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Correlating Projected and Surveyed Population using Google Building Footprints in Jigawa State, Nigeria: Targeting Zero Dose Children Aligned with SDG Goal 3

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Abstract

This study evaluates the accuracy of projected population data and its implications for estimating zero-dose children in Jigawa State, Nigeria. The specific objectives were to correlate projected and surveyed population data using Google Building Footprints and assess the gap in zero-dose children across various settlement types. A quantitative approach was employed, utilizing data from Google's Building Footprints, Copernicus Human Settlement, Sentinel Hub, OpenStreetMap, and NASA Earth data. A geolocated household survey was conducted, covering 1,600 buildings across 27 LGAs using stratified random sampling. Essential demographic and socio-economic data were collected. Ordinary Least Squares (OLS) regression analysis was performed to validate projected population data, and paired t-tests compared population estimates for rural and urban areas. For zero-dose children estimation, a model was developed incorporating settlement types, NDVI, time distance to health facilities, and nightlight data. The OLS regression analysis demonstrated a strong correlation between projected and surveyed data (coefficient = 0.823, p < 0.01) with an Adjusted R-Squared of 0.95. However, paired t-tests indicated significant discrepancies, with the projected data overestimating rural populations and underestimating urban populations. The total zero-dose children were estimated at 113,143 (32% of Target Population) based on projected data and 91,415 (26% of Target Population) based on survey data. Addressing these discrepancies is vital for effective public health planning and resource allocation, particularly in targeting interventions for zero-dose children in rural areas of Jigawa State. The findings emphasize the importance of localized adjustments and continuous monitoring to reflect actual demographic changes and improve healthcare accessibility.

Keywords: Google Building Footprints, Zero Dose Children, SDG Goal 3, Public Health, OLS regression.

1. Introduction

In Africa, and particularly in Nigeria, access to accurate and spatially explicit population data is fundamental to effective healthcare planning, equitable service delivery, and monitoring progress toward universal health coverage (Ojerinde & Iroju, 2015; Bukola & Appunni, 2024; Grassly et al., 2004; Rehle & Shisana, 2003). Reliable demographic information is also central to achieving **Sustainable Development Goal 3 (SDG 3)**, which aims to ensure healthy lives and promote well-being for all ages (Bhatia & Khetrapal, 2020; Das et al., 2021). Jigawa State, located in northern Nigeria, represents a critical case due to its predominantly rural settlement structure, high fertility rates, rapid urban expansion, and persistent health service access challenges (Aliyu & Amadu, 2017).

The last comprehensive population census in Jigawa State was conducted in 2006, and subsequent population estimates have largely relied on projection-based approaches that inadequately capture spatial demographic change (Okolo, 2024). In particular, rural-to-urban migration has not been sufficiently incorporated into population models, resulting in significant mismatches between projected and actual population distributions (Potts, 2012). National population projections in Nigeria commonly assume uniform growth rates across Local Government Areas (LGAs), an assumption that overlooks spatial heterogeneity driven by migration, urbanization, and socio-economic transitions (Onwujekwe et al., 2011). These limitations have contributed to systematic overestimation of rural populations and underestimation of urban populations, thereby undermining health resource allocation and service planning (Potts, 2012).

Inaccurate population estimates also hinder the identification and targeting of **zero-dose children**, defined as children who have not received any routine vaccination (Wonodi & Farrenkopf, 2023). Spatial misrepresentation of population size and settlement patterns reduces the effectiveness of immunization strategies, particularly in underserved and rapidly growing peri-urban communities (Weber et al., 2018). Recent evidence suggests that zero-dose populations are disproportionately concentrated in areas characterized by poor accessibility, informal settlements, and weak health system coverage (Ozigbu, 2023; Gavi, 2023).

This study addresses these challenges by implementing a **bottom-up population mapping framework** that integrates Google Open Building Footprint data with micro-census household surveys to estimate population distribution at the building level (Google, 2024; Huang et al., 2020). By combining settlement typologies, normalized difference vegetation index (NDVI), travel time to health facilities, and nighttime light intensity, the study develops a spatially explicit model for identifying zero-dose populations. This integrative approach improves population estimation accuracy and strengthens evidence-based immunization planning in data-scarce contexts.

Research Objectives

1. To correlate projected population estimates with surveyed population data using Google Building Footprints in Jigawa State.
2. To estimate the spatial distribution of zero-dose children based on projected and surveyed population data.

The findings of this study contribute to improved population estimation, enhanced healthcare planning, and more effective identification of zero-dose children, thereby supporting Nigeria's progress toward SDG 3.

2. Materials and Methods

2.1 Study Design and Analytical Framework

This study adopts a quantitative, spatially explicit analytical framework to evaluate the accuracy of projected population estimates and their implications for identifying zero-dose children in Jigawa State, Nigeria. The methodology integrates bottom-up population mapping, household survey data, regression-based validation, and GIS-based multi-criteria modeling. The overall workflow consists of four sequential components: (i) population estimation using building footprints, (ii) field-based household survey validation, (iii) statistical comparison of projected and surveyed populations, and (iv) spatial estimation of zero-dose children using a weighted overlay model.

2.2 Data Sources and Preparation

Multiple geospatial and demographic datasets were used to characterize population distribution, settlement patterns, accessibility, and environmental context. All spatial datasets were projected to a common coordinate reference system and resampled where necessary to ensure spatial consistency.

Table 1. Data types and sources used in the study

Data	Purpose	Source
Google Building Footprints	Building-level population allocation	Google Open Buildings
Built-up Characteristics	Urban intensity characterization	Copernicus Human Settlement
Settlement Model	Settlement typology (urban–rural gradient)	Copernicus Human Settlement
Land Use / Land Cover	Contextual land characterization	Sentinel Hub
Projected Population	LGA-level population totals	City Population
Road Network	Travel time modeling	OpenStreetMap
Health Facilities	Accessibility analysis	GRID3
Elevation (DEM)	Terrain influence on accessibility	NASA Earthdata
Drainage Network	Physical accessibility constraint	PAUWES
NDVI	Environmental proxy	Copernicus
Night-Time Lights	Socio-economic proxy	EOG Mines

2.3 Bottom-Up Population Estimation Using Building Footprints

Projected population totals at the LGA level were spatially redistributed to individual buildings using Google Building Footprint data. Population density was first computed as the ratio of total projected population to total building footprint area within each LGA. This density value was then used to estimate the population residing in each building footprint.

$$PD = \frac{P_{LGA}}{\sum A_b} \qquad (1)$$

where PD is population density (persons/m²), P_{LGA} is the projected LGA population, and $\sum A_b$ is the cumulative building footprint area within the LGA.

The estimated population per building was calculated as:

$$P_b = PD \times A_b \qquad (2)$$

where P_b is the estimated population of building b, and A_b is its footprint area.

Ancillary spatial attributes—including settlement type, NDVI, nighttime light intensity, and travel time to the nearest health facility—were extracted for each building footprint to support subsequent modeling.

2.4 Household Survey and Sample Size Determination

A geolocated household survey was conducted between March and May 2024 across all 27 LGAs in Jigawa State. A total of 1,600 buildings were fully enumerated using stratified random sampling to capture both rural and urban settlement types. Data collected included household size, age structure, immunization status, travel time to health facilities, and selected socio-economic characteristics.

