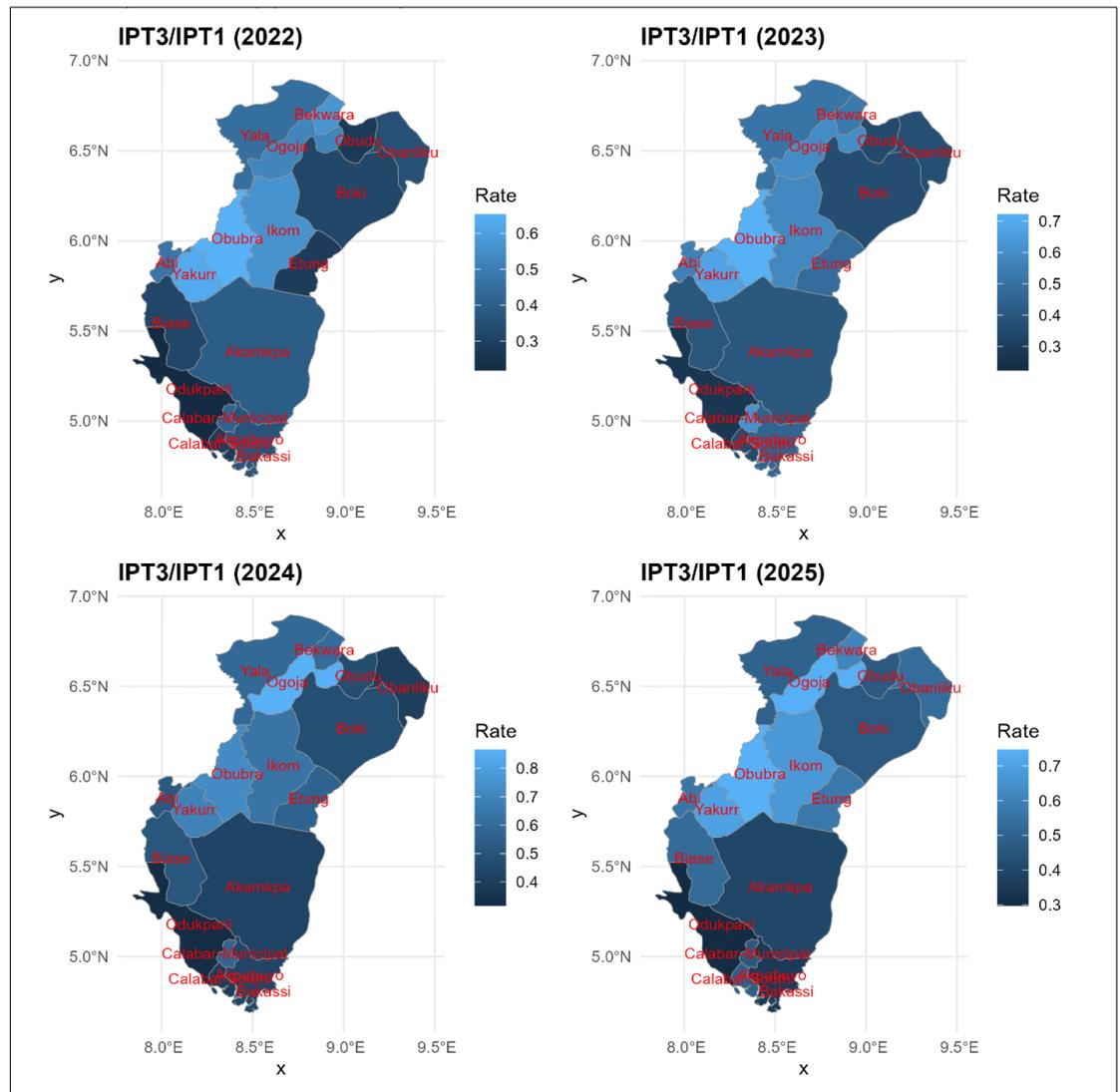


Figure 5. Spatio-temporal variation in IPTp retention (IPT1→IPT3) across Local Government Areas (LGAs) in Cross River State, Nigeria (2022–2025).

