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Informing the expansion of integrated community case management in Nigeria

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Contents

Acronyms

CHIPs	Community Health Influencers, Promoters and Services program
CHWs	Community Health Workers
FCT	Federal Capital Territory
FMoH	Federal Ministry of Health
GRID3	Geo-Referenced Infrastructure and Demographic Data for Development
HRH	Human Resources for Health
iCCM	Integrated Community Case Management
IGME	UN Inter-agency Group for Child Mortality Estimation
IMCI	Integrated Management of Childhood Illness
ITN	Insecticide-Treated Net
LGA	Local Government Authority
LGHA	Local Government Health Authority
LSHTM	London School of Hygiene and Tropical Medicine
MACEPA	Malaria Control and Elimination Partnership in Africa
MAP	Malaria Atlas Project
MCDA	Multi-Criteria Decision Analysis
NPHCDA	National Primary Health Care Development Agency
NHWR	Nigeria Health Workforce Registry
NMEP	National Malaria Elimination Programme
Pf	Plasmodium Falciparum
PHC	Primary Health Care
RHCC	Rotary Healthy Communities Challenge project
SDGs	Sustainable Development Goals
SPHCB	State Primary Health Care Board
UHC	Universal Health Coverage
UNICEF	The United Nations Children's Fund
WHO	World Health Organization

Abstract

Background

High under-five mortality rates persist due to inadequate health services and geographical inaccessibility, with Nigeria's rate nearly three times the global average in 2022. Nigeria introduced integrated community case management, leveraging community health workers (CHWs) to reach populations beyond the coverage of primary health care (PHC) facilities. This project introduced geospatial approaches to provide evidence for CHW expansion strategies of National Malaria Elimination Programme (NMEP) during a new investment from Rotary Healthy Communities Challenge (RHCC) project.

Methods

We assessed accessibility to PHC facilities using modelled surfaces of population density, travel time, and georeferenced health facility data. Disease burden estimates and intervention coverage indicators from surveys and geospatial datasets enabled us to create a comprehensive ward-level dataset. An interactive dashboard was developed to facilitate multi-criteria decision analysis (MCDA) and stakeholder engagement in stepwise approach to prioritize wards for CHW deployment. A spatial optimization algorithm was then applied to estimate the required number of CHWs and identify optimal placement locations.

Results

Significant disparities were identified in ward-level data on accessibility, disease burden, intervention coverage, and health security. Applying prioritisation criteria as discussed with PATH and NMEP, malaria prevalence and mortality rates were selected as the indicators for malaria burden over incidence rates in the vulnerability scoring index. Among the six pre-selected states (areas currently without CHWs), 292 out of 1,181 wards were prioritized based on vulnerability scores that were derived as a combination of accessibility, malaria burden, conflict situations, and proximity to Abuja. Applying a spatial optimization model in Delta state revealed that 273 CHWs are needed to serve 85,395 people across 36 wards in 14 LGAs.

Conclusions

Using MCDA in prioritizing wards through an interactive dashboard, and application of spatial optimization to determine optimal CHW placement, this project enhances data-driven strategies in improving health accessibility for underserved populations.

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1. Introduction

In sub-Saharan Africa, the under-five mortality rate remains high due to factors, including inadequate health services and geographical inaccessibility. (1) In 2022, Nigeria's under-five mortality rate was 107 per 100,000 live births, nearly three times the global average. (2) Addressing these issues requires integrated, high-quality services, supported by sustainable financing and effective resource mobilization for community health and primary health care (PHC). (1) At the 2019 Astana Global Conference on PHC, Nigeria and other member states reaffirmed their commitment to delivering integrated services with a functional referral system between care levels, while also pledging to improve PHC workforce retention in rural and underserved areas. (3) The health workforce is crucial for achieving universal health coverage (UHC) and the Sustainable Development Goals (SDGs). The Global Strategy on Human Resources for Health (HRH) Workforce 2030 highlights the need for sufficient, well-trained, and equitably distributed health staff. (4)

In 2012, Nigeria's Ministry of Health adopted the integrated community case management (iCCM) strategy, focusing on treating malaria, pneumonia, and diarrheal diseases at the community level. Since 2018, Community Health Influencers, Promoters, Services Programme (CHIPS) has been introduced where trained community volunteers, such as traditional birth attendants (TBA), village health workers (VHW) and other community-based service providers that have been duly trained and are recognized by the local government health authorities (LGHA). (5) According to DHS 2018, 12.5% of children who sought treatment received care from community health workers (CHWs), with higher CHW involvement in poorer, rural, and remote areas, indicating that CHWs are successful in targeting the poorest household. (6) This approach has proven sustainable, as VHWs continue to provide quality care for uncomplicated malaria, pneumonia, and diarrhoea even five years after training. (7)

Despite efforts to strengthen the health workforce in the WHO African Region, significant challenges in workforce shortages and distribution persist, hindering the achievement of UHC and SDGs. Poor HRH planning has contributed to these challenges. (4) An exploratory study in southeast Nigeria highlighted significant inequities in health worker distribution between rural and urban areas, exacerbated by uncoordinated HRH planning. (8) Given resource constraints, ensuring access to malaria services in remote, low-income areas is crucial, where inequitable access raises social justice concerns. (9)

There remain knowledge gaps around the number of CHWs needed to cover populations and expected workloads. In the resource-constraint settings, addressing emerging threats and supporting countries and partners to prioritize activities rely on emerging data and scientific evidence. (10) Geospatial analysis, incorporating geographic information systems and disease burden estimates, can optimize the deployment. However, few countries have utilized geospatial analysis to address HRH distribution challenges and improve access to health services. In Nigeria, no previous efforts have applied geospatial techniques to guide CHW expansion strategies.