The minimum sample size was determined using the standard proportion-based formula:

$$n = \frac{Z^2\, p(1-p)}{E^2} \qquad (3)$$

where $Z = 1.96$ corresponds to a 95% confidence level, $p = 0.5$ represents the assumed population proportion (maximizing sample size), and $E = 0.0245$ is the margin of error (2.45%).

To reduce the influence of extreme values, sampling weights were truncated at the 90th percentile.

2.5 Validation Using Ordinary Least Squares (OLS) Regression

To assess the agreement between projected and surveyed population estimates, Ordinary Least Squares (OLS) regression was applied at the ward level ($n = 288$). Projected population served as the dependent variable, while surveyed population was used as the explanatory variable.

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (4)$$

where Y is the projected population, X is the surveyed population, β_0 is the intercept, β_1 is the slope coefficient, and ε is the error term.

This analysis enabled evaluation of systematic bias in projected population estimates across rural and urban wards.

2.6 Zero-Dose Children Estimation Framework

Zero-dose children under one year of age were estimated using a GIS-based weighted overlay model integrating accessibility, environmental, and settlement factors. Four key variables were selected based on survey evidence and public health relevance.

Table 2. Factors and weights used in the zero-dose model

Factor	Influence on Zero-Dose Likelihood	Weight
Travel time to health facilities (TD)	Higher time increases likelihood	0.30
Night-time light intensity (NLT)	Lower intensity increases likelihood	0.20
NDVI	Lower vegetation increases likelihood	0.20
Settlement type (ST)	Rural classes increase likelihood	0.30

2.7 Normalization of Model Variables

Continuous variables were normalized using min–max scaling to ensure comparability:

$$TD_{norm} = \frac{TD - TD_{min}}{TD_{max} - TD_{min}} \qquad (5)$$

$$NLT_{norm} = \frac{NLT - NLT_{min}}{NLT_{max} - NLT_{min}} \qquad (6)$$

$$NDVI_{norm} = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \qquad (7)$$

Settlement types were normalized using ordinal weights, with rural settlements assigned higher values than urban classes to reflect increased vulnerability.

2.8 Weighted Overlay and Zero-Dose Estimation

The composite zero-dose index was calculated as a weighted sum of normalized factors:

$$ZD_{index} = (0.3 \times TD_{norm}) + (0.3 \times ST) + (0.2 \times NDVI_{norm}) + (0.2 \times NLT_{norm}) \qquad (8)$$

The final number of zero-dose children was estimated by combining the index with the target population:

$$ZD = P_{target} \times ZD_{index} \qquad (9)$$

where P_{target} represents the estimated population of children under one year of age.

3. Results

The total projected population for Jigawa State as of 31st March 2024 is 8,231,942, whereas the survey-based population is 7,771,359. The mean of the projected population (μ_p=28,583) is higher than that of the surveyed population (μ_s=26,983), while their medians are 21,67321 and 67321,673 respectively. This suggests that the projected population tends to overestimate compared to the surveyed data. The standard deviation of the surveyed population (σ_s=26,819) is higher than that of the projected population (σ_p=22,677), indicating greater variability in the surveyed data. Additionally, both datasets exhibit positive skewness, with the surveyed population being more skewed ($\gamma 1_s$=2.71) compared to the projected population ($\gamma 1_p$=2.41). The kurtosis values indicate that both distributions are leptokurtic, with the surveyed population having a higher kurtosis ($\gamma 2_s$=9.80) than the projected population ($\gamma 2_p$=7.437) suggesting more extreme values in the surveyed data (Figure 1).

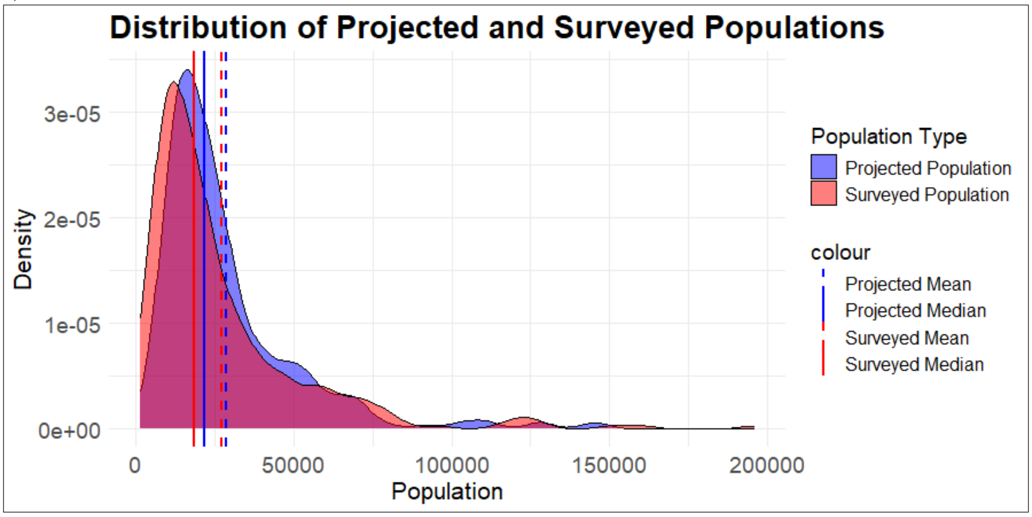

Figure 1 Distribution of Projected vs Surveyed Data

In urban areas, the projected population (μ_p: 29,690; median: 12,931) shows a lower standard deviation (σ_p:35,622) compared to the surveyed population (μ_s: 35,332; median: 14,295.5; σ_s: 46,398), indicating more variability in surveyed data. Urban populations exhibit moderate skewness and kurtosis, with higher values in the surveyed population. However, in rural areas, the projected population (μ_p: 28,491; median: 22,237; σ_p: 21,361) also shows less variability than the surveyed population (μ_s: 26,293.42; median: 18,544; σ_s: 24,538). Both distributions exhibit high skewness and kurtosis, with the surveyed population slightly more skewed. These findings underscore the variability and distribution differences between urban and rural population estimates (Figure 2).