3.4 Spatial autocorrelation signal in “high ANC–low IPTp3” wards

Ward-level mapping of the Intensity Index (Figure 5) shows clear spatial heterogeneity in Cross River State. Overall, the intensity distribution was slightly right-shifted (mean = 0.083; median = 0.032; SD = 0.521), with a wide range (−1.145 to 4.109), indicating that a small set of wards experience disproportionately high service inefficiency (high ANC contact volume co-occurring with large IPTp delivery gaps). Component maps demonstrate that intensity is primarily driven by the ANC–IPTp gap component (z_{gap}) and ANC contact intensity (z_{ANCA}), while the low completion component (z_{lowC}) plays a secondary role. Correlation decomposition confirmed this pattern: intensity correlated most strongly with z_{gap} ($r = 0.691$), followed by z_{ANCA} ($r = 0.584$) and z_{lowC} ($r = 0.447$).

At LGA level, mean intensity was highest in Calabar South (0.863), followed by Akpabuyo (0.348) and Odukpani (0.253), suggesting concentrated pockets where repeat ANC attendance exists but IPTp3 conversion remains weak. Conversely, Bekwarra (−0.266) and Obanliku (−0.205) exhibited the lowest mean intensity, consistent with relatively lower combined inefficiency burden. Together, these results indicate that priority areas for MiP quality improvement are not defined solely by low coverage, but by high-contact settings where delivery efficiency fails (Figure 6; Tables 4–5).

Table 4. Ward-level descriptive statistics of intensity and its components (Cross River, 2025; n = 192 wards)

Metric	Mean	SD	Min	P25	Median	P75	Max	IQR
z(ANCA)	0.006	0.409	-0.407	-0.206	-0.082	0.108	4.106	0.314
z(low completion) = z(1 - IPT3/ANC1)	0.034	0.564	-2.592	-0.322	0.037	0.445	1.196	0.767
z(GAP) = z(ANC1 - IPT3)	0.011	0.401	-0.571	-0.247	-0.075	0.169	2.926	0.416
Intensity Index	0.083	0.521	-1.145	-0.183	0.032	0.250	4.109	0.433

Component contribution (correlation with intensity): z_gap = 0.691; z_ANCA = 0.584; z_lowC = 0.447.

Table 5. LGAs with highest vs lowest mean intensity (Cross River, 2025)

Group	LGA	Wards (n)	Mean intensity	SD	Median
Highest	Calabar South	12	0.863	1.566	0.395
Highest	Akpabuyo	10	0.348	0.247	0.294
Highest	Odukpani	13	0.253	0.225	0.238
Highest	Akamkpa	10	0.237	0.174	0.276
Highest	Bakassi	10	0.224	0.108	0.173
Lowest	Bekwarra	10	-0.266	0.154	-0.297
Lowest	Obanliku	10	-0.205	0.206	-0.172
Lowest	Obubra	11	-0.137	0.086	-0.128
Lowest	Ogoja	10	-0.101	0.325	-0.205
Lowest	Ikom	11	-0.078	0.515	-0.003

