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Socioeconomic, demographic and environmental factors may inform malaria intervention prioritization in urban Nigeria

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**Abstract:** Urban population growth in Nigeria may exceed the availability of affordable housing and basic services, resulting in living conditions conducive to vector breeding and heterogeneous malaria transmission. Understanding the link between community-level factors and urban malaria transmission informs targeted interventions. We analyzed Demographic and Health Survey Program cluster-level data, alongside geospatial covariates, to depict spatial and temporal variations in malaria burden in children under 5 years of age. Univariate and multivariable models explored the relationship between malaria test positivity rates and community-level factors. Generally, malaria test positivity rates in urban areas are low and declining. The factors that best predicted malaria test positivity rates within a multivariable model were post-primary education, wealth quintiles, population density, access to improved housing, child fever treatment-seeking, precipitation, and the enhanced vegetation index. Malaria transmission in urban areas will likely be reduced by addressing socioeconomic and environmental factors that promote exposure to disease vectors. Enhanced regional surveillance systems in Nigeria can provide detailed data to further refine our understanding of these factors in relation to malaria transmission.

**Keywords:** urbanization; malaria; risk factors; cities; Nigeria

1. Introduction

Nigeria accounts for 27 percent of all global malaria cases and 31 percent of global malaria deaths, making it the greatest contributor to the global malaria burden [1]. Underlying Nigeria’s malaria burden are spatial and temporal differences in malaria risk driven by diverse factors, including ecological and climatic factors, intervention histories, health system factors, land-use practices, and urbanization trends [2–4]. Notably, Nigeria is among the top three countries expected to contribute to nearly one-third of the world’s urban population growth between 2018 and 2050 [5]. In 2018, approximately half of Nigeria’s 200 million population resided in urban areas, and this proportion is projected to surge to 70 percent by 2050 [5]. These trends in urban population expansion raise concerns about the concentration of Nigeria's malaria burden in urban areas. This is even more concerning that these population shifts are occurring in an atmosphere of declines in donor funding for malaria interventions. Given the confluence of rapid urbanization in Nigeria and funding limitations, the scientific community and policymakers are increasingly interested in understanding how urbanization-related factors may impact malaria transmission to inform improved allocation of available resources.

An examination of data compiled from across Africa, coupled with in-depth investigations into the consequences of urbanization in Brazzaville, Republic of Congo, illuminates several key urban community-level factors that influence malaria transmission in cities [6–8]. Infrastructure development, heightened population density, and improved access to healthcare services are factors that are generally expected to reduce malaria transmission within urban settings. However, the rapid and unplanned urbanization characterized by the establishment of farms within urban neighborhoods as observed in Cotonou, Benin, [9] and the adaptation of the *Anopheles gambiae* sensu lato mosquito to polluted waters, witnessed in Ghana [10], Cameroon [11] and Sudan [12], pose significant threats that can elevate the risk of malaria transmission in cities. Furthermore, reports of the proliferation of *Anopheles stephensi*, a major malaria vector well-suited to urban environments, in East Africa and Nigeria [13], add to these concerns. In addition to these factors, the increasing mobility of individuals between urban areas and other settings as documented in Uganda [14] and Burkina Faso [15] is among the factors that could perpetuate malaria transmission within urban spaces.

Existing online research literature specific to Nigeria indicates that community determinants of urban malaria transmission risk encompass factors such as proximity to water bodies, travel to rural areas, environmental hygiene practices, and housing quality [16–20]. For instance, a study conducted by Awosolu and colleagues, focusing on patients receiving care at two hospitals in Ibadan, revealed that factors such as residing within a 1km distance from streams and recent travel to a rural area were statistically significant risk factors for malaria infection. Similarly, findings from a cross-sectional survey conducted in an urban town in Nigeria's South-West region indicated that the types of windows and environmental hygiene practices significantly predicted malaria prevalence within households[19]. While these studies provide valuable insights, their limited sample sizes and focus on individual cities may constrain their applicability for making informed decisions regarding appropriate malaria interventions. Therefore, complementary research endeavors are essential to provide a comprehensive overview of key factors associated with malaria transmission across various cities in Nigeria.

Georeferenced survey data, such as the Malaria Indicator Surveys (MIS) and Demographic and Health surveys (DHS), alongside modeled geospatial data offer valuable tools for comprehending the risk of malaria transmission in urban areas. Unlike routine surveillance systems, which typically lack individual-level georeferenced data on malaria infections and mostly includes individuals who seek care in public healthcare institutions [21,22], the MIS and DHS collect georeferenced data on an individual’s infection status and risk factors in both urban and rural areas [23]. Data from individuals are organized by clusters or enumeration areas, representing aggregation of households. The geographic coordinates from the MIS/DHS pertain to point data collected at the centroids of clusters. These clusters ensure comprehensive coverage of the administrative unit being sampled, with data collected through a random selection during household surveys. Augmented by geospatial covariates, these survey datasets facilitate the examination of associations with potential correlates of malaria infections within urban areas.

A notable limitation of using the MIS/DHS data is the restriction of malaria testing to children under five years of age, coupled with the absence of detailed information about the urban extent of clusters and their corresponding cities. Nonetheless, it's important to emphasize that children under five are a key demographic for malaria prevention and control efforts, regardless of the intensity of transmission and seasonality [24]. This underscores the relevance of our analysis. As for the second limitation, the study's significance is maintained because the cluster centroids are situated within areas classified as urban by local authorities. This alignment enhances the potential for policymakers to accept and act upon the results of the analysis

In light of these data limitations and the imperative to comprehend malaria transmission risk in Nigerian cities, this study embarked on an analysis with the following objectives: 1) To delineate the geographic and temporal variations in the malaria test positivity rate among children under the age of five (U5) at both the cluster and geopolitical level, 2) To identify factors that predict the U5 malaria test positivity rate, and 3) To construct model effect plots that elucidate the associations between covariates and the U5 malaria test positivity rate. The unadjusted effect plots reveal correlations between dependent and independent variables, providing insights into potential thresholds for intervention prioritization. Meanwhile, the adjusted effects illuminate the independent contributions of covariates, crucial for understanding their broader public health implications.

2. Materials and Methods

* 1. *Data*

Cluster-level data from the 2010, 2015, and 2021 MIS, the 2018 DHS, and publicly available geospatial malaria covariate data were used for this study (refer to Table 1 for references). The DHS program conducts complex multistage surveys to gather and disseminate accurate, nationally representative data on health and population in over 90 countries [25]. [25]Data collection occurs at the individual level following probability proportional to size sampling of clusters and random selection of households within these clusters [25]. For this study, only clusters classified as being situated in urban areas were retained. It's important to note that the DHS program intentionally displaced the GPS coordinates of urban clusters by 0 to 2 km to ensure the confidentiality of survey participants [26]. However, the displacement is done in such a manner that each cluster remains within the state-level boundaries. Given that the DHS exclusively collects data on children aged 6 to 59 months, the number of positive malaria tests by microscopy and the testing sample population for this age group were summarized for each cluster. The selection of covariates was guided by relevant research literature, which highlights socio-economic, demographic, behavioral, accessibility, and environmental factors as potential explanatory variables for malaria transmission [2,4,15,27–30]. A description of all 29 covariates considered is provided in Table 1. A detailed description of the considered covariates can be found in Table 1. To account for the distance displacement of MIS and DHS clusters when calculating values for geospatial covariates, raster values were aggregated across buffers of up to 4 km around each MIS and DHS cluster.

