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Identifying Hidden Severe Malaria Burden, Treatment Gaps, and Priority Investment Areas in Kano State, Nigeria, via an Accessibility-Adjusted Geospatial Index

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Abstract

Malaria remains a major public health challenge in northern Nigeria, yet substantial spatial inequalities persist in severe malaria burdens, treatment access, and healthcare service delivery. This study developed a geospatial framework to identify hidden severe malaria burdens and prioritize underserved local government areas (LGAs) for malaria investments in Kano State, Nigeria. Annual severe malaria surveillance records, artesunate treatment data, population distributions, health facility locations, nighttime light intensities, and malaria endemicity indicators from the Malaria Atlas Project were integrated at the LGA level. A hidden burden–treatment gap index (HBTGI) was first developed to identify LGAs where the severe malaria burden exceeded the observed treatment response. An Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI) was subsequently constructed by combining disease burden, treatment deficits, healthcare accessibility, and socioeconomic indicators. Kano State recorded 190,875 severe malaria cases, 170,995 of which received artesunate treatment, leaving an estimated treatment gap of 24,425 cases. The HBTGI revealed pronounced spatial disparities, with Gwarzo, Tsanyawa, Bichi, Rogo, and Dambatta exhibiting the greatest hidden burden–treatment gaps. The AASMTGI identified Gwarzo, Dambatta, Rogo, Takai, and Dawakin Tofa as the highest-priority LGAs for malaria investment. Correlation analysis indicated that treatment deficits and severe malaria burden were the strongest determinants of investment priority. The proposed framework provides a practical decision-support tool for geographically targeted malaria interventions and resource allocation in high-burden settings.

Keywords: malaria seasonality; climate suitability; AgERA5; transmission windows; Nigeria.

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1. Introduction

Malaria remains one of the most significant public health challenges worldwide, with sub-Saharan Africa accounting for approximately 94% of all malaria cases and deaths worldwide [1]. Despite substantial investments in vector control, diagnosis, treatment, and surveillance, progress toward malaria elimination has slowed in recent years, particularly in high-burden countries where transmission remains persistent and unevenly distributed [1,2]. Nigeria bears the largest malaria burden globally, contributing more than one quarter of all reported malaria cases and deaths worldwide [1]. The disease continues to have profound health, social, and economic impacts, particularly among children under five years of age and pregnant women, while placing considerable strain on already constrained healthcare systems [3,4].

Although substantial attention has been given to overall malaria incidence and prevalence, severe malaria remains a major cause of mortality and hospitalization across many regions of Nigeria [5]. Severe malaria represents the most life-threatening manifestation of the disease and requires rapid diagnosis and treatment with injectable artesunate to prevent fatal outcomes [6]. Consequently, understanding the spatial relationship between severe malaria burden and treatment coverage is essential for improving resource allocation and strengthening health-system responses. However, routine surveillance statistics often focus on reported case counts without adequately accounting for treatment gaps, healthcare accessibility, population exposure, or underlying malaria endemicity. As a result, areas with substantial unmet treatment needs may remain hidden within aggregated statistics, limiting the effectiveness of intervention planning and investment prioritization [7].

Recent advances in geospatial epidemiology have demonstrated the value of integrating disease surveillance data with environmental, demographic, and healthcare-access indicators to identify spatial inequalities in health outcomes [8–10]. Geographic information systems (GISs), remote sensing, and spatial modeling techniques have increasingly been applied to malaria research to characterize transmission patterns, estimate population-at-risk, assess healthcare accessibility, and identify priority intervention areas [11–13]. Studies have shown that spatial variations in the malaria burden are influenced not only by environmental suitability and transmission intensity but also by population density, healthcare infrastructure, socioeconomic conditions, and accessibility to treatment services [14–16]. Consequently, geographically targeted interventions are increasingly recognized as more efficient and cost-effective than uniform allocation strategies [17].

Several studies have employed malaria prevalence surfaces from the Malaria Atlas Project (MAP) and gridded population datasets to investigate malaria risk and intervention effectiveness across Africa [18–20]. However, most existing studies have focused primarily on malaria transmission risk, parasite prevalence, or environmental determinants, whereas comparatively little attention has been given to the relationship between severe malaria burden and treatment response. Furthermore, healthcare accessibility and service availability are frequently considered separately from disease burden, despite growing evidence that treatment outcomes are strongly influenced by spatial access to healthcare facilities and local service capacity [21–23]. This creates an important knowledge gap for malaria control programmes seeking to identify areas where the disease burden remains high despite ongoing interventions.

Kano State represents an important case study for examining these challenges. As one of the most populous states in Nigeria, Kano experiences substantial malaria transmission and considerable heterogeneity in healthcare accessibility, urbanization, and population density. These characteristics provide an opportunity to investigate how severe the malaria burden, treatment coverage, healthcare accessibility, and malaria endemicity interact spatially across local administrative units. Identifying LGAs where treatment response is disproportionately low relative to disease burden can provide valuable evidence for targeted intervention planning and resource allocation.