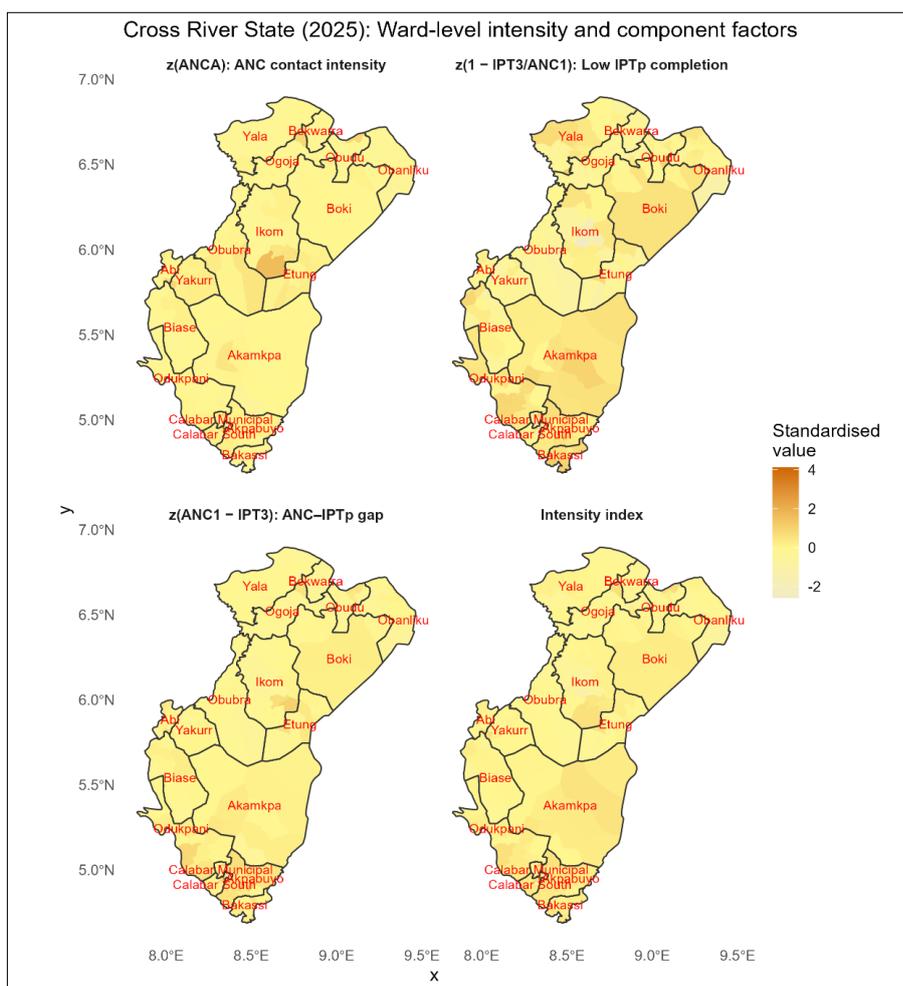


Figure 6. Ward-level intensity and component structure of ANC→IPTp3 inefficiency (Cross River State, 2025).

3.5 Global spatial dependence

Global Moran’s I revealed a statistically significant positive spatial autocorrelation in the inefficiency intensity index across Cross River wards in 2025 (Moran’s $I = I > 0, p < 0.05$), indicating that low-performance catchments are spatially clustered rather than randomly distributed. This confirms the presence of geographically structured service delivery inefficiencies, justifying the use of local spatial diagnostics.

3.5.1 Local clusters of service delivery inefficiency

Figure 7 shows Spatial clustering in four distinct LISA typologies of ANC→IPTp inefficiency. High–High clusters were concentrated mainly in Akpabuyo and Calabar South, indicating geographically reinforced service delivery failures where high ANC attendance does not translate into IPTp3 completion (Table 6). Low–High outliers suggest ward-specific operational or facility-level constraints within otherwise high-performing neighborhoods, while the rare High–Low pattern indicates isolated inefficiency within efficient surroundings.