* 1. *Descriptive analysis and covariate selection*

To comprehensively grasp the spatial and temporal patterns of malaria in children under the age of five (U5), a descriptive analysis was conducted on the U5 test positivity rate. This rate, calculated as the number of U5 children with positive malaria tests divided by the total number of U5 children tested for malaria in each cluster, was mapped by state and further compared across different months and years of survey. Following this analysis, covariates were summarized to assess their distribution and identify potential sources of information bias. Pearson correlation coefficients were calculated within thematic groups (as shown in Table 1) to identify any strong correlations among the covariates. The ggplot2 package in R [31] was utilized to fit a Poisson regression model, allowing for the visual examination of bivariate relationships between covariates and malaria test positivity rates. Non-linear relationships with covariates were estimated using natural cubic splines from the splines package in R [32]. In instances where two covariates exhibited a correlation coefficient of 60% or higher, the one displaying a weaker visual relationship with the malaria test positivity rate, along with wider confidence bands, was excluded from the subsequent multivariable analysis.

* 1. *Multivariable modeling*

A model of U5 malaria test positivity rate was constructed to identify predictive factors and generate effect plots. For this purpose, multivariable generalized linear models were employed, organized by thematic group and a combination of variables across thematic group. The glmmTMB package was employed, considering modeling related factors such as zero-inflation, temporal dynamics, and spatial dependence [33]. The dependent variable in these models represented the count of positive malaria tests among U5 children, adjusted for the total number of U5 children tested for malaria in each cluster using an offset term. Similar to the descriptive models previously discussed, we accounted for non-linear relationships by employing natural cubic splines. Temporal dependencies were addressed by incorporating the survey month and year for each cluster into the model, while spatial dependencies were considered by including the geographical coordinates of each cluster. The Akaike Information Criterion (AIC) statistic was used to select the best predictive model of malaria test positivity rate. Ultimately, the selected final model took the form of a zero-inflated Poisson model. This choice was made based on goodness-of-fit tests, including the Kolmogorov–Smirnov test, dispersion test, and outlier tests, which were conducted using the DHARMa package. DHARMa utilizes simulation-based methods to produce interpretable scaled residuals for fitted generalized linear mixed models[34]. The model equation can be written as follows:

where each of the are vectors of coefficients multiplying their associated vector natural spline basis functions and represents the model intercept; are covariate values; is a cluster specific stationary autoregressive (1) process (type of autoregressive model) for modeling temporal dependence by month and year of survey, , for each study cluster ; is spatial Matern process for modeling spatial random effects using each cluster coordinate,; NSZ is the event non-structural zero; represents the offset term which is the number of children, 6 – 59, years tested for malaria and the zero components were modeled with the equation in (2) with representing the probability of observing zero counts. Due to the large computational power required to generate cubic plots from complex models, unadjusted and adjusted effect plots for the final model covariates were produced and described using linear splines. All code written in support of this manuscript is available via this doi: [10.5281/zenodo.6350331](https://doi.org/10.5281/zenodo.6350331)

**Table 1.** Variable names, definitions, and source for a selection of cluster-level variables considered for modeling

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| --- | --- | --- |
| **Variable name** | **Variable definition** | **Source** |
| Dependent variable |  |  |
| Number of U5 positive malaria tests | The number of positive malaria tests by microscopy among children 6 – 59 months old aggregated per cluster | MIS and DHS [23,35–37] |
| Explanatory variables by thematic group |  |  |
| *Socio-economic factors* |  |  |
| 1. % with post-primary education | Percentage (%) of women in each cluster with secondary or higher educational attainment | MIS and DHS [23,35,36] |
| 1. % in the rich wealth quintiles | % of cluster population in the rich and richest wealth quintiles. Wealth quintiles were constructed using various indicators of household living standard [36] | MIS and DHS [23,35–37] |
| 1. % in homes with improved flooring | % of cluster population living in homes with improved flooring (finished floors, parquet or polished wood, ceramic tiles, cement and carpet) | MIS and DHS [23,35–37] |
| 1. % in homes with metal or zinc roof | % of cluster population living in homes with a metal or zinc roof | MIS and DHS [23,35–37] |
| 1. % in homes with improved wall type | % of cluster population living in homes with a improved wall type (finished wall, cement, bricks, cement blocks, covered adobe) | MIS and DHS [23,35–37] |
| 1. % living in improved housing (2000) | Predicted % of the cluster population living in improved housing in 2000. Improved housing is defined as homes with improved water and sanitation, sufficient living area and durable construction according to Tusting et al [37]. | Malaria Atlas Project (MAP) [38,39] |
| 1. % living in improved housing (2015) | Predicted % of the cluster population living in improved housing in 2015 | MAP [38,39] |
| *Demographic factors* |  |  |
| 1. All age population density | Estimated population density per cluster at the time of the 2010 and 2015 DHS/MIS surveys. Population density data for 2020 was extracted for the 2018 and 2021 surveys (UN World Population Prospects-Adjusted Population Density, v4.11). Unit is persons per square kilometer | Center for International Earth Science Information Network, Columbia University [40] |
| 1. Population density, children five years and under | Estimated population density for children under the age of five in 2020. Unit is number of children per square kilometer | Humanitarian Data Exchange [41] |
| 1. % of pregnant women | % of pregnant women | MIS and DHS [23,35–37] |
| 1. % of female population | % of females per cluster | MIS and DHS [23,35–37] |
| 1. Median household size | Median household size per cluster | MIS and DHS [23,35–37] |
| 1. Median age | Median age per cluster | MIS and DHS [23,35–37] |
| 1. State | State where the cluster is located | MIS and DHS [23,35–37] |
| 1. Region | Geopolitical region where the cluster is located (Geopolitical regions in Nigeria are six – North East, North West, North Central, South East, South West, South South) | MIS and DHS [23,35,36] |
| *Behavioral factors* |  |  |
| 1. % of individuals using bednets | % of cluster population that slept under a treated bednet the night before the survey | MIS and DHS [23,35–37] |
| 1. % of children 6 – 59 months using bednets, among those tested by microscopy | % of children 6 – 59 months tested for malaria by microscopy that slept under a treated bednet the night before the survey | MIS and DHS [23,35–37] |
| 1. % of U5 children that sought medical treatment for fever | % of children under the age of five that received medical treatment given that they had fever or cough in the two weeks before the survey. Medical treatment must be received in the public sector or medical private sector except for pharmacy | MIS and DHS [23,35–37] |
| 1. % of U5 children with fever that received an artemisinin-combination therapy (ACT) | % of children under the age of five that received an ACT given that they had fever | MIS and DHS [23,35–37] |
| *Accessibility-related factors* |  |  |
| 1. Motorized travel time to health care in minutes | Predicted travel time to healthcare facility in minutes in 2019 | MAP [42] |
| *Environmental factors* |  |  |
| 1. Total precipitation (depth in meters) | Estimated total precipitation during survey month and year per cluster. Units are in depth in meters. It is measured as the depth water would have if it were spread evenly over a grid box. | European Center for Medium Range Weather Forecasts (ECMWF), Climate Data Store [43] |
| 1. Temperature (0C) | Estimated temperature of air at 2m above the surface of land, sea, or in-land waters in Celsius per cluster during the survey month | ECMWF, Climate Data  Store [43] |
| 1. Surface soil moisture (GSM) | Estimated depth averaged amount of water present in a specific soil layer beneath the surface is measured as gravimetric soil moisture (GSM) per cluster. GSM is the mass of water compared to the mass of solid materials per unit volume of soil | Goddard Earth Sciences Data and Information Services Center [44] |
| 1. Distance to water bodies (meters) | Straight line distance to water bodies in meters | MAP (unpublished data) |
| 1. Elevation (meters) | Cluster elevation above sea level in meters | Multi-Error-Removed Improved-Terrain DEM [45] |
| 1. Enhanced Vegetation Index | Enhanced vegetation index for quantifying vegetation greenness in units of spectral index | MAP gap filled EVI (communication with MAP) |
| Other adjustment variables |  |  |
| 1. Number of children tested | Number of children 6 – 59 months old tested for malaria per cluster | MIS and DHS [23,35–37] |
| 1. Interview date | Year the DHS survey was conducted per cluster and  survey month per cluster (some clusters were surveyed over a two-month period, the first interview month was used in those cases) | MIS and DHS [23,35–37] |
| 1. Longitude and latitude | Longitude and latitude positions where the clusters were geolocated after displacement to protect participant confidentiality | MIS and DHS [23,35–37] |