Therefore, this study aimed to (i) identify LGAs where the severe malaria burden exceeds the expected treatment coverage after accounting for population size, malaria endemicity, healthcare accessibility, and service availability and (ii) develop an Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI) to prioritize underserved LGAs for malaria investments. By integrating routine severe malaria surveillance records, artesunate treatment data, health facility locations, population distributions, nighttime light intensities, and malaria endemicity indicators derived from the Malaria Atlas Project, this study provides a comprehensive geospatial framework for identifying hidden treatment deficits and investment priorities. The results reveal substantial spatial disparities in severe malaria burden and treatment coverage across Kano State, with several LGAs exhibiting disproportionately high disease burdens relative to treatment response and healthcare accessibility. These findings demonstrate the value of accessibility-adjusted geospatial indices for supporting evidence-based malaria control planning and geographically targeted investments in high-burden settings.

2. Materials and methods

2.1 Study area

Kano State is located in northwestern Nigeria between approximately 10°33′–13°02′ N latitude and 7°40′–10°37′ E longitude. The state covers an area of approximately 20,131 km² and is administratively divided into 44 local government areas (LGAs). Kano is the most populous state in Nigeria, with an estimated population exceeding 15 million people, making it one of the country's most important economic, commercial, and demographic centers. The state shares boundaries with Jigawa State to the east, Katsina State to the north and west, and Bauchi and Kaduna States to the south.

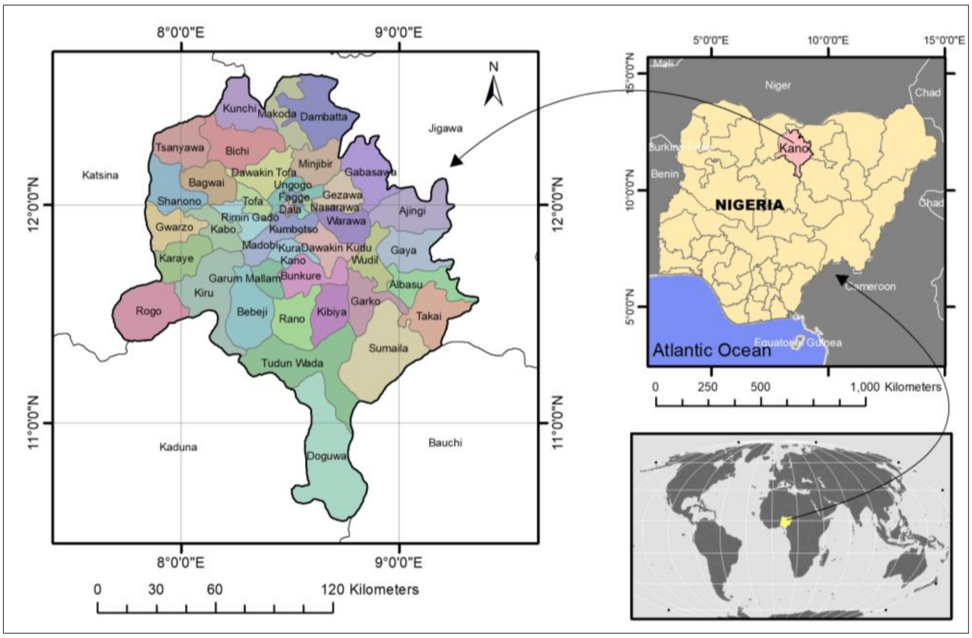


Figure 1. Location and extent of Nigeria.

The climate of Kano State is characterized by a tropical savanna (Aw) climate, with distinct wet and dry seasons controlled by the seasonal movement of the Intertropical Convergence Zone (ITCZ). The rainy season typically extends from May to October, whereas the dry season prevails from November to April. The mean annual rainfall generally ranges from 600 to 1,000 mm, with precipitation decreasing northward. The average temperatures remain high throughout the year, commonly exceeding 25°C, with maximum temperatures frequently surpassing 35°C during the prerainy season. These climatic conditions provide favorable environments for seasonal malaria transmission and vector proliferation.

The state exhibits considerable spatial variation in population density, urbanization, healthcare infrastructure, and socioeconomic development. The Kano Metropolitan Area contains densely populated urban LGAs with relatively greater access to health services, whereas many rural LGAs experience lower health facility density and reduced accessibility to healthcare. These disparities contribute to differences in disease surveillance, healthcare utilization, treatment coverage, and malaria outcomes across the state.

Kano remains one of Nigeria's malaria-endemic states and contributes substantially to the national malaria burden. The combination of high population density, persistent malaria transmission, varying healthcare accessibility, and substantial socioeconomic heterogeneity makes Kano an appropriate setting for investigating hidden severe malaria burdens, treatment inequities, and spatial prioritization of malaria control investments. The state's diverse epidemiological and healthcare landscape provides an opportunity to identify LGAs where the severe malaria burden remains disproportionately high relative to the available treatment response and healthcare service capacity.

2.2 Study Design and Analytical Workflow

The analytical framework adopted in this study is presented in **Figure 2**. The workflow consisted of four sequential stages: (i) data integration, (ii) burden–response metric development, (iii) accessibility-adjusted index modeling, and (iv) investment prioritization. First, multiple geospatial and epidemiological datasets, including severe malaria cases, artesunate treatment records, population distributions, health facility locations, malaria endemicity indicators, and nighttime light data, were integrated within a common spatial framework and aggregated to the local government area (LGA) level for Kano State.