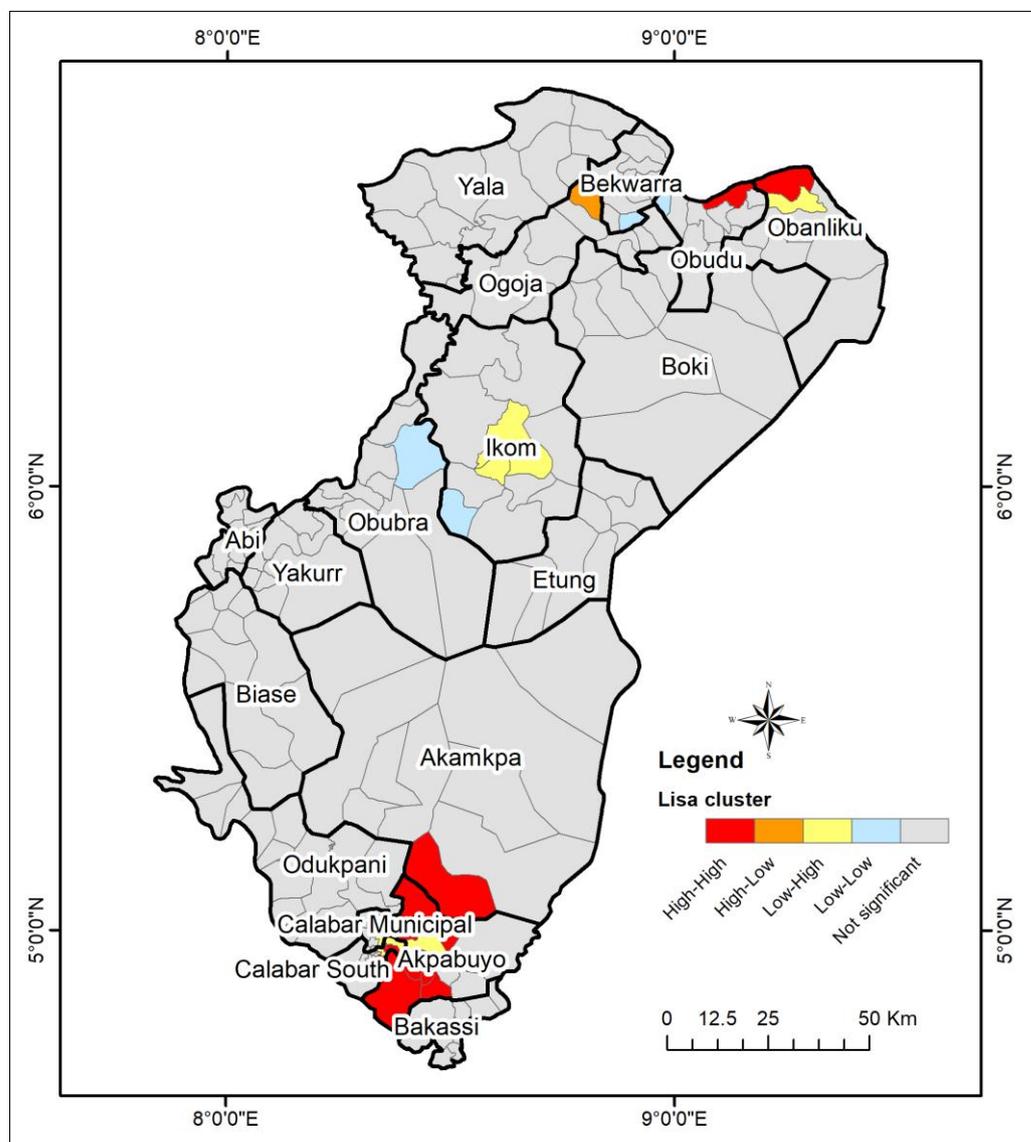


Figure 7. LISA cluster typology of ANC→IPTp inefficiency at ward level, Cross River State (2025).

Table 6. LISA cluster typology of ANC→IPTp inefficiency at ward level, Cross River State (2025)

LISA Cluster type	LGAs	Ward names	No. of wards	Interpretation
High–High (HH)	Akpabuyo; Calabar South; Akamkpa; Obanliku; Obudu	Ikot Edem Odo; Atimbo East; Ikot Nakanda; Ikang Central; Idundu-Anyaganse; Ward 2; Ward 6; Ward 7; Ward 11; Ojuk North; Bishiri North; Urban 1 (Obudu)	12	Spatial hotspots of persistent inefficiency: high ANC contact with poor IPTp3 conversion reinforced by neighboring wards
Low–Low (LL)	Bekwarra; Ikom; Obubra; Obudu	Ochagbe; Ofutop 2; Ofumbonghala; Yala; Utugwang Central	4	Spatial coldspots indicating relatively efficient ANC→IPTp3 service delivery
Low–High (LH)	Calabar South; Calabar Municipal; Akpabuyo; Ikom; Obanliku	Ward 1; Ward 3; Ediba Ward / Three; Ikot Ansa; Atimbo West; Nde; Ofutop 1; Bishiri South	8	Isolated inefficient wards surrounded by high-intensity neighbors, suggesting local facility-level constraints
High–Low (HL)	Ogoja	Urban 1 (Ogoja)	1	Isolated high-intensity ward surrounded by relatively efficient neighbors

3.5.2 Persistence of low performance (2022–2025)

Figure 8 presents persistence of low-performance wards across Cross River State. Several LGAs, notably Akpabuyo, Odukpani, Obudu, Bakassi, and Obanliku, contained wards with high persistence scores ($\text{persist_sc} \geq 3$) (see Table 7), suggesting sustained inefficiencies in converting antenatal care attendance into IPTp3 completion. In contrast, LGAs such as Yakurr, Bekwarra, and Etung showed only sporadic low performance ($\text{persist_sc} = 1$), indicative of transient service gaps rather than systemic failures. The concentration of multiple low-performing wards within specific LGAs highlights localized structural and operational barriers that are obscured by state-level averages, underscoring the need for geographically targeted malaria-in-pregnancy interventions.