This project was designed to provide evidence for a real-world CHW expansion strategy under Rotary Healthy Communities Challenge (RHCC) project, which aims to reduce severe disease and death from malaria, pneumonia, diarrhoea among children under 5 years of age. With a focus on vulnerable populations and improving access to sustainable community health systems, MACEPA project at PATH is supporting NMEP in area targeting approach of RHCC project.

2. Aim and Objectives

2.1 Aim

To ensure effective deployment of CHWs through evidence-based prioritization using an interactive decision support tool and geospatial analysis

2.2 Objectives

- Develop data-driven targeting rationale to identify which wards should be prioritized for CCM expansion
- Develop an interactive dashboard that allows stakeholders to explore different targeting criteria and thresholds
- Apply a spatial optimization model to determine the optimal placement of CHWs to ensure all populations are within a certain travel time of health care

3. Methods

3.1 Project design

This is a ward-level analysis to prioritize wards for real-world expansion of iCCM through CHW deployment under a new investment by RHCC. We utilized secondary datasets on health facilities, population density, accessibility to health facilities and disease burden estimates. Datasets were acquired through modelled surfaces, surveys outputs and routine data sources. Within the prioritized wards, spatial optimization method was used for location-allocation analysis, to estimate number CHWs needed and to find optimal locations for placement. The scope of the study is 9,308 wards across 774 LGAs of 36 states and Federal Capital Territory (FCT) in Nigeria.

3.2 Settings

Administrative and geographic structure

Nigeria is located at the Gulf of Guinea on the west coast of Africa, bordered by Benin on the west, Niger on the north and Cameroon on the east. Geography of Nigeria consists of plains in the north and south, interrupted by plateaux and hills in the middle. The most mountainous area is along the southeastern border with Cameroon. (11)

Nigeria is three-tiers government system: federal, state, and local government areas (LGA). Geographically, the country has six geopolitical zones, comprising 36 states and FCT. Under the state-level, there are 774 LGAs, who are responsible for well-being of the local population. Each LGA is subdivided into wards, and there are 9,410 wards nationwide. Each ward is further divided into localities, then each locality into convenient areas called census enumeration areas (EAs). EAs serve as primary sampling units in 2023 Population and Housing Census and 2021 Nigeria Malaria Indicator Survey (MIS). (12)

Figure 1. Administrative map of Nigeria displaying 6 geopolitical zones and 37 states (12)

Demographic features

In 2024, Nigeria's population is estimated at slightly over 229 million and it is the largest country in Africa by population, ranking 6th globally. (13) Nigerians belong to over 250 ethnic groups. The largest groups are Hausa in the north, Yoruba in the southwest and Ibo in the southeast, who account for around a fifth of the population each. The middle belt is diverse in ethnic groups. (11)

The 2021 Multiple Indicator Cluster Survey (MICS) in Nigeria found that less than 40% of women and just over 50% of men had lived in their current location since birth. United Nations projected urban population growth from 47% to 55% between 2014 and 2024. Economic opportunities drive much of this migration, with people moving from rural to urban areas for better jobs, education, healthcare, and amenities. States with more agricultural employment tend to have higher rural-to-urban migration. Rural-rural migration is also significant, with only 44.3% of rural women and 37.3% of rural men never having migrated. (14) Women are more likely to migrate between the ages of 18 and 24. Persistent conflicts also appear to be a significant driver of migration across Nigeria. (15)

Conflicts situation

Nigeria is the epicentre of violence in North and West Africa. From 2021 to 2022, 40% of violent events and over half of the region's fatalities occurred in Nigeria. The Boko Haram insurgency, active since 2009, and Islamic State West Africa Province (ISWAP) have heavily impacted Borno, Adamawa, and Yobe states in the North-East zone. In the north-western area, violences in Kaduna, Zamfara and Katsina states caused 37% of civilian death during 2021 – 2022. Additionally, armed groups in the Niger Delta clash with the government and oil companies. (16) In the first four months of 2024, 1,401 political violence events led to 3,464 fatalities, with over half in Borno, Zamfara, and Katsina. (17)

Health workers are often targets of collective or political violence, with WHO reporting that 8% to 38% have experienced physical violence during their careers. To achieve universal health coverage, healthcare workers are increasingly serving peri-urban and rural areas. A recent study in Nigeria found that violence now extends from cities to their surrounding rural areas, creating zones of insecurity. (16) ACLED data shows 29 casualties from 60 incidents involving healthcare workers in Nigeria between April 2021 and April 2024. (17)

Health status and Human resource for Health (HRH) overview

In 2021, Nigeria's healthy life expectancy at birth was 54.9 years. UHC service coverage index, i.e., coverage of essential health services as expressed as the average score of 14 tracer indicators, was 38 out of 100, below the African regional average of 44. (18) According to the UN Inter-agency Group for Child Mortality Estimation (IGME), Nigeria's under-five mortality rate was 107.17 per 100,000 live births in 2022, the second highest globally and nearly three times the global average. There were significant state variations, with rates ranging from 252.54 in Kebbi to 52.25 in Bayelsa. (2)

Malaria was the leading cause of under-five mortality in Nigeria, with around 180,000 child deaths in 2021. (2) WHO and UNICEF recommended that children under 5 years with a recent fever received care within 24 hours onset of the symptoms, but only less than one in three received timely care in Nigeria. (12, 19) The 2021 MIS revealed significant geographical disparities: over two-thirds of children in Abia received timely care, while this figure was only one in ten in Borno. (12) In sub-Saharan Africa, high under-five mortality rates are also linked to geographical inaccessibility, inadequate services, and weak community engagement. (1)