3. Results

* 1. *Describing spatial-temporal variation in malaria test positivity in urban areas*

3.1.1. Sample overview

A total of 988 clusters were sampled in 2010, 2015,2018, and 2021 DHS and MIS surveys. The number of all age individuals surveyed within each cluster exhibited a wide range in all surveys: ranging from 98 to 2,949 in the 2010 survey, 167 to 2,954 in the 2015 survey, 3 to 3,471 in the 2018 survey, and 166 to 4,765 in the 2021 survey. Malaria test results by microscopy were available for children 6 – 59 months in 972 of the 988 sampled clusters. The study dataset consisted of 81 clusters from the 2010 survey, 136 clusters from 2015, 560 clusters from 2018, and 195 clusters from 2021 (Figure 1a). On average, a higher number of children were tested per cluster in 2010, 2015 and 2021 when compared to 2018 (Figure 1b). The 2010 clusters were sampled during the months of October, November, and December. The 2015 clusters were sampled in October and November. The 2018 clusters spanned from August to December while the 2021 survey sampling took place in October, November, and December. Visualizing cluster centroids highlights the abundance of sampled clusters from the 2018 survey and that most clusters, 364 of them,were sampled in October while the least number of clusters was sampled in August (Figure 1c-d).

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**Figure 1.** Urban clusters sampled in the 2010, 2015, 2018, and 2021 survey: **(a)** Number of clusters per survey year. Eighty-one clusters were sampled in 2010, 136 in 2015, 560 in 2018, and 195 in 2021; **(b)** Number of children 6 – 59 months tested for malaria using microscopy per cluster and by year of survey. (c) Cluster centroids mapped by year of survey within state-level administrative boundaries; and (d) Cluster centroids mapped by month of survey within state-level administrative boundaries

* + 1. Low malaria test positivity across majority of urban clusters

On average, ten children (mean = 10.2, standard deviation (SD) = 7.5) were tested per cluster. The distribution of the number of children that tested positive for malaria per cluster was predominantly skewed towards zero (Figure 2a), with a mean of 2.9 (SD = 2.8). The median test positivity rate was zero (interquartile range (IQR): 0.2). No child tested positive for malaria in roughly 49% (473) of clusters. Stratifying clusters by year of survey revealed that the median test positivity rate was 0.1 for those surveyed in 2010 and 2015, and zero in 2018 and 2021, and that test positivity rate declined over time (black line in Figure 2b depicts the median). Most clusters in Lagos (90%), Rivers (76%), Abia (75%), Akwa Ibom (75%), and Benue (75%) had a zero-test positivity rate (Figure 2c). Nonetheless, it's essential to note that the DHS 2018 report highlighted the exclusion of 11 Local Government Areas (LGAs) in Borno during the initial sampling phase due to security concerns [45]. This exclusion raises concerns about the representativeness of the test positivity rate distribution within this state. At the regional level, 64% of clusters in the South-South geopolitical region had a zero-test positivity rate, 63% of clusters in the Northeast, 61% in the North-Central, 50% in the South-East, 49% in the South-West and 48% in the North-West (Figure 2d).

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**Figure 2.** Distribution of malaria tests by microscopy, positive tests and test positivity rates among children 6 – 59 months within urban clusters in the DHS/MIS 2010 – 2021: **(a)** Distribution of number of positive malaria tests (conducted by microscopy) per cluster (green), mean = 2.9 (SD = 2.8) is depicted with a black line, and the distribution of the number tested for malaria per cluster (yellow), mean = 10.2 (SD = 7.5) is depicted with a black line. Forty-nine percent (473) of the 972 clusters with non-missing values had zero positive tests. In all clusters, at least one child was tested for malaria; **(b)** Density distribution of cluster test positivity rate by year of DHS survey. Thick black line is median test positivity rate; **(c)** Positive tests as a fraction of the number of children tested geo-located within state-level geographical boundaries. The majority of surveyed clusters in Lagos, Borno and Akwa Ibom states had zero test positivity rate; **(d)** Regional differences in the proportion of clusters at and above zero malaria test positivity rate.

* + 1. Test positivity rates in sampled clusters declined over time

To assess whether the observed temporal declines in test positivity rates, as depicted in Figure 2b, were influenced by variations in the months during which the 2010, 2015, 2018, and 2021 surveys were conducted, we conducted a comparison of clusters sampled in the same months but surveyed in different years. The analysis involved 740 clusters surveyed in the months of October and November, with data spanning all four survey years, as well as December, with data available for three survey years. Specifically, when examining clusters sampled in October, it was observed that 51% of clusters in the 2021 survey reported zero positive tests, in contrast to 53% in the 2018 survey, 50% in the 2015 survey, and 32% in the 2010 survey (Supplementary 1a). For clusters sampled in November, the percentages of clusters reporting zero positive tests were 54% in both 2021 and 2018, compared to 46% in 2015 and 43% in 2010 (Figure 1b). Likewise, for clusters sampled in December, 100% of clusters in the 2021 survey had zero positive tests, whereas this figure was 66% for the 2018 survey and only 13% for the 2010 survey (Supplementary 1c)." To evaluate whether the observed findings were affected by regional differences, including climate variations and malaria transmission rates, we analyzed and visualized malaria test positivity rates by geopolitical region for each survey month. According to Figure 3, except for the clusters sampled in December, the samples from October and November covered all geopolitical zones across all DHS/MIS survey years. While the year-over-year decline in median test positivity rates wasn't consistently linear, it's notable that the median rate in 2021 was substantially lower than the rates observed in 2010 in the months of October and November. However, the number of children tested for malaria varied annually. The 2021 survey featured the largest number of children tested for malaria per geopolitical region, particularly in October and December. It is uncertain whether these differences in the number of children tested account for the observed trend.

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**Figure 3:** Malaria test positivity rate by disaggregated by geopolitical region, year and month of survey. Each point is sized by the number of children tested for malaria by microscopy.