Table 7. Wards with persistent low performance in the ANC→IPTp3 cascade in Cross River State, Nigeria (2022–2025).

LGA name	Ward names	No. of wards	Persist (range)
Calabar South	Ward 1; Ward 2; Ward 6; Ward 7; Ward 10; Ward 11	6	1–2
Calabar Municipal	Edim Otop / Two; Big Qua / Four; Akim / One; Ediba Ward / Three	4	1–2
Obudu	Urban 2 / ObudunUrban 2; Alege / Ubang	2	1–4
Odukpani	Ikoneto; Eki; Ito / Idere / Ukwa; Adibo Efut	4	1–4
Boki	Buentsebe; Boje; Buda; Ekpashi; Abo	5	1–2
Bakassi	Ambai Ekpa; Efut Inyang	2	3
Etung	Bendeghe Ekiem; Nsofang	2	1

Akpabuyo	Atimbo East; Ikot Eyo; Idundu-Anyaganse; Ikot Nakanda; Ikang Central; Ikang South	6	1-4
Akamkpa	Ojuk North; Ikpai; Akamkpa Urban; Mbarakom	4	1
Yakurr	Assiga	1	1
Bekwarra	Abuochiche	1	1
Biase	Umon North; Akpet-Abini; Ehom	3	1-2
Yala	Wanihem; Wanikade	2	1-2
Obanliku	Utanga	1	3