HRH strategic plans aim to ensure the right number of qualified, skilled, and equitably distributed health workers for quality service at all levels. (20) Equitable distribution requires up-to-date workforce information. (21) Nigeria is developing the Nigeria Health Workforce Registry (NHWR), aligned with the DHIS2 system. (4) Data on 89,988 health worker from 11 states were successfully imported into the NHWR, including 18,233 community health workers: community health officers (CHOs), community health extension workers (CHEWs), and junior community health extension workers (JCHEWs). (20)

Primary Health Care services

The 1999 Constitution grants the states the power to strengthen social welfare and ensure adequate medical facilities, limiting the Federal Government's role in primary health care governance. However, due to the states' limited financial and technical resources, the Federal Government has consistently played an active role in shaping health policies. (5)

Achieving UHC and SDG targets will require strong primary health care systems, including institutionalization of community health. (1) Established in 1992, the National Primary Health Care Development Agency (NPHCDA) aims to embed PHC as the foundation of Nigeria's health system. NPHCDA provides technical and programmatic support to states, LGAs and other stakeholders in the development, planning, implementation, supervision, and monitoring of PHC. (5) At each state, State Primary Health Care Board (SPHCB) oversees service delivery while Local Government Health Authorities (LGHAs) coordinate and supervise services at LGA-level. (22) At ward-level, ward development committee (WDC) or village development committee (VDC) ensures community participation, monitoring and supports for PHC facilities.

Introduced in 2001 by NPHCDA, the Ward Health System Strategy (WHSS) aims to revitalize PHC by using political wards as catchment areas for PHC interventions. The strategy seeks to deliver essential health services by building community capacity and fostering grassroots political participation. It requires at least one functional PHC facility per ward to provide integrated services across all PHC components. In 2018, 88% of public health facilities were PHC facilities. Within the communities, properly trained, supervised, and supported CHWs deliver a range of preventive, promotive and curative health services to enhance access and reduce health inequity. According to NPHCDA, all communities 5 kilometres and above from the health facility should be covered by outreach services. (5)

Health Facility Type	Health Outreach Post	PHC Leve l	PHC Level II	PHC Level III
Catchment Area	4 Settlements or village level	Group of settlements/neighbourhoods, villages (village areas) or communities	Political ward	Focal PHC in a political ward
Estimated Coverage Population	Average of 2,000	5,000 to 10,000	10,000 to 20,000	20,000 to 30,000

Table 1. Screenshot of coverage standards for PHC infrastructure according to revised WHSS (5)

Integrated community case management (iCCM)

Integrated programming in PHC facilities has shown to be effective with better coverage of essential interventions and better health outcomes. Given the focus of SDG 3.2 (ending preventable deaths of newborns and children under 5 years of age) and SDG 3.8 (achieving universal health coverage), more countries are scaling-up iCCM to strategically increase access to essential health services with equitable health coverage. (1, 19, 23) WHO and UNICEF have recommended iCCM of childhood illnesses as a core component of integrated management of childhood illness (IMCI). By targeting hard-to-reach areas and vulnerable populations, iCCM enhances access to life-saving interventions for children with malaria, pneumonia, and diarrhoea. It also promotes rational medication use, healthy nutrition, timely care-seeking, and referrals. In Nigeria, WHO's Rapid Access Expansion (RAcE) program introduced iCCM in 2012, enabling community-oriented resource persons (CORPs) to manage these conditions in Abia and Niger states. (24) According to Africa Health Workforce Observatory, Nigeria had 116,454 community health workers, with a density of 6 per 100,000 population, above the African regional average of 4.5 per 100,000 in 2018. (4, 25) Despite iCCM policy documents outlining CHW selection approaches, criteria and methods, these guidelines were not consistently applied. (9, 23, 25)

Community Health Influencers, Promoters and Services (CHIPS) program

Launched in 2018 during Phase IV of PHC revitalization, the CHIPS program builds on the village health worker concept established by NPHCDA and endorsed by the Federal Government. It aims to harmonize community health services and create demand. CHIPs agents, categorized as 'support staff', include trained community volunteers including trained traditional birth attendants (TBA), village health workers (VHW) and other community-based service providers who are recognized by LGHA. They help households access healthcare and strengthen PHC through iCCM, crucial for achieving UHC. CHIPS activities are reported monthly to Officer-In-Charge at PHC facility. (5)

In the standards and regulatory framework for PHC, it is planned to have 10 CHIPS at each community. (5, 25) As of October 2021, 13 states had completed the training of 8,289 CHIPS Agents across 886 wards in 145 LGAs. Eight states—Nasarawa, Niger, Kano, Gombe, Yobe, Sokoto, Kaduna, and Borno—had deployed these CHIPS personnel, while five states—Adamawa, Bauchi, Osun, Ebonyi, and Jigawa—had completed training but had not yet commenced service deployment. (26)

3.3 Literature review

Existing HRH strategies in Nigeria

Lack of evidence-based HRH planning has contributed to the HRH crisis in Africa. (4) The obsolete population-based calculations and perceived needs are not responsive to demographic and epidemiologic variations. Evidence-based strategies guiding the expansion of CHWs in Nigeria include the Workload Indicators of Staffing Needs (WISN) tool and the Minimum Services Package (MSP) tool.