* 1. *Identifying predictors of malaria test positivity and visualizing bivariate associations to inform intervention prioritization*

Bivariate analysis provided insight into the unadjusted functional relationships between the number of malaria positives and all 26 potential risk factors. It played a crucial role in guiding variable selection for the multivariable regression, especially for highly correlated variables, defined as those exhibiting a correlation coefficient of 60% or higher. Visualizations of the individual covariate distributions, the outcomes of the correlation analysis, and the results of the bivariate analysis can be found in the supplementary materials.

The final multivariable prediction model for malaria test positivity, chosen based on the lowest AIC values among a series of 21 models with varying covariates, was a Poisson model. The model QQ plot demonstrated that the model predictions closely aligned with the Poisson distribution (see Supplementary Figure 27a). The selected final model incorporated the following covariates: percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, percentage of individuals residing in improved housing in 2015, all-age population density, median age, percentage of children under the age of five seeking medical treatment for fever, total precipitation, and enhanced vegetation index. The subsequent sections present findings from both single-variable and multivariable models, elucidating how changes in these covariates impact malaria test positivity rates in the comprehensive DHS dataset spanning from 2010 to 2018 and 2021.

* + 1. Clusters with the lowest educational attainment and wealth were at highest risk for malaria

Socioeconomic variables exhibited a negative association with malaria transmission intensity, although this effect appeared less pronounced and exhibited greater uncertainty in the multivariate analysis (Figure 4b). Malaria test positivity rate declined with increases in the percentage of individuals with post-primary education in both unadjusted and adjusted analyses. Notably, the malaria test positivity rate displayed a consistent decline with increasing percentages of individuals with post-primary education, evident in both unadjusted and adjusted analyses. However, it's worth noting that the impact of educational attainment appeared most robust when the percentage was below 50%, as illustrated in Figure 4. Similarly, reductions in malaria test positivity rates were observed with increasing percentages of individuals falling within the rich wealth quintiles, particularly within the ranges of 0 to 50% and 80 to 100%. This trend was consistent in both the adjusted and unadjusted analyses. Notably, clusters characterized by the lowest socioeconomic status exhibited the highest risk of malaria in both analyses.

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Description automatically generated with medium confidence**Figure 4.** Effect plots of bivariate and multivariate regression analysis for indicators of educational attainment and wealth: **(a)** unadjusted and **(b)** adjusted effect of the percentage of individuals with post-primary education on malaria test positivity rate. Percentage of individuals with post-primary education was adjusted for percentage of individuals in the rich wealth quintiles, percentage of individuals living in improved housing in 2015, all age population density, median age, percentage of children under the age of five that sought medical treatment for fever, total precipitation, and enhanced vegetation index; **(c)** unadjusted and **(d)** adjusted effect of the percentage of individuals in the rich wealth quintiles on malaria test positivity rate. Percentage of individuals in the rich wealth quintiles was adjusted for percentage of individuals with post-primary education, percentage of individuals living in improved housing in 2015, all age population density, median age, percentage of children under the age of five that sought medical treatment for fever, total precipitation, and enhanced vegetation index.

* + 1. High population density and younger median age correlated with higher malaria transmission intensity

In the unadjusted analysis, the malaria test positivity rate displayed a decline with increasing all-age population density, up to a threshold of 8,000 persons per square kilometer, after which the decline plateaued (Figure 5a). However, in the adjusted analysis, the malaria test positivity rate remained relatively stable up to 17,000 persons per square kilometer, beyond which an increase in malaria test positivity was observed, albeit with significant uncertainty (Figure 5b). Furthermore, reductions in malaria test positivity rates were evident with rising median age, particularly beyond a median age of 18 years old, as shown in the unadjusted model. However, it is noteworthy that the impact of median age on malaria positivity appeared to diminish in the adjusted analysis (Figure 5c - d)

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**Figure 5.** Effect plots of the bivariate and multivariate regression analysis for all age population density and median age: **(a)** unadjusted and **(b)** adjusted effect of all age population density (persons per square kilometer) on malaria test positivity rate. All age population density was adjusted for the percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, percentage of individuals living in improved housing in 2015, median age, percentage of children under the age of five that sought medical treatment for fever, total precipitation, and enhanced vegetation index; **(c)** unadjusted and **(d)** adjusted effect of median age in years on the number of malaria test positivity rate. Median age was adjusted for percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, all age population density, percentage of individuals living in improved housing in 2015, percentage of children under the age of five that sought medical treatment for fever, total precipitation, and enhanced vegetation index.

* + 1. Higher enhanced vegetation index was positively associated with U5 malaria test positivity rate

In the unadjusted analysis, there was a notable correlation between increasing malaria test positivity rate and higher values of the enhanced vegetation index, which is indicative of vegetation cover and growth. The most substantial reductions in malaria test positivity rate, although characterized by a high degree of uncertainty, were observed at approximate vegetation indices of 0.5 and 0.76 (as depicted in Figure 6a). However, it's important to note that the influence of the enhanced vegetation index on malaria test positivity was notably reduced in the adjusted analysis (refer to Figure 6b).

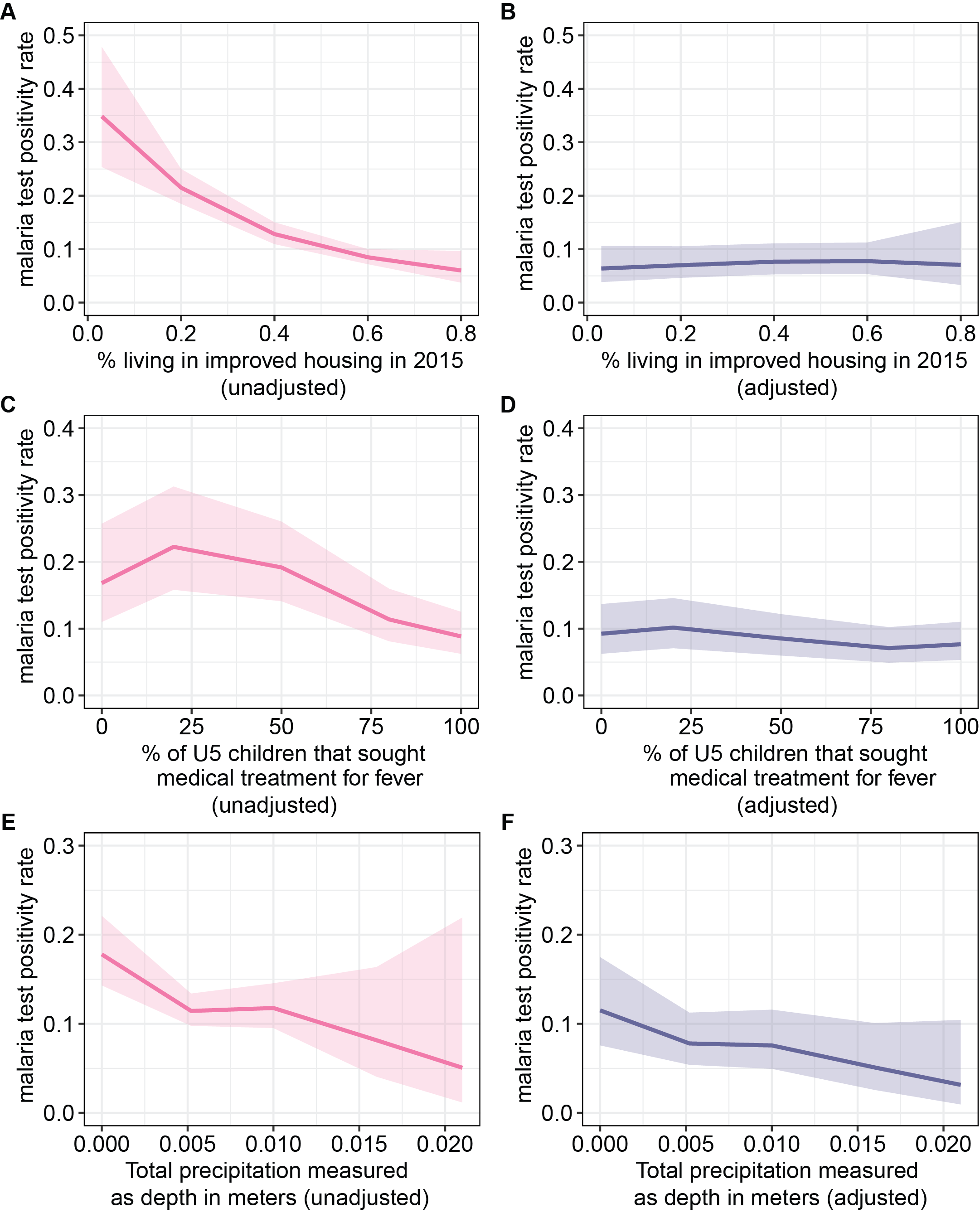
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**Figure 6.** Effect plots of the bivariate and multivariate regression analysis for enhanced vegetation index: **(a)** unadjusted and **(b)** adjusted effect of enhanced vegetation index on malaria test positivity rate. Enhanced vegetation index was adjusted for the percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, percentage of individuals living in improved in housing in 2015, all age population density, median age, percentage of U5 children that sought medical treatment for fever and total precipitation.