Subsequently, key burden–response metrics, including the severe malaria burden rate (SMR), treatment coverage (TCOV), treatment gap (TG), and health facility density (HFD), were derived. These indicators were used to characterize the magnitude of severe malaria burden, treatment performance, and healthcare accessibility across LGAs. In the third stage, the indicators were standardized and combined into three thematic components: the Burden–Endemicity Index (BEI), Treatment Gap Index (TGI), and Accessibility Weakness Index (AWI). These components were integrated via a weighted composite approach to generate the Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI), which was subsequently normalized to a 0–100 scale to facilitate comparisons among LGAs.

Finally, LGAs were classified into five investment-priority tiers ranging from immediate priority (Tier 1) to lowest priority (Tier 5). The resulting framework enabled the identification of locations characterized by high severe malaria burdens, inadequate treatment coverage, and weak healthcare accessibility, thereby providing an evidence-based decision-support system for targeted malaria intervention planning and resource allocation.

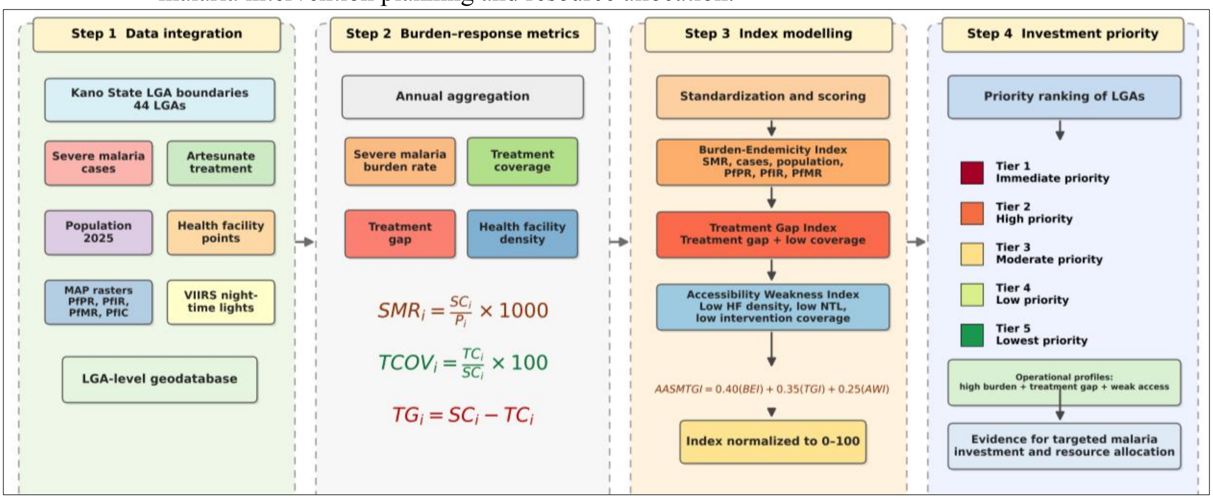


Figure 2. Conceptual framework illustrating the study design and analytical workflow used to develop the Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI) for identifying priority LGAs for malaria investment in Kano State, Nigeria.

2.3 Data Sources

Multiple epidemiological, demographic, environmental, and healthcare datasets were integrated to quantify severe malaria burden, evaluate treatment coverage, and identify priority LGAs for malaria intervention. Severe malaria surveillance records and treatment data were obtained from Nigeria's routine health information system and aggregated at the local government area (LGA) level. Population exposure was estimated via a 2025 gridded population surface, whereas malaria transmission intensity was characterized via malaria endemicity products from the Malaria Atlas Project. Healthcare access and service availability were represented via health facility locations and nighttime light intensity as proxies for socioeconomic development and infrastructure. All datasets were harmonized to a common geographic reference system and analyzed at the LGA level via geospatial overlay, zonal statistics, and composite index modeling.

Table 1. Summary of datasets used in the study.

Data Name	**Data Type**	**Purpose**	**Source**
Severe Malaria Cases	Vector (LGA)	Disease burden	RHIS/DHIS2
Severe Malaria Treated	Vector (LGA)	Treatment coverage	RHIS/DHIS2
Health Facilities	Vector (Point)	Service availability	GRID3
Population 2025	Raster	Population	WorldPop
PfPR 2024	Raster	Malaria prevalence	Malaria Atlas Project
PfIR 2024	Raster	Infection intensity	Malaria Atlas Project
PfMR 2024	Raster	Malaria mortality	Malaria Atlas Project
PfIC 2024	Raster	Clinical incidence	Malaria Atlas Project
PfMC 2024	Raster	Clinical burden	Malaria Atlas Project
VIIRS Nighttime Lights 2025	Raster	Development proxy	NASA/NOAA VIIRS
Administrative Boundaries	Vector (Polygon)	Spatial aggregation	OCHA Nigeria

Abbreviations: 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.

2.3 Data Preprocessing

Prior to analysis, all the datasets were harmonized to ensure spatial and thematic consistency. Administrative boundaries, severe malaria records, treatment records, health facility locations, and ancillary spatial datasets were projected to a common coordinate reference system (WGS 84) and checked for geometric validity. Attribute tables were inspected for missing values, duplicate records, inconsistent administrative names, and coding errors. LGA names and administrative identifiers were standardized to ensure accurate spatial joins among epidemiological, demographic, and environmental datasets.