(1) Workload Indicators of Staffing Needs (WISN) tool

WISN determines how many health workers of a particular type are required for a given workload of a specific health facility. (27) In Nigeria, WISN has been used to determine staffing needs, optimize worker distribution, and guide recruitment. (28-30) In 2019, WISN was applied to 26 PHC facilities in two LGAs of Rivers State, identifying staffing gaps. (28) A 2021 WISN exercise in 20 LGAs of Bauchi State revealed suboptimal staffing in 80% of LGAs for CHOs/CHEWs and 60% for JCHEWs, indicating significant pressure on frontline workers. (29) In 2022, WISN assessed 196 ward-level PHC facilities across 18 LGAs in Cross River State, finding that only 40% of required nurses/midwives and 60% of CHOs/CHEWs were present. (30) However, WISN's accuracy depends on the validity of existing service statistics, which limits its effectiveness without updated data from HRH information systems. Additionally, determining workloads requires cross-disciplinary technical expertise. (27)

(2) Minimum Services Package (MSP) tool

The Primary Health Care Under One Roof (PHCUOR) policy, developed following WHO guidelines for integrated district-based service delivery, aims to establish an effective referral system across different care levels for cost-effective public health and clinical services. include a HR planner tool designed to calculate the required staff numbers, cadres, and budgets per facility, facilitating the identification and addressing of HRH gaps. Implementing the MSP process requires a committee of stakeholders and health managers, along with an MSP policy to define service minimums, classify facilities, estimate costs, develop a State MSP medium-term expenditure framework, and allocate resources. (22) Nigeria adopted the MSP concept to address the basic health needs and advance UHC. MSP implementation builds on the support of NPHCDA and development partners.

Enhancing accessibility to health services

In many countries with malaria, there are insufficient health facilities and community-based services, compounded by the lack of skilled and motivated health workers. Operational strategy of WHO's global malaria program uses Tanahashi framework to identify health system limitations, including service availability, accessibility and demand, which affect the delivery of quality malaria interventions. Even when services are available, geographical barriers, affordability issues, and time constraints can render them inaccessible. Recent strategies aim to enhance service availability and address inequities by leveraging community-based health workers to improve access to essential health services for vulnerable populations. (10)

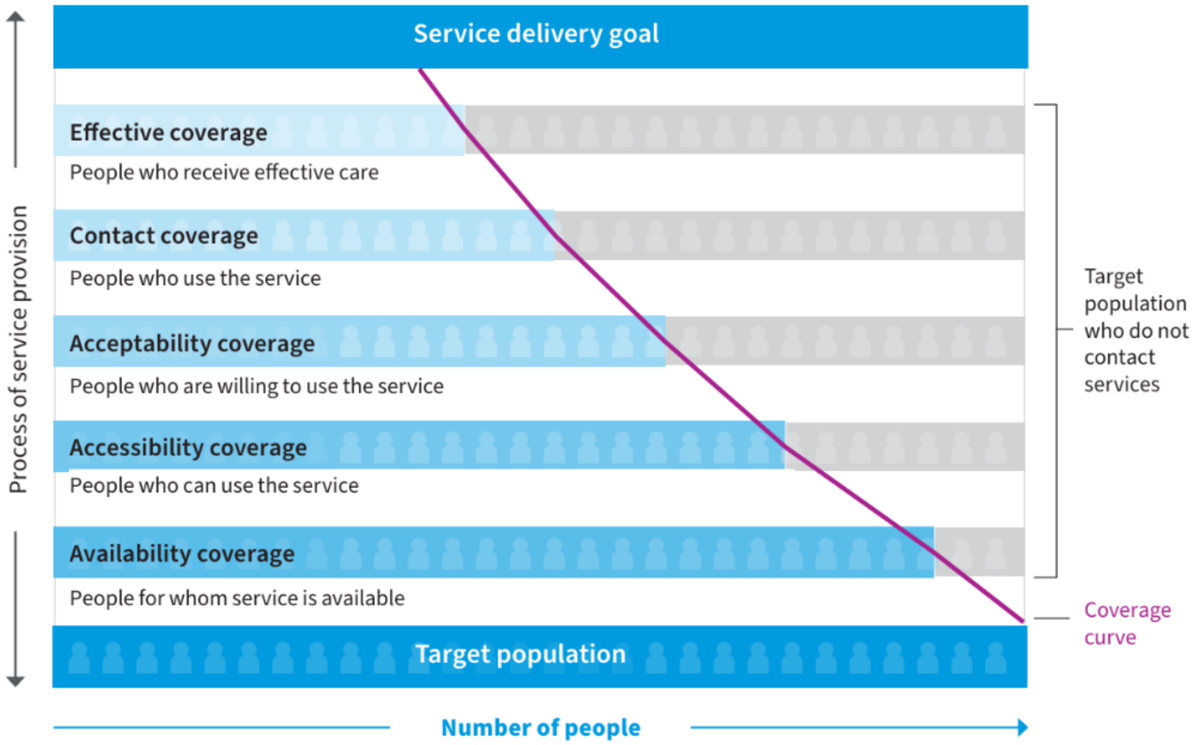


Figure 2. Tanahashi framework for effective coverage of health system (10)

Extended analysis of treatment-seeking behaviour among children under five years indicates that travel time to health facilities significantly impacts treatment-seeking likelihood, particularly in low-income settings. Long travel times in rural areas, exacerbated by poor transportation infrastructure and a lack of motorized transport, increase both travel time and costs, disproportionately affecting lower-income populations. (31) Achieving targets under SDG health-related goals, such as reducing maternal and neonatal mortality rates and deaths from infectious diseases, relies heavily on the availability of a robust health workforce. A dose-response study on community case management effectiveness found that adding one malaria service point per 1,000 people is associated with a 19% reduction in admissions and a 23% reduction in deaths among children under five years of age. (32)

Analysis of DHS datasets from 21 countries over 9 years, using poverty, rurality and remoteness metrices to characterise potentially underserved populations, indicates that CHWs are being successfully targeted to address inequities in health care access. Clear trends show that CHWs are more instrumental in diagnosing and treating individuals in lower wealth quintiles. Additionally, most CHW activities occur in rural areas. (6) Based on Tanahashi framework, we tried to enhance the geographical accessibility to PHC facilities by recruiting CHWs in areas where PHC facilities are not available within considerable walking distance.