* + 1. Effects of housing, care-seeking, and precipitation

In the unadjusted analysis, an increase in the proportion of individuals residing in improved housing in the year 2015 was associated with a reduction in malaria test positivity rates. However, in the adjusted analysis, these trends appeared relatively flat (Figure 7a – b). Variables used for the adjustment were the percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, all age population density, median age, percentage of U5 children that sought medical treatment for fever, total precipitation, and enhanced vegetation index. Examining the relationship between the proportion of children under the age of five seeking medical treatment for fever and malaria test positivity rates, it was evident that the highest test positivity rates in the unadjusted analysis were observed at approximately 25% (Figure 7c – d). T. As for the total precipitation, During the survey month, a consistent negative relationship was observed in both unadjusted and adjusted analyses for total precipitation (Figure 7e – f). Variables used to adjust total precipitation the percentage of individuals with post-primary education, percentage of individuals in the rich wealth quintiles, all age population density, median age, percentage of individuals living in improved housing in 2015, percentage of U5 children that sought medical treatment for fever and enhanced vegetation index.



**Figure 7.** Effect plots of the bivariate and multivariate regression analysis for percentage of individuals living in improved housing in 2015, percentage of U5 children that sought medical treatment for fever and total precipitation: **(a)** unadjusted and **(b)** adjusted effect of the percentage of individuals living in improved housing in 2015. **(c)** unadjusted and **(d)** adjusted effect of the percentage of U5 children that sought medical treatment for fever. E) Unadjusted and F) adjusted effect of total precipitation in meters..

1. Discussion

We conducted an in-depth analysis using urban data from the most recent four years of Nigeria's DHS/MIS surveys. Our primary objectives were to assess spatial and temporal differences in the prevalence of malaria among children under the age of five at the cluster and geopolitical levels, identify predictors at the community level, and create both unadjusted and adjusted effect plots. These analyses were undertaken with the dual purpose of guiding intervention prioritization in urban areas and gaining insights into the public health implications of the identified predictors.

The analysis of malaria test positivity rates among children under the age of five in urban areas revealed consistently low rates that have shown a declining trend over time. The South-South and North-East geopolitical regions had the largest number of clusters where zero test positivity rates were observed. Notably, states with the highest number of urban clusters reporting zero-test positivity rates included Lagos, Rivers, and Abia. Interestingly, prior research has documented low malaria infection rates, as determined by microscopy, in urban Lagos, with rates as low as 8% and 0.9% [46,47]. [47,48][49][46]However, it remains somewhat unclear why lower test positivity rates were observed in urban clusters of Rivers and Abia, especially when previous studies conducted in urban areas have indicated higher test positivity rates among the study populations [50–52]. It's important to note that two of these earlier studies were health facility studies which did not differentiate participants based on whether their specific place of residence was urban or rural. Moreover, recruitment in the health facility surveys could have been biased towards sicker individuals likely to test positive for malaria, potentially contributing to this discrepancy.

The unadjusted fitted lines, which illustrate the relationship between the U5 malaria test positivity rate and various indicators such as educational attainment, wealth, age distribution, vegetation cover, housing quality, and treatment-seeking behavior, suggest that communities at high risk for malaria in urban areas are characterized by lower educational attainment, poverty, younger residents, poorer housing quality, and infrequent fever treatment-seeking behavior. After adjustment, the impact of educational attainment and wealth is diminished, indicating that they could be explained by other factors included in the model, such as housing quality, median age, and environmental factors like vegetation cover. Our results align with findings documented in existing literature [9,47] [53,54]. For example, in a comprehensive review of factors associated with malaria transmission in urban areas across sub-Saharan Africa, Silvia and Marshall highlighted relevant studies demonstrating that poor housing, which increases exposure to mosquitoes, inadequate waste disposal, and urban agriculture are among the factors contributing to elevated malaria risk in urban settings [53]. Additionally, the increased risk of malaria infections among children is well-documented, consistent with our study's findings that clusters with a higher proportion of children are more likely to exhibit a higher malaria burden [54] [9]

Currently, the distribution of insecticide-treated bednets (ITN) and the administration of seasonal malaria chemoprevention (SMC) through mass campaigns are the cornerstones of national malaria control and prevention efforts in Nigeria [55]. However, our study findings suggest that these tools alone may be insufficient to reduce malaria burden in urban areas. ITNs primarily reduce mosquito exposure indoors, with protection limited to sleeping hours and effectiveness diminishing with the aging of the nets. SMC is administered only during the rainy season and relies on adherence to the full treatment course.

To effectively reduce malaria burden in urban areas, it is essential to supplement these interventions with strategies that address malaria risk stemming from environmental and socioeconomic factors, including poor-quality housing. Interventions such as housing modification and larval source management have demonstrated success in reducing malaria infections. For example, window and door screening has been linked to a 62% reduction in malaria incidence in a study conducted in Ethiopia and a 16% reduction in malaria parasite prevalence, even in the absence of bednet usage [56]. Larval source management, involving habitat modification and manipulation, has shown the ability to reduce the density of adult mosquitoes [57]. Behavior change interventions, including educational campaigns and resources to support high-risk communities in understanding the drivers of malaria risk, can be instrumental. A combination of these interventions is likely to lead to a significant decrease in malaria burden in urban areas.