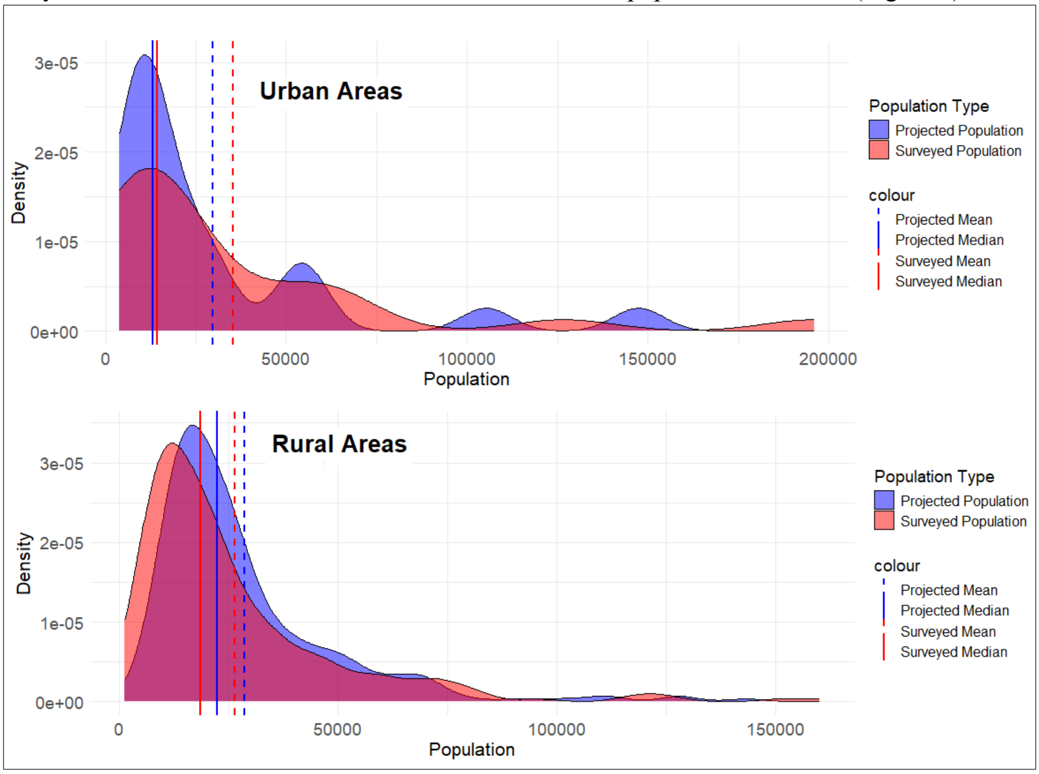

Figure 2 Distribution of Population

Model Performance and Statistical Significance

The model revealed a strong positive relationship with a coefficient of 0.82 ($p < 0.01$). The model's robustness is indicated by an Adjusted R-Squared of 0.94 and significant Joint F-Statistic (5331.61, p < 0.01) and Wald Statistic (1296.06, p < 0.01). Despite significant Koenker (BP) and Jarque-Bera statistics suggesting heteroskedasticity and non-normality of residuals, the robust standard errors and probabilities confirmed the model's reliability, with all variables remaining highly significant (p < 0.01) (Figure 3).

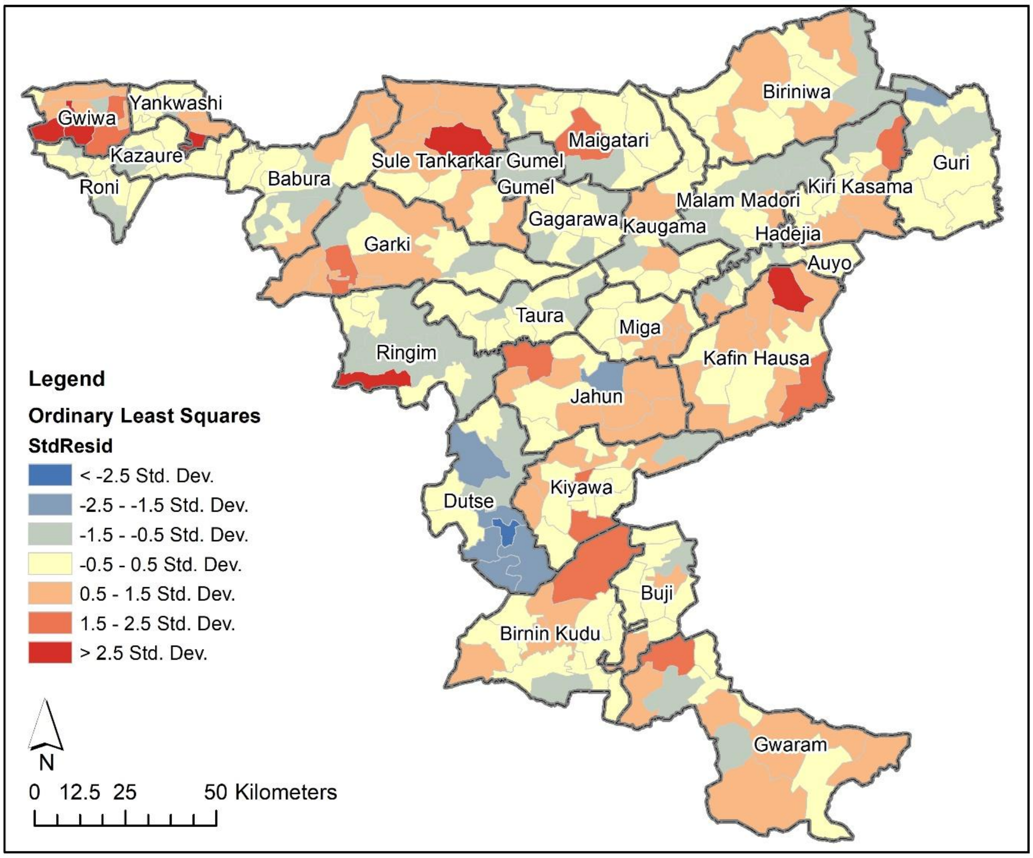

Figure 3 Projected vs Surveyed Data

The results of the paired t-tests comparing projected population data with field survey data provide strong evidence supporting the hypothesis that the projected data overestimates the rural population and underestimates the urban population. The paired t-tests comparing the projected population data with the surveyed population data for both rural and urban areas yielded the following results: In urban areas, the results indicated a significant difference between the two populations with a t-value of -2.1956 (df = 21) and a p-value of 0.03949. The 95% confidence interval for the mean difference was between -10985.1327 and -298.1401, with a mean difference of -5641.636. This suggests that the surveyed population in urban areas is significantly higher than the projected population, supporting the hypothesis that the projected population data for urban areas may be underestimated. Similarly, in rural areas, the results showed a highly significant difference with a t-value of 5.9476 (df = 265) and a p-value of 8.565e-09. The 95% confidence interval for the mean difference was between 1470.433 and 2925.800, with a mean difference of 2198.117. This indicates that the surveyed population in rural areas is significantly higher than the projected population, suggesting that the projected population data for rural areas may also have discrepancies but in the opposite direction (Figure 4).