Estimating travel time to health facilities

Weiss et al. developed global travel time maps at a 1 km² resolution for individuals with and without access to motorized transportation. Friction surfaces were used in this process, which are continuous layers of estimated travel time required to traverse each pixel of the map. In developing the friction surfaces, travel speed was determined by integrating various geospatial datasets, including roads, waterways, land cover types, and terrain slope. In 2020, They updated that friction surface, using recent geospatial datasets, most importantly, road's location and road-type data from Google Maps and OpenStreetMap (OSM). In addition to friction surfaces, travel time calculation needs georeferenced dataset of health facilities. To get a reliable list of health facilities, they leveraged multiple datasets on health facilities list, combined with geographic locations of health facilities acquired from other published data sources, including Google Maps and OSM.

Finally, they used a least-cost-path algorithm to calculate travel time to the nearest health facility based on the updated friction surfaces and health facilities list. The resulting maps included an optimal travel time map for communities with motorized transport access and a walking-only time map for disadvantaged communities with limited road access. (31, 33) These maps enable policymakers to identify spatial disparities in healthcare access and facilitate more efficient resource allocation. Furthermore, the friction surfaces and code for travel time mapping are publicly available, allowing public health professionals to create custom travel time maps for various applications.

Geospatial approaches in CHW expansion

With the availability of emerging sources in high resolution modelled surfaces of population density and health burdens, mathematical modelling tools using geospatial information have been increasingly used to inform strategic planning of HRH. The model outputs could suggest optimised placement scenarios based on disease burden, access to care and population distribution. (34-38)

Champagne et al. used an approach, combining existing gridded estimates of population density and travel time, using optimisation methods, to derive theoretical CHW geographical placement scenarios in Haiti. To account for operational limitations, pre-defined constraints on walking distance to be covered (catchment area) by a CHW and geographic coverage of existing health facilities were used. Number of people to be served by one CHW was also defined for urban and rural areas, where urban rural classification was done based on modelled population density. As the result, four theoretical expansion scenarios could advise the development of the national Strategic Community Health Plan. The author also suggested that the model can be adjusted to include malaria incidence, alongside capacity and walking time constraints, within areas with significant malaria transmission. (36)

Another location-allocation analysis in Ghana used generalized additive models to guide the placement of health facilities. The model estimates the relationship between indicators of malaria burden and travel time to the nearest health facility and other geospatial covariates, such as Euclidean distance to urban centres, elevation, normalized difference vegetation index (NDVI), and population density. Then location of new health facilities was optimised using one of the three different optimization criteria that are likely to be relevant for decision-makers, i.e., maximal reduction in district-level prevalence, incidence, or travel time. Finally, the optimal locations of health facilities were identified under two scenarios: adding new health facilities to the existing facilities and after excluding the existing facilities. (37)

In studies by Oliphant et al. in Niger (35), Sierra Leone (34) and Mali (38), spatial optimization models used georeferenced data on health facilities and CHWs, along with datasets on disease burden, population density, and friction surfaces. The models estimated the additional health workers needed to improve accessibility for populations living 3-5 km beyond current coverage. Each CHW's catchment area was defined as a 30-minute walking distance (3-4 km), with population coverage standards set at; 700 people for the Centre and South regions, and 500 for the Northern regions where minimum threshold size of 150 in Mali (38), 500 people in easy-to-reach areas and 300 in hard-to-reach areas in Sierra Leone (34), and 1,000 people with minimal threshold of 250 in Niger (35). Three hypothetical CHW networks were proposed based on different priorities: geographic coverage, estimated malaria cases, and under-five mortality rates. Efficiency was assessed by comparing these priorities between existing and hypothetical networks.

As added benefits to the traditional subjective planning process, these geospatial approaches could improve decision-making processes by suggesting on rightsizing and retargeting for better coverage and cost-savings of CHW deployment. (34, 35, 38)

Application of decision support tools

Healthcare decisions often rely on informal judgment unsupported by analysis of evidence. Multi-criteria decision analysis (MCDA) is rarely used to guide transparent decision-making in health. Typically, health intervention prioritization considers effectiveness, cost-effectiveness, disease burden, and equity. MCDA aggregates these criteria to assess overall performance and supports priority setting by allowing stakeholders to define and weight relevant criteria for resource allocation. (39) Using interactive decision support tools in MCDA approach effectively bridges the knowledge gap between technical experts and stakeholders, facilitating better communication and decision-making.

Recommendations from public health scientists may lack field feasibility. Engaging stakeholders throughout the process, rather than presenting finalized results, allows them to interact with parameters and view various outcomes. In Ghana, a web-based tool enabled the Ministry of Health and stakeholders to propose and optimize new health facility locations, with updates on malaria prevalence, incidence, and travel time maps reflecting these changes. This collaborative approach fostered discussion, builds consensus, and it could enhance the development of impactful decision-support tools. (37)

3.4 Data management

Data sources and extraction

Administrative boundaries – We used a LGA boundaries (administrative-level 2) dataset with 774 spatial areas (40) and a ward boundaries (administrative-level 3) dataset with 9,410 spatial areas. (41) These datasets were released in March 2021 and available through Geo-Referenced Infrastructure and Demographic Data for Development (GRID3).