The study findings offer valuable guidance on how to identify at-risk communities and prioritize them during resource allocation. At a regional scale, resources for urban malaria control could follow the order shown in Figure 2D, with a priority focus on the North West and South West regions, as well as the information provided in supplementary Figure 11. The latter highlights states at risk of malaria, such as Kebbi in the North West and Ondo in the South West. However, when determining intervention prioritization, population sizes in these regions and states must also be considered. Even areas with a lower burden may have a greater population at risk. To apply the insights gained from the multivariable models, employee data from major city employers can be utilized to identify areas where residents have lower levels of post-primary education. This information can then inform resource allocation, especially if local factors are believed to drive malaria transmission. Alternatively, it can guide the provision of prophylactic measures if transmission is predominantly influenced by mobility patterns. Furthermore, geospatial data, such as the enhanced vegetation index generated from high-resolution satellite imagery, can be employed to identify, and prioritize high-risk areas. Nevertheless, it is crucial to emphasize that the meaningful application of these study methodologies for informing intervention prioritization and deprioritization decisions requires improved data that effectively captures malaria burden, associated socio-demographic and environmental factors, and the geographic extent of urban areas, as well local knowledge of major risk factors. Previous attempts to prioritize administrative units in Nigeria for ITN distribution, with the aim of addressing malaria risk, highlighted the challenges of distinguishing between high and low priority areas in the absence of high-quality data and a comprehensive understanding of the local context [58]. In addition, it is important to consider that predictive factors for malaria could vary based on geographic scale of analysis [59].

This study faces certain limitations associated with data quality and availability. One notable limitation is the potentially low malaria test positivity rate observed in Nigeria's Northeast region, which may be attributed to under-sampling due to security concerns in that area. Additionally, it's important to recognize that DHS/MIS surveys typically provide data that may not fully represent urban settings at the state and zonal levels. Moreover, the timing of the surveys aligns with malaria transmission months in the Southern geopolitical zones. As a result, drawing definitive conclusions regarding low malaria burden across urban settings or making comparisons across geopolitical zones becomes challenging. To address potential biases related to temporal and regional variations when comparing malaria test positivity across survey years, we made efforts to mitigate this issue by comparing clusters sampled during the same months and in the same region. Fortunately, our findings from these analyses remained consistent, indicating a decline in malaria burden over time. However, it is worth noting that these findings may be influenced by differences in the sampling strategy employed across the survey years. In addition, it is likely that the results of the 2021 survey may have been impacted by SARS-CoV-2 pandemic as it could have led to lower participation rates in the survey, care-seeking behavior, and interventions access. In addition, it is likely that the results of the 2021 survey may have been impacted by the SARS-CoV-2 pandemic, as it could have led to lower participation rates in the survey, decreased care-seeking behavior, and reduced access to interventions. The 2022 World Malaria Report lends support to the occurrence of disruptions in malaria services, such as bednet distribution through mass campaigns, and access to malaria diagnosis and treatment in 2021 [60].

Furthermore, it's essential to note that the reported test positivity rates do not account for potential changes in transmission that may occur over a 12-month period. Shifts in test-positivity rates outside the months covered by the DHS/MIS surveys could lead to different conclusions regarding the burden and trends in malaria prevalence within urban areas. Additionally, the distribution of covariates derived from the DHS/MIS data is likely to be unrepresentative of urban settings. For instance, the measurement of educational attainment, as indicated by the percentage of individuals with post-primary education (secondary or college education), showed low values in most of the sampled clusters. In contrast, a greater proportion of clusters fell within the higher wealth quintiles or had improved housing infrastructure. If individuals accurately reported their educational attainment, it seems improbable that most clusters would fall within the higher wealth quintiles or have improved housing infrastructure, given the well-established positive correlation between educational attainment and these socioeconomic factors. [61,62]. We have made efforts to address these limitations by utilizing modeled covariates where possible. However, to provide a comprehensive understanding of the data and to guide future study or data collection efforts, we have included visualizations of these study covariates in the supplementary materials.

The distance displacement of clusters designed to protect the confidentiality of respondents meant that we could not examine the impact of the proximity of clusters on disease risk. Additionally, the lack of data on co-morbidities such as HIV/AIDS and sickle cell, which increases the risk of developing severe malaria, meant that we could not adjust for them in the modeling analysis. In addition, due to data availability, our analysis is confined to children under the age, whose malaria burden likely exhibit a different spatial and temporal transmission dynamics and determinant from older children and adults.

[3][61,62][63][64,65]

1. Conclusion

This study contributes to the existing research literature by examining spatial-temporal variations in the malaria test positivity rate among children under five (U5) in urban Nigeria and investigating associated risk factors. Improving the efficiency of intervention distribution has the potential to significantly reduce the malaria burden. As locally representative data becomes available for individual cities, the methodologies employed in this study can be easily adapted to inform intervention stratification strategies. Specifically, the identified predictive factors can help determine thresholds for prioritizing or de-prioritizing interventions, such as the distribution of bednets, in states and geopolitical regions with a high urban malaria burden. Our study underscores the importance of addressing environmental risk factors through housing improvements. With the ongoing trend of urbanization, there is a growing interest in tackling malaria within urban settings, as highlighted by the recent release of a framework by the WHO for responding to malaria in urban areas. By shedding light on the existing data gaps within the Nigerian DHS/MIS, we aim to encourage increased investments aimed at enhancing both its design and usefulness. Additionally, we advocate for improvements in routine surveillance systems to further support malaria research and intervention efforts.

**Appendix**

Supplementary material.

References

1. World Health Organization. World Malaria Report 2021. Geneva; 2021.

2. Okunlola OA, Oyeyemi OT. Spatio-temporal analysis of association between incidence of malaria and environmental predictors of malaria transmission in Nigeria. Sci Rep. 2019;9: 1–11. doi:10.1038/s41598-019-53814-x

3. National Malaria Control Programme, suMAP, World Health Organization, INFORM project. A description of the epidemiology of malaria to guide the planning of control in Nigeria. A report prepared for the Federal Ministry of Health, Nigeria, the Roll Back Malaria Partnership and the Department for International Development, UK. 2013.

4. Jane Ugwu CL, Zewotir T. Evaluating the effects of climate and environmental factors on under-5 children malaria spatial distribution using generalized additive models (GAMs). J Epidemiol Glob Health. 2020;10: 304–314. doi:10.2991/jegh.k.200814.001

5. United Nations Department of Economic and Social Affairs. World Urbanization Prospects: The 2018 Revision. 2019. doi:10.18356/b9e995fe-en

6. Byrne N. Urban malaria risk in sub-Saharan Africa: Where is the evidence? Travel Med Infect Dis. 2007;5: 135–137. doi:10.1016/J.TMAID.2006.04.003

7. Trape JF, Zoulani A. Malaria and urbanization in Central Africa: the example of Brazzaville. Part III: Relationships between urbanization and the intensity of malaria transmission. Trans R Soc Trop Med Hyg. 1987;81: 19–25. doi:10.1016/0035-9203(87)90473-1

8. Hay SI, Guerra CA, Tatem AJ, Atkinson PM, Snow RW. Urbanization, malaria transmission and disease burden in Africa. Nat Rev Microbiol. 2005;3: 81. doi:10.1038/NRMICRO1069