The monthly severe malaria case records and severe malaria treatment records were aggregated into annual totals for each local government area (LGA). Health facility point data were spatially overlaid with administrative boundaries to calculate the number of facilities within each LGA. Population exposure was estimated by extracting zonal population totals from the 2025 WorldPop raster. Similarly, the mean values of malaria endemicity indicators, including the parasite prevalence rate (PfPR), parasite infection rate (PfIR), parasite mortality rate (PfMR), parasite incidence cases (PfIC), and parasite malaria cases (PfMC), were extracted from raster datasets via zonal statistics. The mean nighttime light intensity was also extracted for each LGA as a proxy indicator of socioeconomic development and infrastructure availability.

To improve comparability among variables measured in different units, continuous variables were transformed and standardized prior to index construction. Highly skewed variables, including severe malaria counts and population totals, were log-transformed as follows:

$$X_{log} = \ln(X + 1) \tag{1}$$

The variables used in the Hidden Burden–Treatment Gap Index were subsequently standardized via z score normalization:

$$Z(X) = \frac{X - \mu}{\sigma} \tag{2}$$

where X is the original value, μ is the mean, and σ is the standard deviation.

For the Accessibility-Adjusted Severe Malaria Treatment Gap Index, variables were normalized to a common 0–100 scale via min–max normalization:

$$X' = 100\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \tag{3}$$

The resulting geodatabase contained, for each LGA, the annual severe malaria burden, treatment coverage, treatment gaps, population exposure, health facility density, malaria endemicity indicators, and nighttime light intensity. These processed datasets formed the basis for the subsequent burden assessment, treatment-gap analysis, and accessibility-adjusted prioritization modeling.

2.4 Data analysis

2.4.1 Identification of Hidden Severe Malaria Burden and Treatment Inequity

A geospatial analytical framework was developed to identify local government areas (LGAs) where the severe malaria burden exceeded the observed treatment coverage after accounting for population size, malaria endemicity, healthcare infrastructure, and development conditions. The analysis was conducted for Kano State, Nigeria, using annual severe malaria surveillance records, records of severe malaria cases treated with injectable artesunate, gridded malaria prevalence products from the Malaria Atlas Project, population distribution data, nighttime lights, and health facility locations.

The monthly severe malaria counts and monthly artesunate treatment records were aggregated into annual totals for each LGA. The annual severe malaria burden (SC_i) and annual treated severe malaria cases (TC_i) were calculated as follows:

$$SC_i = \sum_{m=1}^{12} SC_{im} \tag{4}$$

$$TC_i = \sum_{m=1}^{12} TC_{im} \tag{5}$$

where SC_{im} and TC_{im} represent monthly severe malaria cases and treated cases recorded in LGA i during month m.

The population exposure was quantified via the 2025 population raster. The total population within each LGA was extracted through zonal summation:

$$P_i = \sum_{j=1}^{n} p_j \tag{6}$$

where p_j represents the population value within raster cell j.

Malaria endemicity indicators were obtained from the Malaria Atlas Project and included the parasite prevalence rate ($PfPR$), parasite infection rate ($PfIR$), parasite mortality rate ($PfMR$), and parasite intervention coverage ($PfIC$). The mean values of each raster were extracted for all LGAs via exact zonal statistics.

The severe malaria burden rate was computed as follows:

$$SMR_i = \frac{SC_i}{P_i} \times 1000 \tag{7}$$

where SMR_i denotes severe malaria cases per 1,000 people.

The observed treatment coverage was calculated as follows:

$$TCOV_i = \frac{TC_i}{SC_i} \times 100 \quad (8)$$

The absolute treatment gap was estimated as:

$$TG_i = SC_i - TC_i \quad (9)$$

and the population-adjusted treatment gap rate as:

$$TGR_i = \frac{TG_i}{P_i} \times 1000 \quad (10)$$

Health facility density was calculated as follows:

$$HFD_i = \frac{HF_i}{P_i} \times 100000 \quad (11)$$

where HF_i represents the number of health facilities within LGA i.

To allow comparisons among variables measured on different scales, all indicators were standardized via z score transformation:

$$Z(X) = \frac{X - \mu}{\sigma} \quad (12)$$

where X is the original value, μ is the mean, and σ is the standard deviation.

A composite burden score was computed as:

$$BS_i = Z(\ln(SMR_i + 1)) + Z(PfPR_i) + Z(PfIR_i) + Z(PfMR_i) + Z(\ln(P_i + 1)) \quad (13)$$

A response capacity score was then calculated as follows:

$$RCS_i = Z(TCOV_i) + Z(HFD_i) + Z(NTL_i) + Z(PfIC_i) \quad (14)$$

where NTL_i denotes the average nighttime light intensity.

The Hidden Burden–Treatment Gap Index (HBTGI) was derived as follows:

$$HBTGI_i = BS_i - RCS_i \quad (15)$$

Higher values indicate that LGAs experience disproportionately high severe malaria burdens relative to the available treatment response and service capacity.

For comparison across LGAs, the index was rescaled to a 0–100 range:

$$HBTGI_i^* = 100\left(\frac{HBTGI_i - HBTGI_{min}}{HBTGI_{max} - HBTGI_{min}}\right) \quad (16)$$

The resulting values were classified into five categories representing very low, low, moderate, high, and very high hidden burden–treatment gap classes via quantile-based thresholds. Additional burden–treatment mismatch typologies were generated to distinguish high-burden–low-burden treatment LGAs from other combinations of disease burden and treatment performance.