Population surface (100x100m) – We used gridded population estimates (version 2.1) which is a GeoTIFF raster at a spatial resolution of 3 arc-seconds (approximately 100m at the equator), containing estimates of total population size per grid cell across Nigeria. It was produced with bottom-up approach using sampled data from recent survey datasets to build a statistical model to estimate population in unsampled locations. NA values represent areas that were mapped as unsettled based on a gridded settlement layer derived from building footprints (Maxar Technologies, Inc. and Ecopia Tech Corporation, 2021). This dataset was produced by WorldPop Research Group at the University of Southampton which was initially released in 2019 and updated in 2023. (42)

Health facilities list– In this analysis, we acquired geo-referenced list of PHC facilities from GRID3 which was released in September 2020. There are total of 46,146 primary, secondary, and tertiary health care facilities nation-wide. (43)

Friction surface (1x1km) –We used walking-only surface to more realistically measure for access to health care services due to limited access to motorized transportation in remote areas. The 'get_friction_surface' function from PATHtools package in R was used to extract walking-only friction surface.

Modelled surfaces for malaria indicators (5x5km) – Raster layers from Malaria Atlas Project (MAP), the number of newly diagnosed Plasmodium falciparum cases per 1,000 population and deaths per 100,000 population, proportion of population with access to and use of an Insecticide-Treated Net (ITN) in their household (on the basis that one net provides coverage for two people) in Nigeria during 2022. In 36 high-burden countries in sub-Saharan Africa, including Nigeria, cartographic approach was used to map Plasmodium falciparum parasite rate at the pixel level and subsequently converted these results into estimates of clinical incidence and mortality. Geostatistical models were applied to datasets consisting of parasite rate points and routine surveillance reports, and a rich set of temporally dynamic geospatial environmental and socioeconomic data. (44) For ITN related indicators, Bayesian mixed modelling framework built upon data from net manufacturers, national programs, and cross-sectional household surveys over the past 20 years to estimate the history of ITN coverage metrics in 40 sub-Saharan African countries are applied. (45)

Conflict – Data from the Armed Conflict Location & Event Data project (ACLED) during 1 May 2021 to 30 April 2024 were included in this project. Disorder type of 'political violence' is defined as the use of force by a group with a political purpose or motivation, or with distinct political effects. In this analysis, we used two political violence event types; 'Battles' – Violent interactions between two organized armed groups at a particular time and location, and 'Violence against civilians' – Violent events where an organized armed group inflicts violence upon unarmed non-combatants. (46) For the academic purpose, the georeferenced dataset is available via ACLED's data export tool on ACLED Access Portal.

State-level Malaria indicators – Survey datasets from Nigeria Malaria Indicator Survey 2021 (MIS-VIII) were accessed through DHS program. (12) Following datasets were used:

Dataset	**Unit of analysis**	**Indicators**
Household Data - Household Recode (HR)	Household	• Household ownership of ITNs *'hh_ITN'*
Household Listing Data - Household Member Recode (PR)	Household member	• Parasitaemia (via microscopy) in children 6-59 months *'pr_micro_chld'*
Children's Data - Children's Recode (KR)	Children of women born in the last 5 years (0-59 months)	• Children under age 5 years with fever in the 2 weeks preceding the survey *'kr_fever'* • Advice or treatment was sought the same or next day *'kr_fev_day'*

LGA-level Malaria prevalence data – We used updated dataset on percentage of children under 5 years of age who have PF parasitaemia with RDT test at LGA-level by MAP.

Data manipulation

PHC facilities dataset – Out of 46,146 health facilities, we focused on 21,329 functional PHC facilities for this analysis. To determine duplicate entries, we firstly examined the Euclidean distance between pairs of PHC facilities using distHaversine function ('Haversine' great circle distance) of geosphere package in R. There were 648 (3%) out of 21,329 PHC facilities locate within 100 meters from the nearest PHC facilities. Deduplication could not be done, because we could not conduct physical verification and the proportion is less than 5%. Then, we checked for duplicates among facilities within 250 meters. First, we used 'clean_strings' function from 'fedmatch' package in R to tidy PHC names and ward names. In this step, we appended cleaned ward names as prefix to cleaned PHC names to make composite names. Then, 'stringdistmatrix' function from 'stringdist' package was applied to examine duplicates. Jaro distance matching method was used to calculate dissimilarity and we set 75% as threshold to define duplicates between composite names. There were no duplicates detected.

Administrative boundaries – Out of 9,410 ward-level polygons, 102 were listed as 'Invalid' due to missing geometry. After excluding these, 9,308 polygons were included in the analysis.

LGA-level Malaria prevalence data – The MAP prevalence dataset and GRID3's shapefile had 103 mismatched LGA names. We cleaned the names using the 'clean_strings' function and performed multivariable matching with the 'match_plus' function from the 'fedmatch' package in R. This function compared each observation in the GRID3 dataset with those in the MAP dataset, selecting the match with the highest score. We used a multivariable match type, incorporating state and LGA names, to compute a final score through a linear combination. For comparison, we set two 'compare types': (1) 'indicator' for exact matches, and (2) 'stringdist' using Jaro-Winkler distance for approximate matches. Any remaining unmatched names were manually matched.