9. Wang S-J, Lengeler C, Smith TA, Vounatsou P, Akogbeto M, Tanner M. Rapid Urban Malaria Appraisal (RUMA) IV: Epidemiology of urban malaria in Cotonou (Benin). Malar J. 2006;5: 45. doi:10.1186/1475-2875-5-45

10. Kabula BI, Attah PK, Wilson MD, Boakye DA. Characterization of Anopheles gambiae s.l. and insecticide resistance profile relative to physicochemical properties of breeding habitats within Accra Metropolis, Ghana. Tanzan J Health Res. 2011;13: 163–187. doi:10.4314/thrb.v13i3.66915

11. Antonio-Nkondjio C, Fossog BT, Ndo C, Djantio BM, Togouet SZ, Awono-Ambene P, et al. Anopheles gambiae distribution and insecticide resistance in the cities of Douala and Yaoundé (Cameroon): Influence of urban agriculture and pollution. Malar J. 2011;10: 1–13. doi:10.1186/1475-2875-10-154/TABLES/6

12. Azrag RS, Mohammed BH. Anopheles arabiensis in Sudan: A noticeable tolerance to urban polluted larval habitats associated with resistance to Temephos. Malar J. 2018;17: 1–11. doi:10.1186/S12936-018-2350-1/TABLES/5

13. World Health Organization. World Malaria Report 2022. Geneva; 2022.

14. Arinaitwe E, Mpimbaza A, Nankabirwa JI, Kamya V, Asiimwe A, Kuule JK, et al. Malaria Diagnosed in an Urban Setting Strongly Associated with Recent Overnight Travel: A Case–Control Study from Kampala, Uganda. Am J Trop Med Hyg. 2020;103: 1517–1524. doi:10.4269/AJTMH.20-0189

15. Baragatti M, Fournet F, Henry M-C, Assi S, Ouedraogo H, Rogier C, et al. Social and environmental malaria risk factors in urban areas of Ouagadougou, Burkina Faso. Malaria Journal 2009 8:1. 2009;8: 1–14. doi:10.1186/1475-2875-8-13

16. Bello FA, Ayede AI. Prevalence of malaria parasitemia and the use of malaria prevaention measures in pregnant women in Ibadan, Nigeria. Ann Ib Postgrad Med. 2019;17: 124–129.

17. Olukosi AY, Olakiigbe A, Ajibaye O, Orok BA, Aina OO, Akindele SK, et al. Socio-economic behavioural indicators of falciparum malaria parasitaemia and moderate to severe anaemia among pregnant women attending antenatal clinics in Lagos, Southwest Nigeria. Malar J. 2020;19. doi:10.1186/S12936-020-03462-8

18. Adedotun AA, Morenikeji OA, Odaibo AB. Knowledge, attitudes and practices about malaria in an urban community in south-western Nigeria. J Vector Borne Dis. 2010;47: 155–159.

19. Fana SA, Bunza MDA, Anka SA, Imam AU, Nataala SU. Prevalence and risk factors associated with malaria infection among pregnant women in a semi-urban community of north-western Nigeria. Infect Dis Poverty. 2015;4. doi:10.1186/S40249-015-0054-0

20. Awosolu OB, Yahaya ZS, Haziqah MTF, Simon-Oke IA, Fakunle C. A cross-sectional study of the prevalence, density, and risk factors associated with malaria transmission in urban communities of Ibadan, Southwestern Nigeria. Heliyon. 2021;7: e05975. doi:10.1016/J.HELIYON.2021.E05975

21. Alegana VA, Okiro EA, Snow RW. Routine data for malaria morbidity estimation in Africa: Challenges and prospects. BMC Med. 2020;18: 1–13. doi:10.1186/s12916-020-01593-y

22. World Health Organization, Clinton Health Access Initiative. Landscape Assessment of Malaria Surveillance in Nigeria. 2018 Aug.

23. National Population Commission (NPC) [Nigeria] and ICF. Nigeria Demographic and Health Survey 2018. Abuja, Nigeria, and Rockville, Maryland, USA; 2019.

24. Carneiro I, Roca-Feltrer A, Griffin JT, Smith L, Tanner M, Schellenberg JA, et al. Age-Patterns of Malaria Vary with Severity, Transmission Intensity and Seasonality in Sub-Saharan Africa: A Systematic Review and Pooled Analysis. PLoS One. 2010;5. doi:10.1371/JOURNAL.PONE.0008988

25. NPC NPC-, ICF. The Federal Republic of Nigeria Nigeria Demographic and Health Survey 2018 National Population Commission Abuja, Nigeria. 2019 Oct.

26. Burgert-Brucker CR, Colston J, Roy T, Zachary B. Geographic displacement procedure and georeferenced data release policy for the Demographic and Health Surveys. DHS Spatial Analysis Reports No. 7. Calverton, Maryland; 2013.

27. Anyanwu PE, Fulton J, Evans E, Paget T. Exploring the role of socioeconomic factors in the development and spread of anti-malarial drug resistance: a qualitative study. Malaria Journal 2017 16:1. 2017;16: 1–15. doi:10.1186/S12936-017-1849-1

28. Dawaki S, Al-Mekhlafi HM, Ithoi I, Ibrahim J, Atroosh WM, Abdulsalam AM, et al. Is Nigeria winning the battle against malaria? Prevalence, risk factors and KAP assessment among Hausa communities in Kano State. Malar J. 2016;15: 351. doi:10.1186/s12936-016-1394-3

29. Johansen IC, Rodrigues PT, Ferreira MU. Human mobility and urban malaria risk in the main transmission hotspot of Amazonian Brazil. PLoS One. 2020;15. doi:10.1371/JOURNAL.PONE.0242357

30. Weiss DJ, Mappin B, Dalrymple U, Bhatt S, Cameron E, Hay SI, et al. Re-examining environmental correlates of Plasmodium falciparum Malaria endemicity: A data-intensive variable selection approach. Malar J. 2015;14: 1–18. doi:10.1186/S12936-015-0574-X/FIGURES/8

31. Hadley W. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York; 2016.

32. Bates D, Venables WN. splines-package: Regression Spline Functions and Classes. [cited 3 Jan 2022]. Available: https://rdrr.io/r/splines/splines-package.html

33. Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Berg CW, Nielsen A, et al. glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. R Journal. 2017;9: 378–400. doi:10.32614/RJ-2017-066

34. Hartig F. DHARMa: residual diagnostics for hierarchical (multi-level/mixed) regression models. 2021.

35. National Population Commission (NPC), National Malaria Control Programme (NMCP), ICF International. Nigeria Malaria Indicator Survey 2010 . Abuja, Nigeria; 2012.

36. National Malaria Elimination Programme (NMEP), National Population Commission (NPopC), National Bureau of Statistics (NBS), ICF International. Nigeria Malaria Indicator Survey 2015. Abuja, Nigeria, and Rockville, Maryland, USA; 2016.