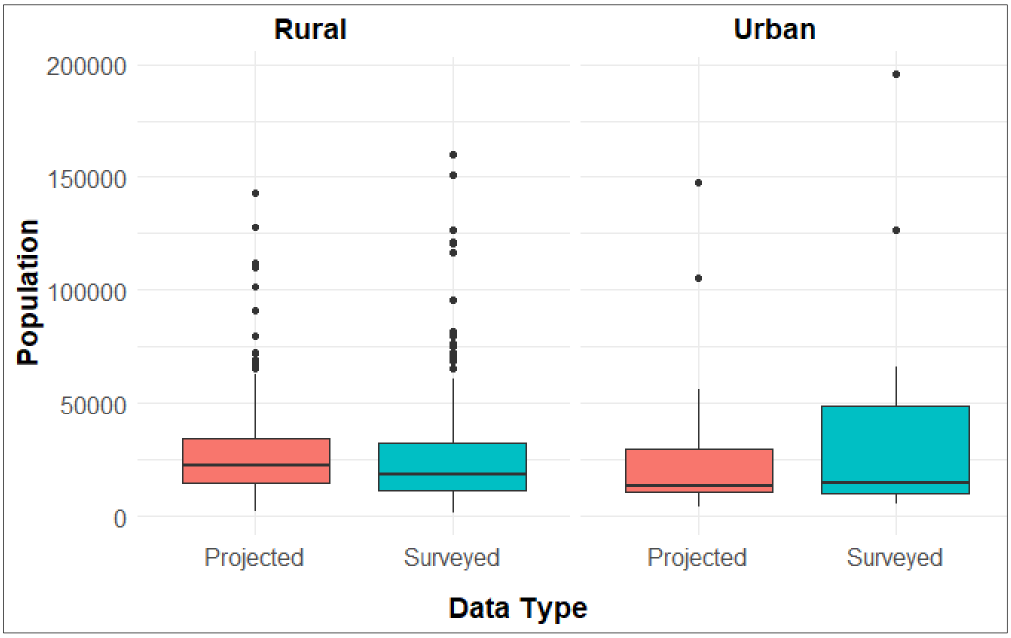

Figure 4 Rural vs Urban Population

Zero Dose Estimation

The estimation of zero-dose children in Jigawa State relies on a comprehensive model that integrates four key factors: Settlement Types (ST) (Figure 5a), Normalized Difference Vegetation Index (NDVI) (Figure 5b), Time Distance to Health Facilities (TD) (Figure 5c) and Nightlight Data (NL) (Figure 5d). These factors are interdependent and collectively influence the likelihood of children being zero-dose.

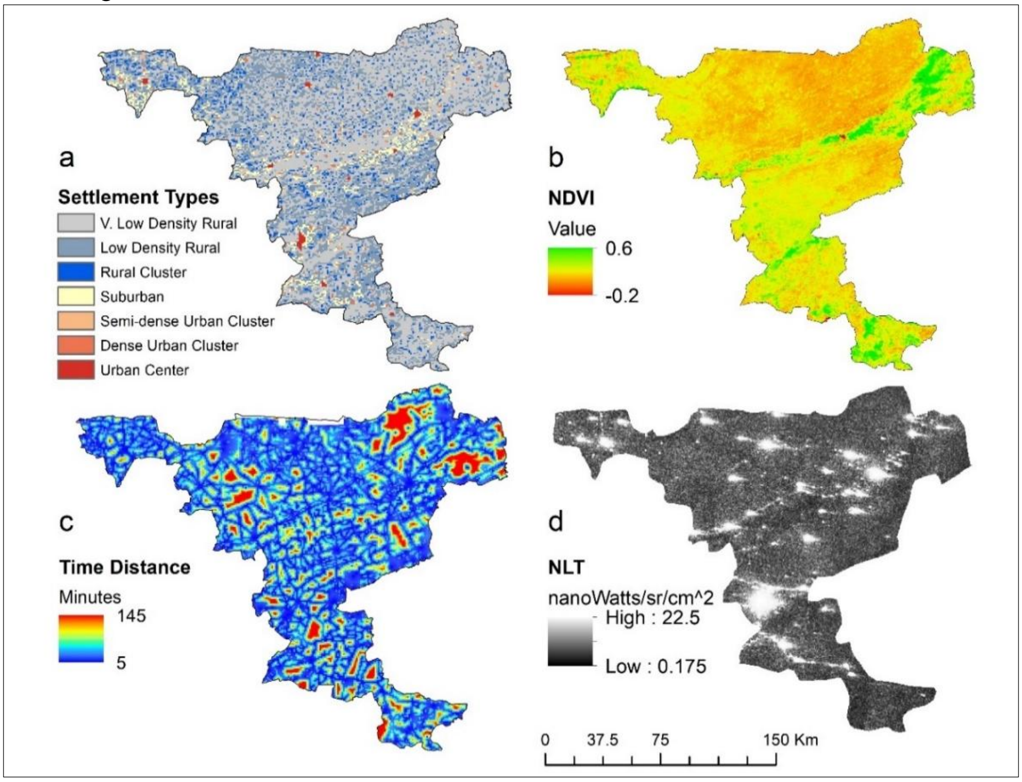

Figure 5 Zero Dose Factors

Settlement Types (ST): Jigawa State predominantly consists of rural settlements (Fig. 4) characterized by limited access to healthcare and infrastructure. The analysis of settlement types across various Local Government Areas (LGAs) in Jigawa, based on the percentage distribution, reveals significant variability. Urban Centres dominate in Hadejia with 95.87%, Gumel with 73.88%, and Malam Madori with 39.12%. Dense Urban Clusters are prevalent in areas like Taura (40.08%) and

Kiri Kasama (33.95%). Suburban settlements show notable presence in Auyo (50.72%) and Roni (37.97%). Rural clusters are predominant in many LGAs, notably Gagarawa (43.29%) and Kaugama (39.91%). Low-density rural settlements are also significant, with Sule Tankarkar showing the highest at 57.16%. These findings highlight the diverse settlement patterns within Jigawa, reflecting the unique demographic and geographic characteristics of each LGA (Figure 6).

These rural areas, as low-density rural settlement, are at a higher risk of having zero-dose children. In contrast, the fewer urban settlements, while better equipped, indicate a lower overall risk. This distribution underscores the importance of focusing health interventions in the more prevalent rural areas to improve vaccination coverage and reduce the number of zero-dose children in Jigawa State.

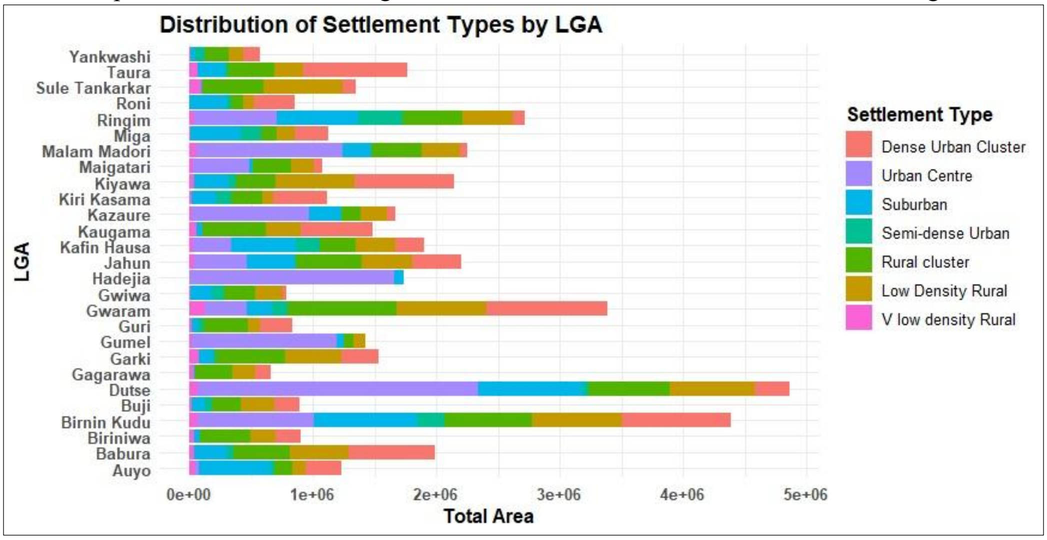

Figure 6 Settlement Types by LGA

Time Distance (TD): This is a critical factor, with longer travel times to health facilities significantly increasing the likelihood of children not receiving vaccinations. This factor is closely linked with Settlement Types, as rural areas typically have higher time distance values due to less infrastructure and healthcare access (Figure 7). In "Very Low-Density Rural" settlements, the meantime distance to health facilities is 22.4 minutes, with a maximum of 138 minutes. Conversely, in "Urban Centres," the mean time is significantly lower at 5.53 minutes, with a maximum of 33.1 minutes. Intermediate values are observed in other settlement types. This analysis highlights that urban areas generally have shorter travel times to health facilities compared to rural areas, illustrating the impact of settlement density on accessibility.