2.4.2 Accessibility-Adjusted Severe Malaria Treatment Gap Index

To support malaria investment planning and intervention targeting, an Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI) was developed to identify LGAs where severe malaria burden, treatment deficits, and healthcare accessibility constraints occur simultaneously.

All variables were first normalized to a common scale via min–max normalization:

$$X' = 100\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \quad (17)$$

Three thematic subindices were subsequently constructed.

The burden and endemicity index (BEI) was used to quantify disease pressure and transmission intensity:

$$BEI = 0.30(SMR) + 0.20(SC) + 0.15(P) + 0.20(PfPR) + 0.10(PfIR) + 0.05(PfMR) \quad (18)$$

where all variables represent normalized scores.

The treatment gap index (TGI) measures deficits in severe malaria management:

$$TGI = 0.60(TG) + 0.40(100 - TCOV) \quad (19)$$

The Accessibility Weakness Index (AWI) represents limitations in healthcare access and service availability:

$$AWI = 0.45(100 - HFD) + 0.35(100 - NTL) + 0.20(100 - PfIC) \quad (20)$$

The final Accessibility-Adjusted Severe Malaria Treatment Gap Index was calculated as

$$AASMTGI = 0.40(BEI) + 0.35(TGI) + 0.25(AWI) \quad (21)$$

where greater weight was assigned to disease burden and treatment deficits while retaining the influence of accessibility constraints.

The final index was standardized to a 0–100 range:

$$AASMTGI^{*} = 100\left(\frac{AASMTGI - AASMTGI_{min}}{AASMTGI_{max} - AASMTGI_{min}}\right) \quad (22)$$

LGAs were subsequently classified into five investment-priority categories ranging from very low to very high priority. A tiered prioritization framework based on percentile thresholds was also developed to identify immediate investment priorities, high-priority intervention zones, moderate-priority areas, and lower-priority LGAs.

To evaluate the robustness of the prioritization framework, a sensitivity analysis was conducted via an equal-weight formulation:

$$AASMTGI_{EW} = \frac{BEI + TGI + AWI}{3} \quad (23)$$

Differences between weighted and equal-weight rankings were examined to assess the stability of the prioritization outcomes. Spearman rank correlation analysis was additionally applied to evaluate the relationships among severe malaria burden, treatment coverage, accessibility indicators, malaria endemicity metrics, and final investment-priority scores. This approach enabled the identification of LGAs where the severe malaria burden remained disproportionately high despite limited treatment response and healthcare accessibility, thereby supporting evidence-based allocation of malaria control resources.

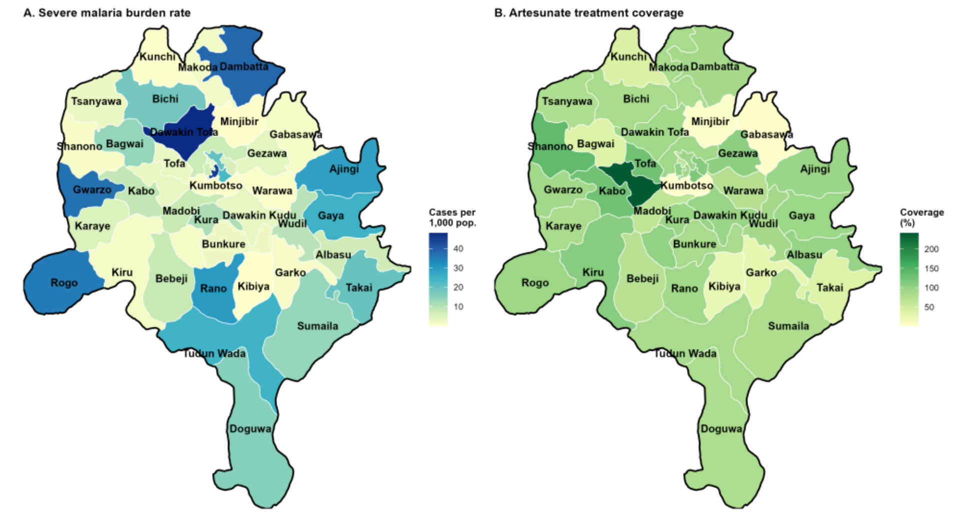
3. Results

3.1 Spatial distribution of severe malaria burden and treatment coverage

A total of 190,875 severe malaria cases were recorded across the 44 LGAs of Kano State, of which 170,995 cases received artesunate treatment, leaving approximately 24,425 untreated or inadequately treated cases. The state has an estimated population of 15.53 million people, corresponding to an average severe malaria burden of 12.44 cases per 1,000 people and an overall treatment coverage of 84.18%.

Substantial spatial heterogeneity was observed in both disease burden and treatment performance (Figure 3).