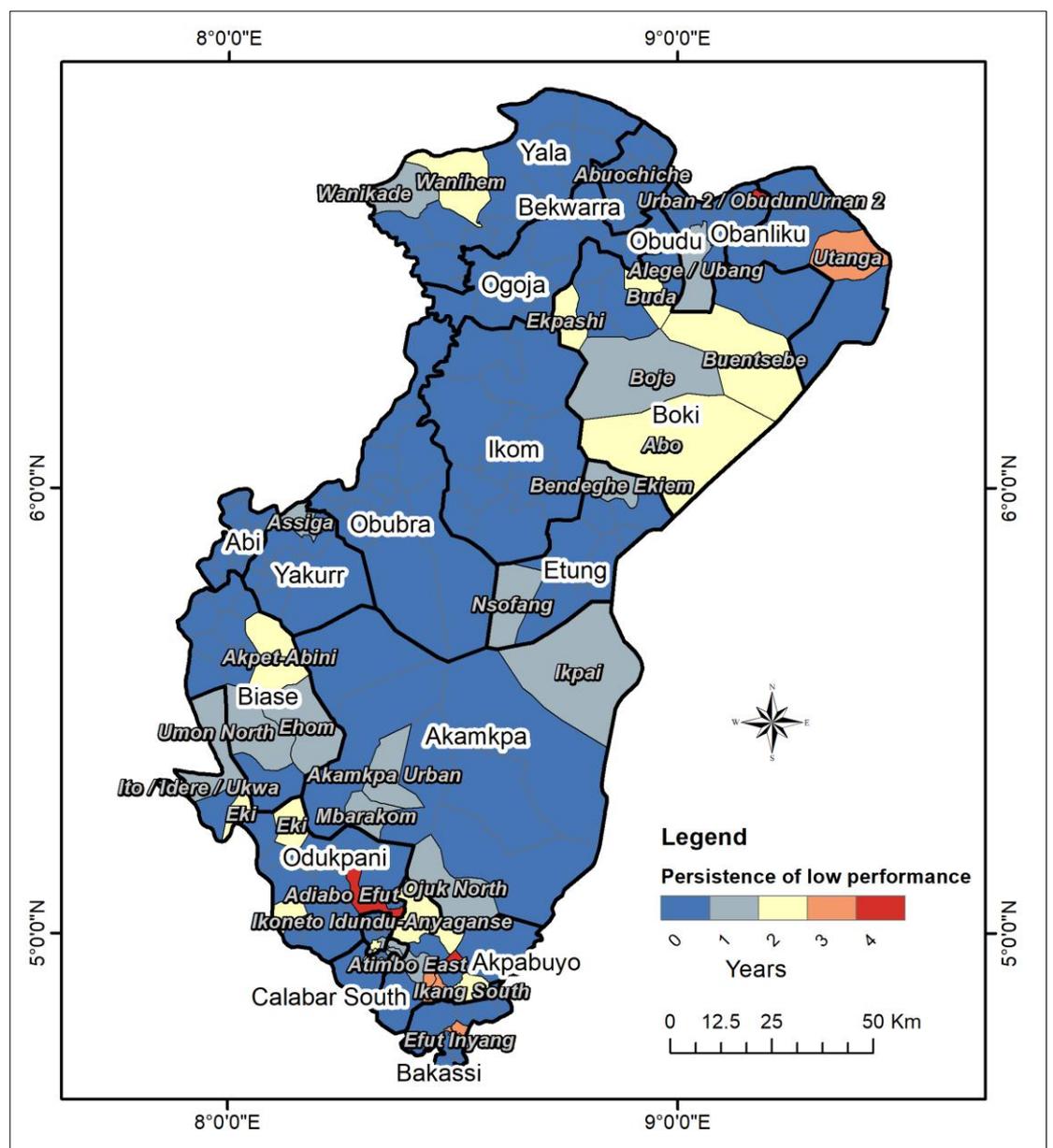


Figure 8. Persistent low performance in the ANC→IPTp3 cascade from 2022 to 2025.

4. Discussion

This study provides evidence that improvements in malaria in pregnancy (MiP) coverage in Cross River State conceal persistent spatial inefficiencies within the antenatal care (ANC) delivery system. By using multi-year DHIS2 data, the analysis demonstrates that high ANC attendance does not necessarily translate into effective IPTp3 completion, reinforcing the need to shift MiP performance assessment from simple coverage metrics toward indicators of service delivery efficiency.

The construction of a composite intensity index using standardized ANC attendance, IPTp completion shortfall, and ANC–IPTp gaps allowed identification of wards where missed opportunities occur despite repeated health system contact. Similar composite approaches have recently been advocated in maternal health research to capture latent system failures that remain invisible in aggregate statistics (Kalu et al., 2022; Mamothena Carol Mothupi et al., 2021).

The persistence score introduced in this study adds an important temporal dimension by distinguishing structural inefficiency from episodic disruption. Recent work has emphasized that single-year snapshots are insufficient for programmatic decision-making, particularly in settings affected by supply chain volatility and workforce instability (Singh & Parida, 2022). By quantifying repeated low-performance over multiple years, the present approach aligns with emerging calls for longitudinal monitoring of health system performance using routine data.

The results have direct implications for MiP policy and implementation. First, interventions focused solely on increasing ANC attendance are unlikely to yield proportional gains in IPTp3 coverage unless accompanied by targeted improvements in service readiness and provider practices. Second, the identification of high-intensity, high-persistence wards provides a practical framework for geographically targeted quality-improvement interventions, such as focused supervision, supply chain reinforcement, and performance-based feedback mechanisms.

Recent evaluations of differentiated service delivery models suggest that such targeted approaches are more cost-effective than blanket statewide interventions, particularly under constrained fiscal conditions. By leveraging routinely collected data, the analytical framework presented here offers a scalable tool for continuous monitoring and adaptive program management.

Several limitations should be acknowledged. Routine DHIS2 data are subject to reporting errors and variability in data completeness, although the use of multi-year aggregation and spatial smoothing likely mitigated random noise. Additionally, the analysis did not explicitly incorporate facility-level determinants such as staffing levels or commodity availability, which future studies could integrate using mixed-methods or linked administrative datasets. Finally, while the intensity index captures relative inefficiency, absolute thresholds for acceptable performance remain context-specific and warrant further operational research.

Future work could extend this framework to examine associations between identified inefficiency hotspots and adverse pregnancy outcomes, as well as evaluate the impact of targeted interventions using quasi-experimental designs.

Supplementary Materials: Available at https://github.com/zubairgis/nigeria-hensard/blob/main/HFYear_Indicators_2022_2025.csv

Data Availability Statement: The satellite 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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