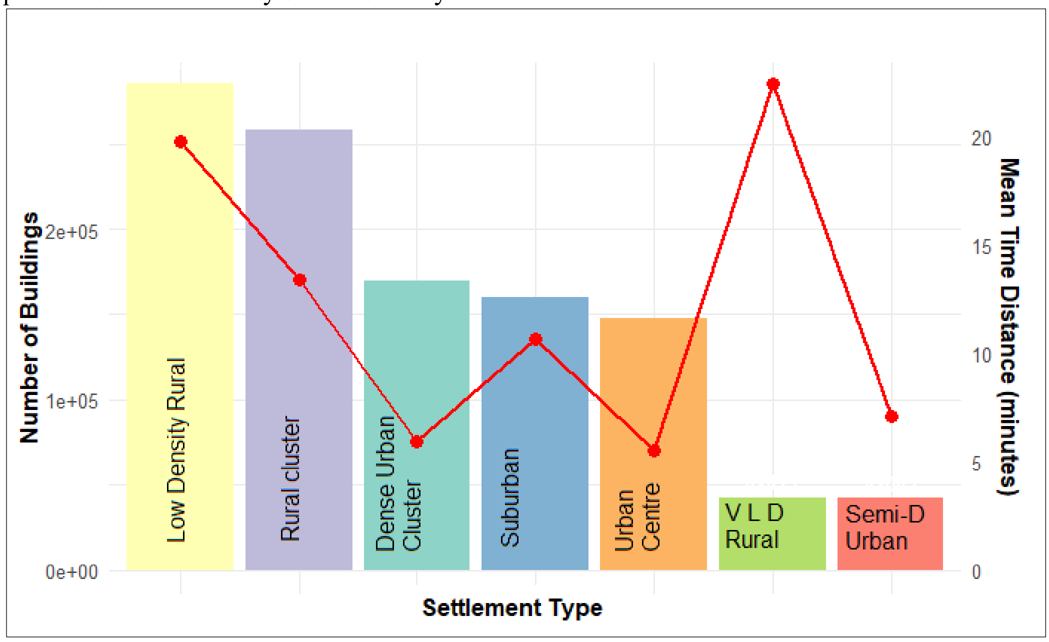

Figure 7 Time Distance to Health Facilities

Nightlight (NL): It serves as an indicator of infrastructure and development, where lower night-light levels correlate with higher zero-dose likelihood, often seen in rural settlements with limited electrification and urbanization (Figure 8).

we observed notable disparities in the spatial distribution of buildings and night-time light levels across different settlement types. The V Low Density Rural settlements contain 42,419 buildings with a total area of approximately 1,097,688 square meters and a mean night-time light value of 0.487. In contrast, Urban Centres have 147,334 buildings, cover a total area of 10,774,633 square meters, and exhibit a significantly higher mean night-time light level of 14.7. This analysis highlights a clear gradient in night-time light intensity, correlating with the urban density of the settlement types.

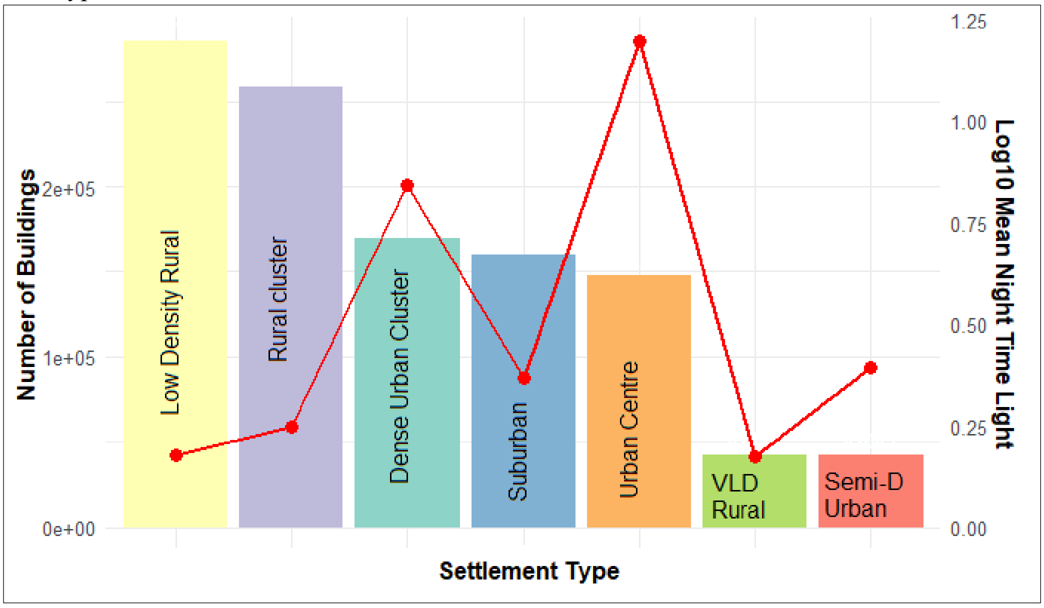

Figure 8 Night light time

The Normalized Difference Vegetation Index (NDVI): NDVI measures vegetation cover, with lower NDVI values indicating lack of cultivable land, contributing to higher zero-dose risks due to poor conditions, isolation and lack of services.

Zero-dose children

The total zero dose children are 113,143 based on projected population for Jigawa State as of 31st March 2024, whereas based on survey population, zero dose children were estimated as 91,415. Significant differences are observed in zero dose estimation between the projected and survey-based data (Figure 9).