Figure 3. Severe malaria burden and artesunate treatment coverage across Kano LGAs

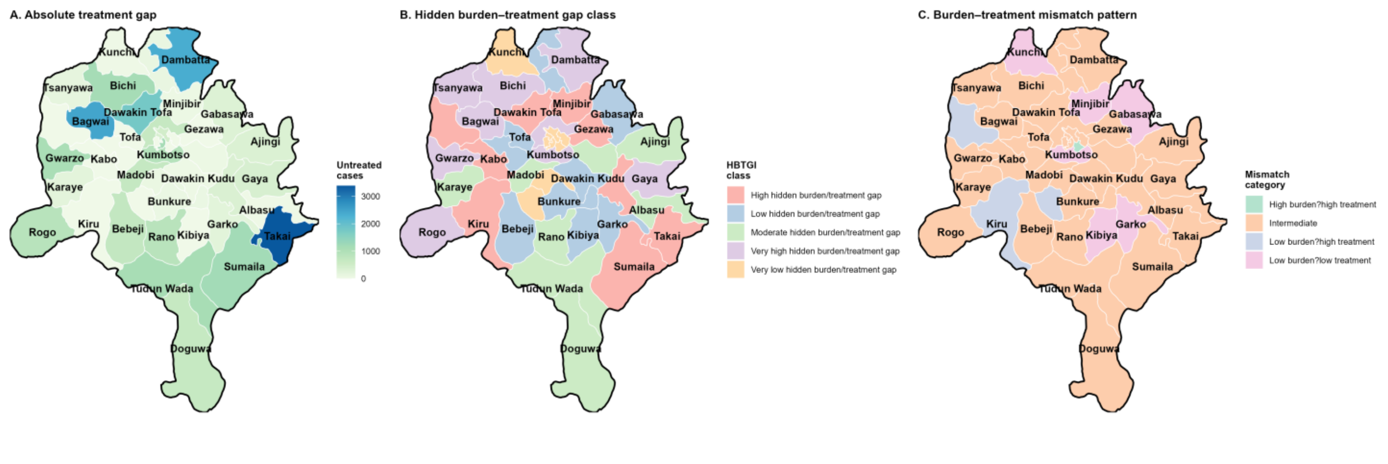


The highest severe malaria burden rates occurred in Dawakin Tofa (47.99 cases per 1,000 population), Dambatta (38.49), Gwarzo (36.90), and Rogo (35.30), identifying a cluster of high-transmission LGAs in central and northern Kano. In contrast, urban and peri-urban LGAs such as Kumbotso, Minjibir, and Warawa recorded very low burden rates, generally less than 1 case per 1,000 people. Treatment coverage remained relatively high across most LGAs; however, marked local variations were evident, indicating that high treatment performance at the state level masks important subnational disparities in access to severe malaria management.

3.2 Hidden Burden–Treatment Gaps and Mismatch Patterns

The hidden burden–treatment gap index (HBTGI) revealed pronounced spatial inequalities in the relationship between severe malaria burden and treatment response (Figure 4). The highest HBTGI scores were observed in Gwarzo (100.0), Tsanyawa (89.0), Bichi (86.9), Rogo (86.9), and Dambatta (83.5), indicating LGAs where treatment provision remained insufficient relative to disease burden.

Figure 4. Treatment gap, hidden burden classes, and burden–treatment mismatch patterns



The classification of LGAs into HBTGI categories revealed that nine LGAs (20.45%) were classified as very high burden–treatment gap areas, whereas another nine LGAs (20.45%) fell within the high category. Moderate burden–treatment gaps accounted for eight LGAs (18.18%), whereas the remaining 18 LGAs (40.90%) were categorized as low or very low burden–treatment gap areas.

Burden–treatment mismatch analysis further highlighted operational disparities. Most LGAs (77.27%) exhibited intermediate mismatch patterns, indicating moderate correspondence between disease burden and treatment response. However, several LGAs have displayed notable inconsistencies. Kumbotso and Minjibir presented very low severe malaria rates but poor treatment performance, whereas LGAs such as Gaya, Rogo, and Dawakin Tofa maintained treatment coverage exceeding 90% despite substantial disease burden.

3.3 Priority LGAs Identified by the Hidden Burden–Treatment Gap Index

The continuous surface area of the HBTGI revealed clear geographic concentrations of unmet severe malaria management needs across Kano State (Figure 5).

Figure 5. Priority LGAs based on the Hidden Burden–Treatment Gap Index

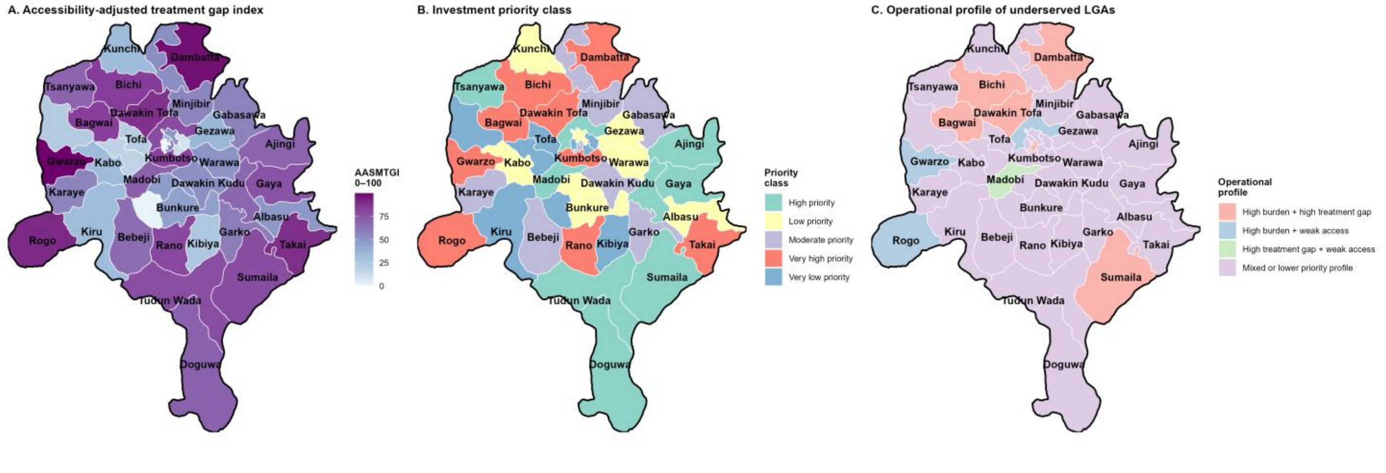
The highest-priority LGAs included Gwarzo, Tsanyawa, Bichi, Rogo, Dambatta, Bagwai, Kumbotso, Ungogo, and Gaya. These LGAs consistently combined elevated disease burden, substantial treatment deficits, high malaria endemicity, or limited healthcare service capacity.