Rescale total population - Using a bottom-up approach for the population surface, the estimates are representative of the year 2019. (42) So, total population from raster surface 216,678,334 was rescaled to 227,883,000 in 2023 to be consistent with United Nation's projection in World Population Prospects 2024. (13) We further rescaled it for 2024 according to World Bank's data on average annual population growth rate of 2.39% during the most recent 3 years. We rescaled the total population as 233,329,404 in 2024.

$$Population_{2024} = Population_{2023} \times (1 + r)$$

Where, r = Average (annual) population growth rate during 2021 to 2023

Data analysis

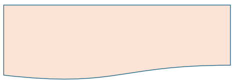
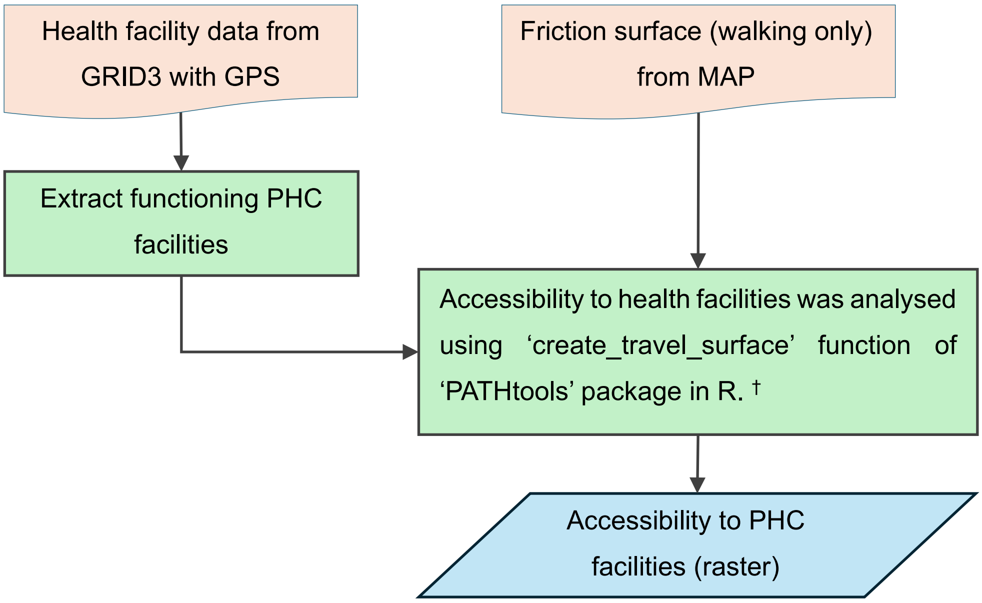
	Document represents 'data source'
	Rectangle represents 'process'
	Parallelogram represents 'input or output data'

Table 2. Symbols used in describing data analysis workflows

Accessibility to PHC facilities



† *Travel times to the nearest PHC facilities for each ward were calculated by intersecting the accessibility surface with the population surface within ward-level boundaries. Although travel time calculations are limited to national borders, they account for travel across subnational boundaries (state, LGA, ward).*

Figure 3. Data analysis workflow for accessibility to PHC facilities (travel time surface)