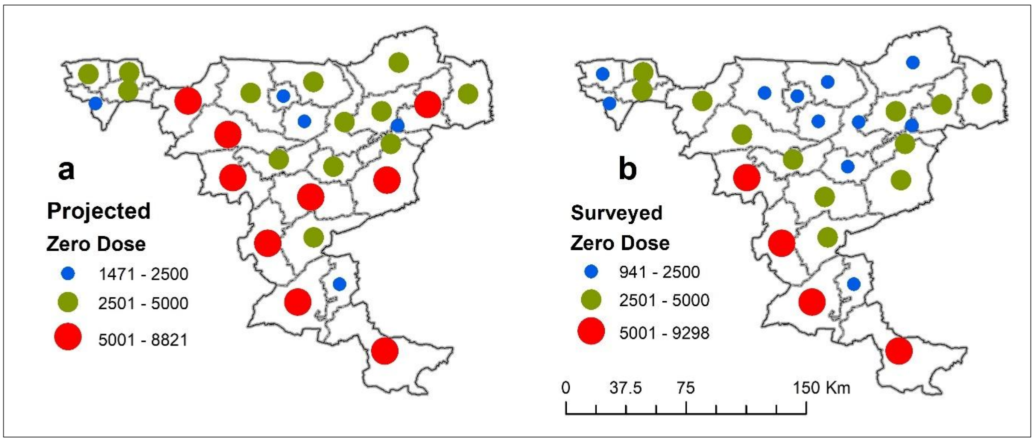

Figure 9 Zero Dose

The analysis of the discrepancy between projected and surveyed zero-dose children reveals a mean gap of 75.44, with a median of 76.50. The standard deviation of 125.31 highlights significant variability, and the gap ranges from -355.00 to 462.00, showing a broad spectrum of discrepancies. Notably, the rural areas Maigatari Arewa and Fandum exhibit the largest overestimations, while urban areas as Kachi, Duste shows substantial underestimation. These findings emphasize the need for improved projection accuracy and localized adjustments to better reflect actual population data and address significant disparities in zero-dose estimates across different regions (Figure 10).

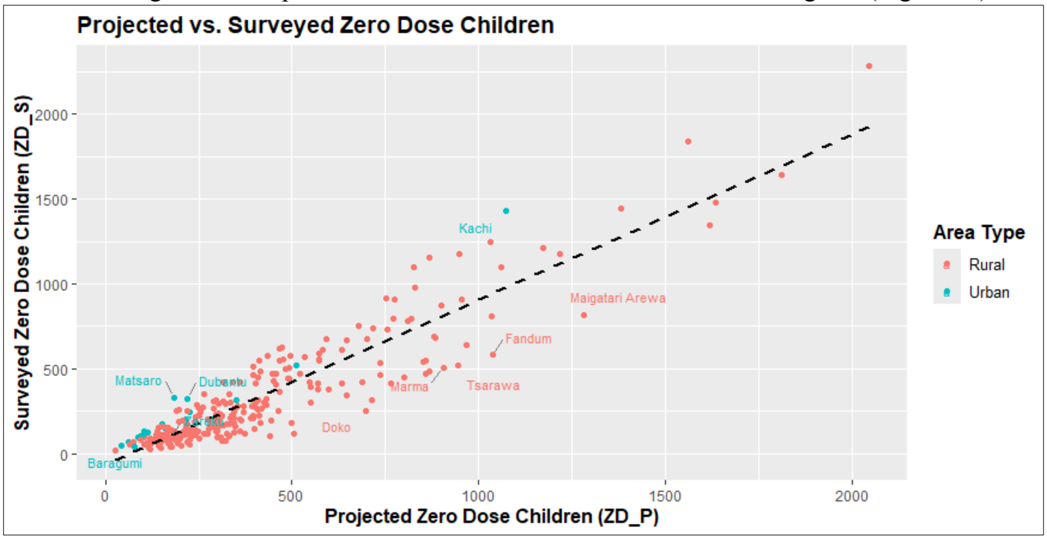

Figure 10 Zero Dose Projected vs Surveyed

Figure 11 shows the gap between projected and surveyed zero dose children by LGA.

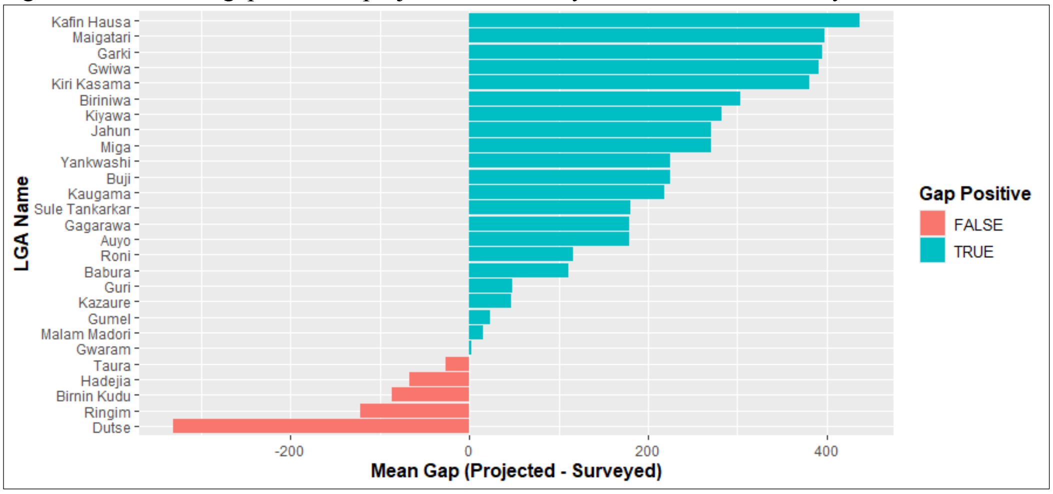

Figure 11 Mean Gap

The Ordinary Least Squares (OLS) regression analysis yields an intercept coefficient of 114.11 ($p < 0.0001$) and a coefficient for the Zero Dose Survey-Based variable of 0.88 ($p < 0.0001$). Diagnostics for the model, using the dependent variable "Zero Dose Projected Base," show a high fit with an R-squared of 0.85 and an adjusted R-squared of 0.85. The model's significance is supported by a Joint F-Statistic of 1661.73 ($p < 0.0001$) and a Wald Statistic of 859.92 ($p < 0.0001$). Diagnostic tests indicate no major issues with model fit or heteroskedasticity (Figure 12).