The spatial distribution of the HBTGI scores suggests that the hidden malaria burden is concentrated within a relatively small number of LGAs rather than being uniformly distributed across the state. This pattern indicates that targeted intervention strategies may yield greater programmatic impact than broad state-wide resource allocation approaches.

3.4 Accessibility-Adjusted Severe Malaria Treatment Gap Index and Investment Priority Classes

Integration of the epidemiological burden, treatment performance, malaria endemicity, healthcare accessibility, intervention coverage, and socioeconomic accessibility produced the Accessibility-Adjusted Severe Malaria Treatment Gap Index (AASMTGI) (Figure 6). AASMTGI values ranged from 0--100, revealing substantial variation in malaria investment needs among LGAs.

Figure 6. Accessibility-adjusted severe malaria treatment gap and investment priority classes



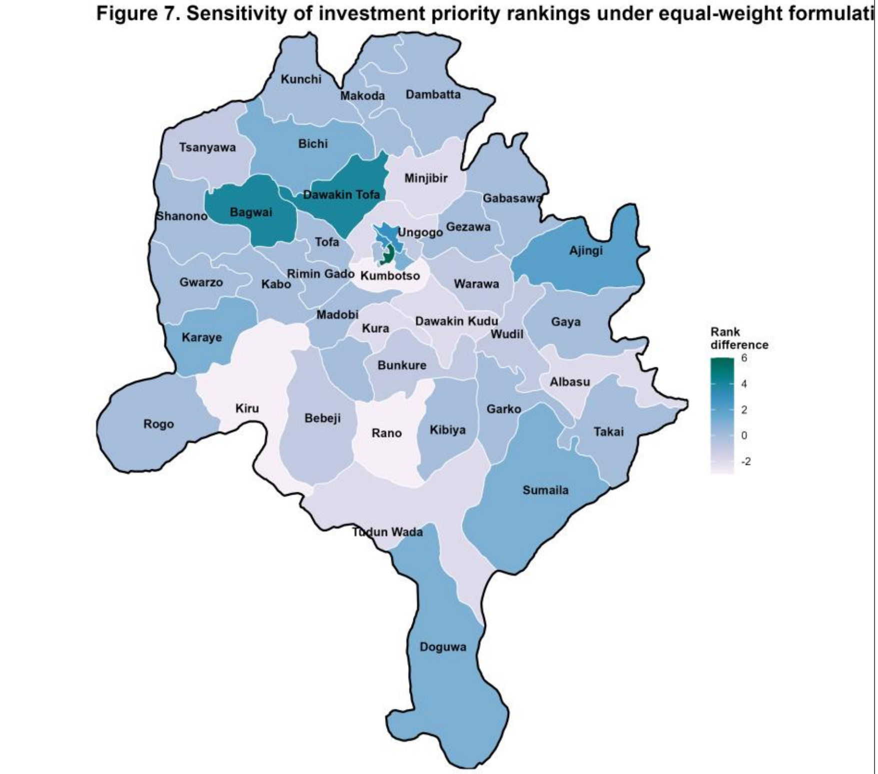
The highest scores were recorded in Gwarzo (100.0), Dambatta (97.4), Rogo (90.5), Takai (89.1), and Dawakin Tofa (88.4). Other high-priority LGAs included Bichi, Bagwai, Kumbotso, Rano, and Ungogo. These areas represent locations where severe malaria burden, treatment deficits, and accessibility constraints converge.

Investment-priority classification demonstrated a balanced distribution across the state. Nine LGAs (20.45%) were categorized as very high priority, and nine LGAs (20.45%) were categorized as high priority. Moderate-priority LGAs accounted for 18.18% of the state, whereas the remaining 40.90% were classified as having low or very low priority. Operational profiling further revealed that six LGAs presented a high burden–high treatment gap profile, three LGAs presented high burden–weak access conditions, and one LGA presented a combined high treatment gap–weak access profile, representing the most vulnerable operational setting in the state.

3.5 Drivers and robustness of malaria investment prioritization

Correlation analysis demonstrated that treatment deficits were the strongest determinants of final prioritization scores.

Figure 7. Sensitivity of investment priority rankings under equal-weight formulati



The AASMTGI exhibited a very strong positive association with the treatment gap ($\rho = 0.912$) and treatment gap index ($\rho = 0.864$), confirming that an untreated severe malaria burden was the primary driver of investment need. Moderate positive correlations were observed with the burden–endemicity index ($\rho = 0.685$) and severe malaria rate ($\rho = 0.553$), indicating that epidemiological pressure also contributed substantially to prioritization outcomes.