37. National Malaria Elimination Programme National(NMEP) [Nigeria], National Population Commission (NPC) [Nigeria], IFC. Nigeria Malaria Indicator Survey 2021 Final Report. Abuja, Nigeria, and Rockville, Maryland, USA: NMEP, NPC, and ICF; 2022. Available: https://www.dhsprogram.com/pubs/pdf/MIS41/MIS41.pdf

38. Tusting LS, Bisanzio D, Alabaster G, Cameron E, Cibulskis R, Davies M, et al. Mapping changes in housing in sub-Saharan Africa from 2000 to 2015. Nature 2019 568:7752. 2019;568: 391–394. doi:10.1038/s41586-019-1050-5

39. The Malaria Atlas Project. The Malaria Atlas Project website. [cited 27 May 2020]. Available: https://malariaatlas.org/

40. Center for International Earth Science Information Network - CIESIN - Columbia University. Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision UN WPP Country Totals, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC); 2018. doi:https://doi.org/10.7927/H4F47M65

41. The Centre for Humanitarian Data. Welcome - Humanitarian Data Exchange. Available: https://data.humdata.org/

42. Weiss DJ, Nelson A, Vargas-Ruiz CA, Gligorić K, Bavadekar S, Gabrilovich E, et al. Global maps of travel time to healthcare facilities. Nature Medicine 2020 26:12. 2020;26: 1835–1838. doi:10.1038/s41591-020-1059-1

43. European Center for Medium Range Weather Forecasts (ECMWF) Climate Data Store. ERA5-Land monthly averaged data from 1981 to present. [cited 2 Sep 2021]. doi:10.24381/cds.68d2bb30

44. Global Modeling and Assimilation Office. MERRA-2 tavgM\_2d\_lnd\_Nx: 2d Monthly mean Time-Averaged Single-Level Assimilation Land Surface Diagnostics V5.12.4. Greenbelt, MD: Goddard Earth Sciences Data and Information Services Center (GES DISC); 2015.

45. Yamazaki D, Ikeshima D, Tawatari R, Yamaguchi T, O’loughlin F, Neal JC, et al. A high-accuracy map of global terrain elevations. Geophys Res Lett. 2017;44: 5844–5853. doi:10.1002/2017GL072874

46. Agomo CO, Oyibo WA. Factors associated with risk of malaria infection among pregnant women in lagos, nigeria. Infect Dis Poverty. 2013;2: 1–8. doi:10.1186/2049-9957-2-19/COMMENTS

47. Brieger WR, Sesay HR, Adesina H, Mosanya ME, Ogunlade PB, Ayodele JO, et al. Urban malaria treatment behaviour in the context of low levels of malaria transmission in Lagos, Nigeria. Afr J Med Med Sci. 2001;30 Suppl: 7–15. Available: https://pubmed.ncbi.nlm.nih.gov/14513932/

48. Oyibo W, Latham V, Oladipo O, Ntadom G, Uhomoibhi P, Ogbulafor N, et al. Malaria parasite density and detailed qualitative microscopy enhances large-scale profiling of infection endemicity in Nigeria. Sci Rep. 2023;13. doi:10.1038/S41598-023-27535-1

49. Oladosu OO, Oyibo WA. Overdiagnosis and Overtreatment of Malaria in Children That Presented with Fever in Lagos, Nigeria. ISRN Infect Dis. 2013;2013: 1–6. doi:10.5402/2013/914675

50. Noland GS, Graves PM, Sallau A, Eigege A, Emukah E, Patterson AE, et al. Malaria prevalence, anemia and baseline intervention coverage prior to mass net distributions in Abia and Plateau States, Nigeria. BMC Infect Dis. 2014;14: 1–13. doi:10.1186/1471-2334-14-168/TABLES/5

51. Nzeako SO, Nduka FO, Origie OA. Prevalence of Malaria in Pregnant Women Attending Ante Natal Care at University of Port Harcourt Primary Health Care Centre Aluu, Port Harcourt, Rivers State, Nigeria. International Journal of Scientific Research in Environmental Sciences. 2013;1: 268–272. doi:10.12983/IJSRES-2013-P268-272

52. Onoja H, Nduka FO, Abah AE. Effectiveness and compliance to the use of sulphadoxine-pyrimethamine as a prophylaxis for malaria among pregnant women in Port Harcourt, Rivers State, Nigeria. Afr Health Sci. 2022;22: 187. doi:10.4314/AHS.V22I2.22

53. Silva PM De, Marshall JM. Factors Contributing to Urban Malaria Transmission in Sub-Saharan Africa: A Systematic Review. J Trop Med. 2012;2012. doi:10.1155/2012/819563

54. Carneiro I, Roca-Feltrer A, Griffin JT, Smith L, Tanner M, Schellenberg JA, et al. Age-Patterns of Malaria Vary with Severity, Transmission Intensity and Seasonality in Sub-Saharan Africa: A Systematic Review and Pooled Analysis. PLoS One. 2010;5. doi:10.1371/JOURNAL.PONE.0008988

55. National Malaria Elimination Programme. National Malaria Strategic Plan, 2021 - 2025. 2020. Available: https://www.dropbox.com/s/cw9qvzdb2uwy4w1/NATIONAL MALARIA STRATEGIC PLAN 2021 - 2025 - Final Draft 2.0 for printing XXX.pdf?dl=0

56. Fox T, Furnival-Adams J, Chaplin M, Napier M, Olanga EA. House modifications for preventing malaria. Cochrane Database of Systematic Reviews. 2022;2022. doi:10.1002/14651858.CD013398.pub4

57. Martello E, Yogeswaran G, Reithinger R, Leonardi-Bee J. Mosquito aquatic habitat modification and manipulation interventions to control malaria. Cochrane Database of Systematic Reviews. 2022;2022. doi:10.1002/14651858.CD008923.pub3

58. Young AJ, Eaton W, Worges M, Hiruy H, Maxwell K, Audu BM, et al. A practical approach for geographic prioritization and targeting of insecticide-treated net distribution campaigns during public health emergencies and in resource-limited settings. Malar J. 2022;21. doi:10.1186/s12936-021-04028-y

59. Gracie R, Barcellos C, Magalhães M, Souza-Santos R, Guimarães Barrocas PR. Geographical scale effects on the analysis of leptospirosis determinants. Int J Environ Res Public Health. 2014;11. doi:10.3390/ijerph111010366

60. World Health Organization. World Malaria Report 2022. Geneva; 2022. Available: https://www.who.int/publications/i/item/9789240064898

61. Gyimah-Brempong K, Paddison O, Mitiku W. Higher education and economic growth in Africa. Journal of Development Studies. 2006;42: 509–529. doi:10.1080/00220380600576490

62. Bloom D, Canning D, Chan K. Higher Education and Economic Development in Africa. 2006.

63. Gracie R, Barcellos C, Magalhães M, Souza-Santos R, Rubens P, Barrocas G, et al. Geographical Scale Effects on the Analysis of  Leptospirosis Determinants. International Journal of Environmental Research and Public Health 2014, Vol 11, Pages 10366-10383. 2014;11: 10366–10383. doi:10.3390/IJERPH111010366

64. Love-Koh J, Griffin S, Kataika E, Revill P, Sibandze S, Walker S. Methods to promote equity in health resource allocation in low- and middle-income countries: an overview. Global Health. 2020;16. doi:10.1186/S12992-019-0537-Z

65. Scott N, Hussain SA, Martin-Hughes R, Fowkes FJI, Kerr CC, Pearson R, et al. Maximizing the impact of malaria funding through allocative efficiency: Using the right interventions in the right locations. Malar J. 2017;16: 1–14. doi:10.1186/S12936-017-2019-1/FIGURES/8

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