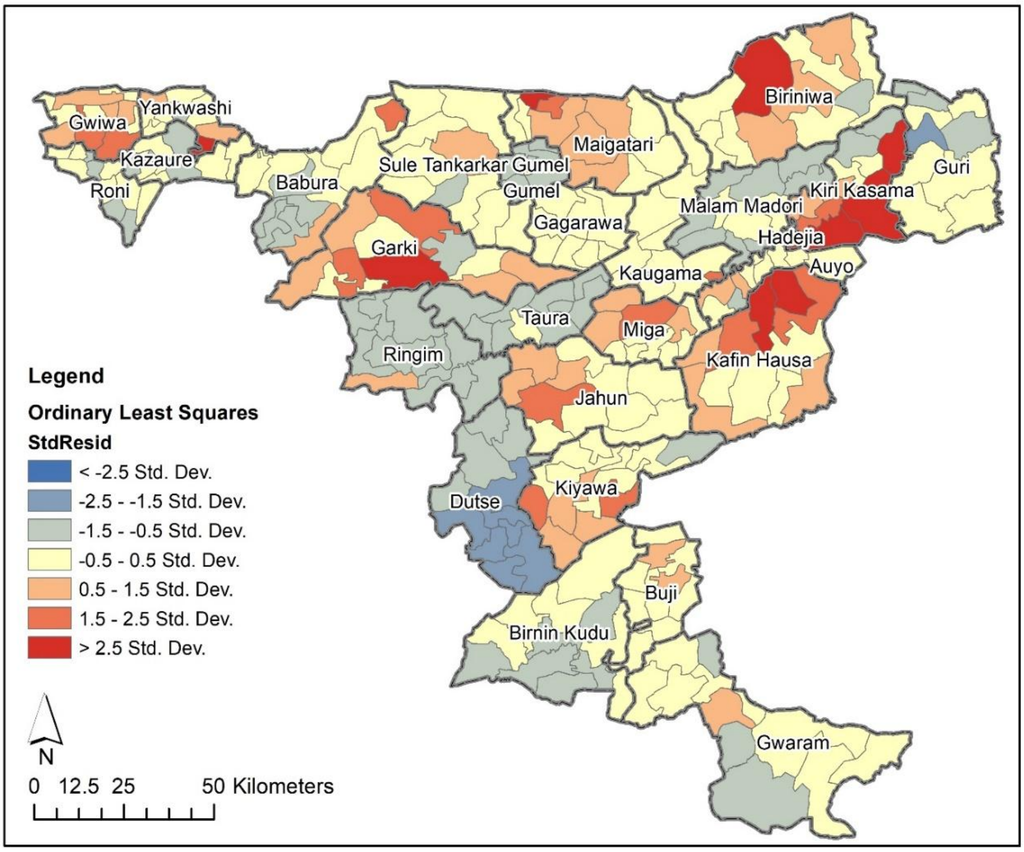

Figure 12 Zero Dose

Discussion

This study presents a framework for bottom-up population modelling that integrates household survey data with Google building footprint attributes. Existing population estimation techniques have demonstrated the advantages of combining building footprint data with household surveys over reliance on country-wide national census coverage (Huang et al., 2020). While many population estimation approaches produce gridded raster outputs at approximately 90 m resolution, this study estimates population at the building level using vector-based representations, enabling finer spatial precision. Household survey data collected through a systematic random sampling design were leveraged to calculate population density based on building footprint area and the number of inhabitants. During the assessment, outliers associated with uncertainties in population density estimates were identified and truncated at the 90th percentile of the statistical distribution to enhance robustness and reduce bias (Havlicek & Peterson, 1974).

The Global Human Settlement Layer (GHSL) was used to approximate the spatial extent and distribution of settled areas and to derive settlement morphological and topological characteristics (European Commission Joint Research Centre, 2023). Gross built-up area was calculated by combining building footprint area with the number of floors derived from building height information. However, these results should be interpreted with caution, as small variations in estimated population density per square meter (e.g., 0.001 persons/m²) can result in substantial differences in the total population allocated to each Local Government Area (LGA).

To identify systematic overestimation and underestimation in population projections, a regression-based validation approach was applied. Population estimates derived from the top-down census-based projection approach were specified as the dependent variable, while population estimates from the bottom-up survey-based approach were treated as the independent variable. Results indicate that urban LGAs were consistently underestimated, whereas rural LGAs were overestimated in the projected population data. This analysis was implemented within a GIS environment using Ordinary Least Squares (OLS) regression.

Despite its widespread application, OLS regression has known limitations when applied to spatial data. One key assumption of OLS is that residuals are spatially independent, an assumption that is often violated in spatial datasets, leading to inefficient coefficient estimates and potentially biased inference when spatial autocorrelation is present (Anselin, 1990). OLS regression is also sensitive to multicollinearity among predictor variables, which can inflate standard errors and obscure the individual effects of correlated predictors (Mansfield & Helms, 1982). Nevertheless, ArcMap provides a suite of diagnostic tools for evaluating OLS model performance, including tests for multicollinearity, heteroscedasticity, spatial autocorrelation, and residual normality, allowing users to assess model validity and reliability (Esri, 2021). In this study, diagnostic results indicate that the model effectively explains variation in the dependent variable and that the identified relationships are statistically sound.

Paired t-tests further revealed a statistically significant difference between projected and surveyed population estimates in urban areas, with surveyed populations consistently exceeding projected values. This finding supports the hypothesis that urban populations are underestimated in census-based projections. Conversely, rural populations were generally overestimated. These findings have important implications for policy formulation and resource allocation. However, several limitations must be acknowledged. The paired t-test assumes normality and homogeneity of variance; violations of these assumptions may affect the robustness of the statistical inference (Havlicek & Peterson, 1974).

To estimate zero-dose children under one year of age, a GIS-based weighted overlay model was developed. Key factors—including travel time to health facilities, nighttime light intensity, NDVI, and settlement type—were normalized and weighted according to their relative influence, producing a composite index of zero-dose likelihood. This approach aligns with existing research in Nigeria emphasizing the importance of geographic, socio-economic, and environmental determinants of immunization coverage (Ozigbu, 2023). Previous studies have demonstrated that proximity to health facilities, settlement characteristics, and socio-economic conditions significantly influence immunization uptake, thereby reinforcing the conceptual validity of the weighted overlay framework used in this study (Wonodi & Farrenkopf, 2023).

Based on projected population data, the study estimates 113,143 zero-dose children, while survey-based estimates indicate 91,415 zero-dose children. According to the *Nigeria Zero-Dose Situation Analysis* reported in the Multiple Indicator Cluster Survey (MICS) and National Immunization Coverage Survey (NICS) 2021, approximately 27% of the target population nationally are classified as zero-dose children (Gavi, 2023). In comparison, projected population data in this study suggest that approximately 30.5% of children are zero-dose, whereas survey-based estimates indicate approximately 26.1%. These findings suggest that census-based projections slightly overestimate the prevalence of zero-dose children, while survey-based estimates closely align with national benchmarks.

Overall, the findings underscore the importance of accurate, localized population data for effective public health planning. The integration of GIS-based modelling with household survey data provides a robust framework for identifying zero-dose children in regions characterized by demographic uncertainty and health disparities. Targeted interventions in underserved rural areas, investment in infrastructure development, and regular updating of population projections are essential for improving vaccination coverage and reducing the burden of zero-dose children in Jigawa State. Future research should further investigate the interactions between geographic, environmental, and infrastructural factors shaping healthcare access and outcomes.

Conclusion

This study highlights the increasing trend of malaria incidence in Abuja from 2014 to 2024, despite a declining trend in malaria parasite suitable days due to climate variability. The findings indicate that population growth is a significant driver of malaria incidence, with urban expansion, high population density, and inadequate infrastructure contributing to sustained transmission. While climate factors influence malaria dynamics, human-driven environmental changes play a dominant role in urban malaria transmission. Effective malaria control in Abuja requires integrated interventions, including vector management, improved urban planning, and climate adaptation strategies to mitigate future risks and enhance public health resilience.

Data Availability Statement:

The data used in this study are available on Zenodo [https://doi.org/10.5281/zenodo.13157028].