Conversely, treatment coverage showed a moderate negative relationship with the AASMTGI ($\rho = -0.480$), whereas intervention coverage ($\rho = -0.347$) and nighttime light intensity ($\rho = -0.291$) displayed weaker negative associations. Health facility density exhibited only a negligible relationship with the final index ($\rho = -0.031$), suggesting that facility counts alone do not adequately represent effective healthcare accessibility.

Sensitivity analysis demonstrated strong ranking stability between the weighted AASMTGI and an equal-weight formulation. Most LGAs experienced only minor rank changes, indicating that the prioritization outcomes were robust to alternative weighting schemes. The persistence of Gwarzo, Dambatta, Rogo, Takai, and Dawakin Tofa among the highest-ranked LGAs under both approaches supports the reliability of the framework as a decision-support tool for geographically targeted malaria investments.

4. Discussion

This study demonstrated that substantial spatial inequalities exist in severe malaria burden, treatment coverage, and healthcare accessibility across Kano State. Although overall treatment coverage exceeded 80%, the Hidden Burden–Treatment Gap Index revealed several LGAs where the severe malaria burden remained disproportionately high relative to treatment response and healthcare capacity. These findings support growing evidence that aggregate malaria indicators can conceal important local disparities and may therefore underestimate operational needs in specific geographic areas [31,32].

The identification of Gwarzo, Dambatta, Rogo, and Bichi as high-priority LGAs suggests that severe malaria burden is not uniformly distributed across Kano State. Similar spatial clustering of malaria burdens has been reported in other endemic regions where environmental suitability, settlement structure, socioeconomic conditions, and healthcare accessibility interact to influence disease outcomes [33,34]. The coexistence of high burdens and large treatment gaps in several LGAs indicates that treatment availability alone may not be sufficient to ensure equitable healthcare delivery. Previous studies have shown that barriers such as travel constraints, delayed care-seeking behavior, facility readiness, and uneven distribution of health resources can substantially reduce effective access to lifesaving malaria treatment [35,36].

The Accessibility-Adjusted Severe Malaria Treatment Gap Index further demonstrated that treatment deficits were among the strongest drivers of investment priority. This finding is consistent with recent evidence indicating that improving access to prompt diagnosis and injectable artesunate remains one of the most effective strategies for reducing severe malaria mortality in high-burden settings [37,38]. The weak association between health facility density and prioritization scores also suggests that healthcare accessibility cannot be adequately represented by facility counts alone. Functional service availability, transportation networks, and healthcare utilization patterns may be equally important determinants of treatment access [39].

From a programmatic perspective, the proposed framework offers a practical approach for identifying underserved LGAs and optimizing malaria investments. Rather than allocating resources solely on the basis of reported malaria cases or prevalence, integrating disease burden, treatment performance, and accessibility indicators enables a more comprehensive assessment of unmet needs. Similar integrated prioritization approaches have been recommended for strengthening health system efficiency and improving equity in resource allocation across low- and middle-income countries [40,41].

Several limitations should be acknowledged. Routine surveillance data may be affected by underreporting and reporting inconsistencies, whereas health facility density does not fully capture facility functionality, staffing, or medicine availability. Furthermore, the analysis was conducted at the LGA level, which may mask important within-LGA heterogeneity. Future studies should incorporate settlement-level accessibility modeling, travel-time analysis, facility readiness indicators, and seasonal surveillance data to better characterize hidden malaria burdens and treatment inequities [42,43].

Overall, the findings demonstrate that high severe malaria burden and treatment inequity remain concentrated in a relatively small number of LGAs within Kano State. By integrating epidemiological, demographic, healthcare, and accessibility indicators, the proposed indices provide a robust evidence base for geographically targeted malaria interventions and investment prioritization.

Data availability statement: Severe malaria case and treatment data were obtained from the Nigerian Routine Health Information System (RHIS) implemented through the District Health Information System 2 (DHIS2) platform managed by the Federal Ministry of Health and are not publicly available due to data governance and confidentiality restrictions but may be available from the relevant authorities upon reasonable request and approval.

Health facility locations were obtained from the GRID3 Nigeria Health Facilities dataset, publicly available at https://data.grid3.org/maps/GRID3::grid3-nga-health-facilities-v2-0.

Population data for 2025 were derived from the WorldPop gridded population estimates, available at https://www.worldpop.org/ and the WorldPop Open Population Repository at https://wopr.worldpop.org/.

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

Nighttime light intensity data for 2025 were obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band products provided by the National Aeronautics and Space Administration (NASA) and the National Oceanic and Atmospheric Administration (NOAA), available at https://eog-data.mines.edu/products/vnl/.

Administrative boundary data for Nigerian states and Local Government Areas (LGAs) 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.

The processed datasets generated and analysed during the current study are available from the corresponding author upon reasonable request.

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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	
AASMTGI	Accessibility-Adjusted Severe Malaria Treatment Gap Index
HBTGI	Hidden Burden–Treatment Gap Index
LGA	Local Government Area
SMR	Severe Malaria Burden Rate
TCOV	Treatment Coverage
TG	Treatment Gap
HFD	Health Facility Density
BEI	Burden–Endemicity Index
TGI	Treatment Gap Index
AWI	Accessibility Weakness Index

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