Building Footprint: https://code.earthengine.google.com/feb22dc3a3172c623141dc826f3cf51e

Night Light Data: https://code.earthengine.google.com/1d0e6f4d68441edf230bb69983b6867c

NDVI: https://code.earthengine.google.com/96f52f762a39bcda163a83796c3166df

DEM: https://code.earthengine.google.com/7ae3608e591682fc81f54c520cecad84

Administrative: https://developers.google.com/earth-engine/datasets/catalog/ FAO/GAUL/2015/level2

Author Contributions: Conceptualization, Z.I. and Y.J.C.; methodology, Z.I. F.M. and U.U.E.; formal analysis, Z.I., Y.J.C., and R.K.H.; investigation, U.U.E., Y.J.D., F.M. and R.K.H.; data curation, U.U.E. and E.L.E.; writing original draft preparation, Z.I. and Y.J.C.; writing—review and editing, U.U.E., E.L.E., and R.K.H.; supervision, Z.I.; project administration, Z.I. F.M.and Y.J.C. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation

DEM – Digital Elevation Model

GHSL – Global Human Settlement Layer

GIS – Geographic Information System

LGA – Local Government Area

NDVI – Normalized Difference Vegetation Index

NLT – Night-Time Light

OLS – Ordinary Least Squares

RI – Routine Immunization

SDG – Sustainable Development Goal

References

Aliyu, A. A., & Amadu, L. (2017). Urbanization, cities, and health: The challenges to Nigeria—A review. *Annals of African Medicine, 16*(4), 149–158. https://doi.org/10.4103/aam.aam_1_17

Anselin, L. (1990). Spatial dependence and spatial structural instability in applied regression analysis. *Journal of Regional Science, 30*(2), 185–207. https://doi.org/10.1111/j.1467-9787.1990.tb00092.x

Bhatia, R., & Khetrapal, S. (2020). Impact of the COVID-19 pandemic on health systems and Sustainable Development Goal 3. *Indian Journal of Medical Research, 151*(5), 395–395. https://doi.org/10.4103/ijmr.ijmr_1920_20

Bukola, A., & Appunni, O. S. (2024). Effect of data accuracy and non-use of quality information on reproductive health: A comparative study of Nigeria and South Africa. *African Journal for Physical Activity and Health Sciences, 30*(1). https://doi.org/10.37597/ajphes.2024.30.1.1

Copernicus Emergency Management Service. (2024a). *Built-up characteristics*. https://human-settlement.emergency.copernicus.eu/download.php?ds=builtC

Copernicus Emergency Management Service. (2024b). *Settlement model*. https://human-settlement.emergency.copernicus.eu/download.php?ds=smod

Copernicus. (2024). *NDVI applications*. https://sentiwiki.copernicus.eu/web/s2-applications

Das, T., Holland, P., Ahmed, M., & Husain, L. (2021). Sustainable Development Goal 3: Good health and well-being. In T. Das & P. D. Nayar (Eds.), *South-East Asia eye health*. Springer. https://doi.org/10.1007/978-981-16-3787-2_4

Esri. (2021). *Ordinary Least Squares (OLS) (Spatial Statistics)*. https://desktop.arcgis.com/en/arcmap/latest/tools/spatial-statistics-toolbox/ordinary-least-squares.htm

European Commission Joint Research Centre. (2023). *Global Human Settlement Layer (GHSL)*. https://data.jrc.ec.europa.eu/collection/ghsl

Gavi. (2023). *Nigeria zero-dose situation analysis*. Zero-Dose Learning Hub. https://zdlh.gavi.org/resources/nigeria-zero-dose-situation-analysis

Google. (2024). *Google open buildings*. https://sites.research.google/open-buildings/

Grassly, N. C., Lewis, J. J., Mahy, M., Walker, N., & Timæus, I. M. (2004). Comparison of household-survey estimates with projections of mortality and orphan numbers in sub-Saharan Africa in the era of HIV/AIDS. *Population Studies, 58*(2), 207–217. https://doi.org/10.1080/0032472042000224431

GRID3. (2024). *Health facilities dataset*. https://data.grid3.org/search?collection=Dataset

Havlicek, L. L., & Peterson, N. L. (1974). Robustness of the t test: A guide for researchers on the effects of violations of assumptions. *Psychological Reports, 34*(3), 1095–1104. https://doi.org/10.2466/pr0.1974.34.3c.1095

Huang, X., Wang, C., Li, Z., & Ning, H. (2020). A 100 m population grid in the CONUS by disaggregating census data with open-source Microsoft building footprints. *Big Earth Data, 5*(2), 112–133. https://doi.org/10.1080/20964471.2020.1776200

Maria, A., Hill, J., Webster, J., Lines, J., & Rowland, M. (2011). Coverage of malaria protection in pregnant women in sub-Saharan Africa: A synthesis and analysis of national survey data. *The Lancet Infectious Diseases, 11*(3), 190–207. https://doi.org/10.1016/S1473-3099(10)70295-4

Mansfield, E. R., & Helms, B. P. (1982). Detecting multicollinearity. *The American Statistician, 36*(3), 158–160. https://doi.org/10.1080/00031305.1982.10482818

NASA Earthdata. (2024). *Digital elevation terrain model (DEM)*. https://www.earthdata.nasa.gov/topics/land-surface/topography/terrain-elevation/digital-elevation-terrain-model-dem

Okolo, A. (2024). *The Nigerian census: Problems and prospects*. JSTOR. https://www.jstor.org/stable/2686050

Onwujekwe, O., Onoka, C., Uzochukwu, B., Hanson, K., & Wiseman, V. (2011). Constraints to universal coverage: Inequities in health service use and expenditures for different health conditions and providers. *International Journal for Equity in Health, 10*, Article 50. https://doi.org/10.1186/1475-9276-10-50

OpenStreetMap Contributors. (2024). *OpenStreetMap*. https://www.openstreetmap.org/

Ojerinde, O. A., & Iroju, O. (2015). *Strategies for managing information flow in Nigeria healthcare system*. Federal University of Technology Minna Repository. http://repository.futminna.edu.ng:8080/jspui/handle/123456789/11549

Ozigbu, C. (2023). *Beyond vaccination coverage: A critical look at zero-dose children in Sub-Saharan Africa* (Doctoral dissertation). ProQuest. https://www.proquest.com/openview/2b51c5adc901394245f3bd6fe15547ab

PAUWES Data Portal. (2024). *Drainage dataset*. https://dataportal.pauwes.dz/geonetwork/srv/api/records/489f7af7-2b3a-41cf-b4a0-4aa2acd1e934

Population. (2024). *Population of Jigawa State*. City Population. https://www.citypopulation.de/en/nigeria/admin/NGA018__jigawa/

Potts, D. (2012). Challenging the myths of urban dynamics in Sub-Saharan Africa: The evidence from Nigeria. *World Development, 40*(7), 1382–1393. https://doi.org/10.1016/j.worlddev.2011.12.004

Rehle, T. M., & Shisana, O. (2003). Epidemiological and demographic HIV/AIDS projections: South Africa. *African Journal of AIDS Research, 2*(1), 1–8. https://doi.org/10.2989/16085906.2003.9626554

Sentinel Hub. (2024). *Impact Observatory land use and land cover map*. https://collections.sentinel-hub.com/impact-observatory-lulc-map/

Weber, E. M., Seaman, V. Y., Stewart, R. N., et al. (2018). Census-independent population mapping in northern Nigeria. *Remote Sensing of Environment, 204*, 786–798. https://doi.org/10.1016/j.rse.2017.09.024

Wonodi, C., & Farrenkopf, B. A. (2023). Defining the zero-dose child: A comparative analysis of two approaches and their impact on assessing the zero-dose burden and vulnerability profiles across 82 low- and middle-income countries. *Vaccines, 11*(10), Article 1543. https://doi.org/10.3390/vaccines11101543