Preparing state-level data

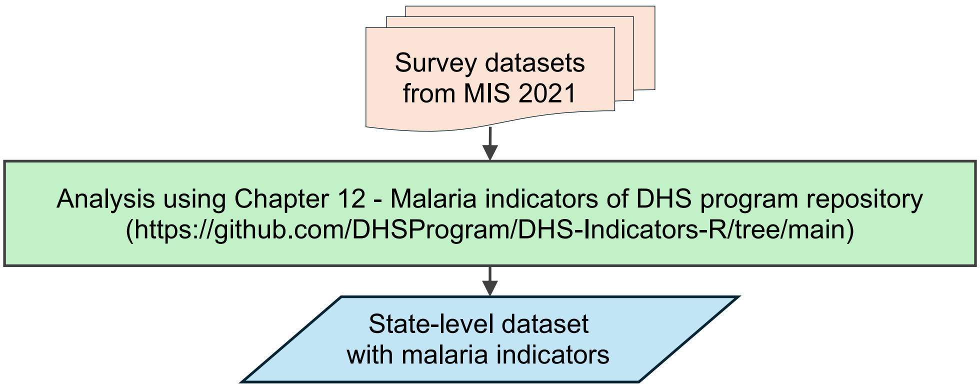


Figure 4. Data analysis workflow for state-level dataset with malaria indicators

Preparing ward-level data

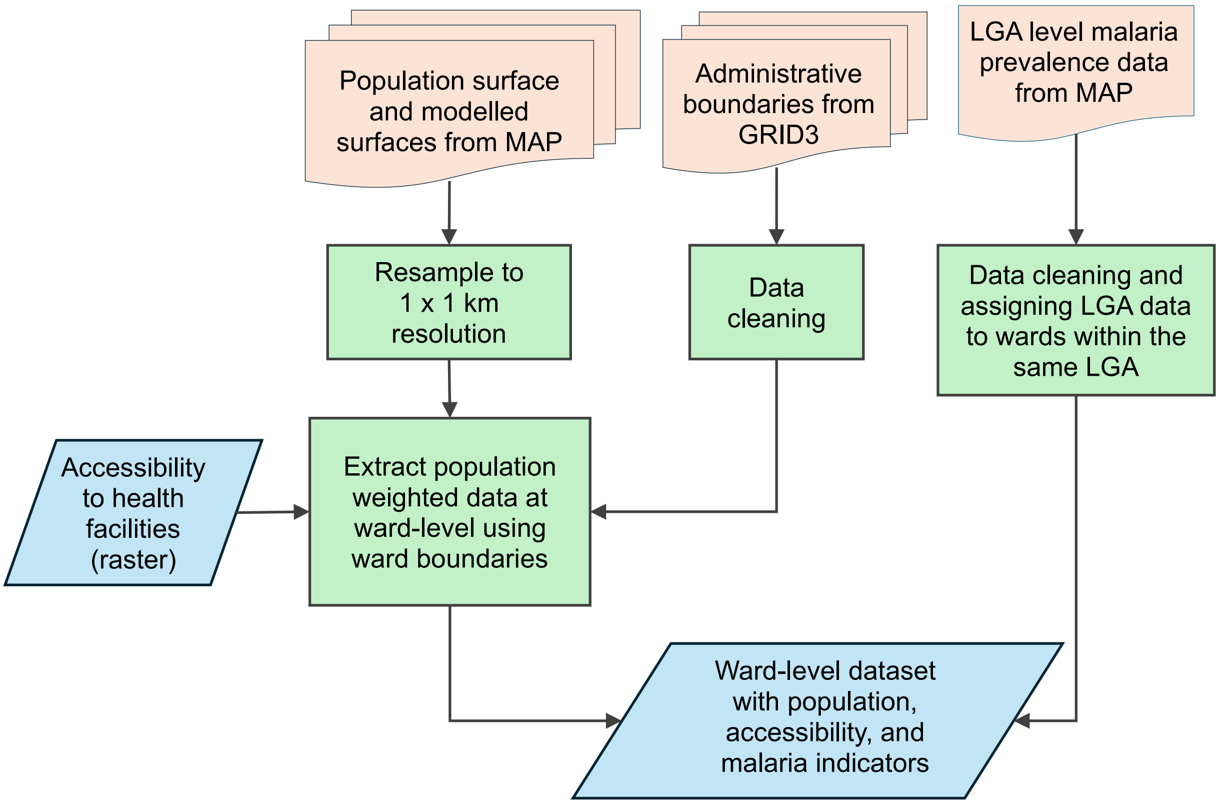


Figure 5. Data analysis workflow for ward-level dataset with required indicators for prioritization

Vulnerability score

To adopt MCDA in this project setting, we used disease burden (malaria incidence, prevalence, mortality) and equity analysis (intervention coverage, accessibility to PHC facilities) as criteria (*parameter*) to calculate priority score (vulnerability score) for different options (wards).

Ward-level dataset with population, accessibility, and malaria

↓

Score calculation for 3 parameters

- *Malaria disease burden*:
  - When *X* = Incidence rate, Mortality rate, or Prevalence rate, the score S_X for variable *X* is defined as:

$$S_X = \begin{cases} 1 \ if \ X \le Q_{0.25} \\ 2 \ if \ Q_{0.25} < X \le Q_{0.50} \\ 3 \ if \ Q_{0.50} < X \le Q_{0.75} \\ 4 \ if \ X > Q_{0.75} \end{cases}$$

  - Then, composite score of disease burden is:

$$S_{Disease\ burden} = S_{Incidence\ rate} + S_{Mortality\ rate} + S_{Prevalence\ rate}$$

- *Intervention coverage and Accessibility to health facilities*:
  - When Y = intervention or accessibility indicator, the score S_Y for variable *Y* is defined as:

$$S_Y = \begin{cases} 4 \ if \ Y \le Q_{0.25} \\ 3 \ if \ Q_{0.25} < Y \le Q_{0.50} \\ 2 \ if \ Q_{0.50} < Y \le Q_{0.75} \\ 1 \ if \ Y > Q_{0.75} \end{cases}$$

  - Where *Y* is selected from:

$$S_{Intervention\ coverage} = \begin{cases} S_{Access\ to\ ITN} \ if \ 'proportion\ with\ access\ to\ ITN' \ is\ used \\ S_{ITN\ usage} \ if \ 'proportion\ with\ use\ of\ ITN' \ is\ used \end{cases}$$

$$S_{Accessibility} = \begin{cases} S_{Proportion} \ if \ 'proportion\ living\ in\ remote\ area' \ is\ used \\ S_{Travel\ time} \ if \ 'mean\ travel\ time\ to\ nearest\ PHC' \ is\ used \end{cases}$$

↓

Vulnerability score calculation

- *Step1*: Apply weights (level of importance) to scores of different parameters
  - When *X* = parameters, weighted score WS_X is defined as:

$$WS_X = S_X \ x \ Weight_X$$

where:

$$WS_X = \begin{cases} 0 \ \ to\ exclude\ the\ parameter\ in\ calculation \\ 1 \ \ if\ level\ of\ importance\ is\ 'Low' \\ 2 \ \ if\ level\ of\ importance\ is\ 'Medium' \\ 3 \ \ if\ level\ of\ importance\ is\ 'High' \end{cases}$$

- *Step 2*: Calculate a composite score of vulnerability at ward-level:
  - $S_{Vulnerability} = WS_{Disease\ burden} + WS_{Intervention\ coverage} + WS_{Accessibility}$

↓

Ward-level dataset with vulnerability score

Figure 6. Data analysis workflow for vulnerability score calculation from disease burden, intervention coverage and accessibility parameters

Conflict index

For country-level conflict severity index, ACLED uses four indicators to measure conflict severity: deadliness, danger, diffusion, and fragmentation. (17) For this project, we defined a subjective and quantitative classification, 'conflict index' at ward-level, based on ACLED methodology. It comprises of 'event rate' and 'deadliness/fatality rate' of battles and violence against civilian events as below. We applied logarithm transformation to the conflict related data to make quantile calculations more robust and less influenced by outliers.

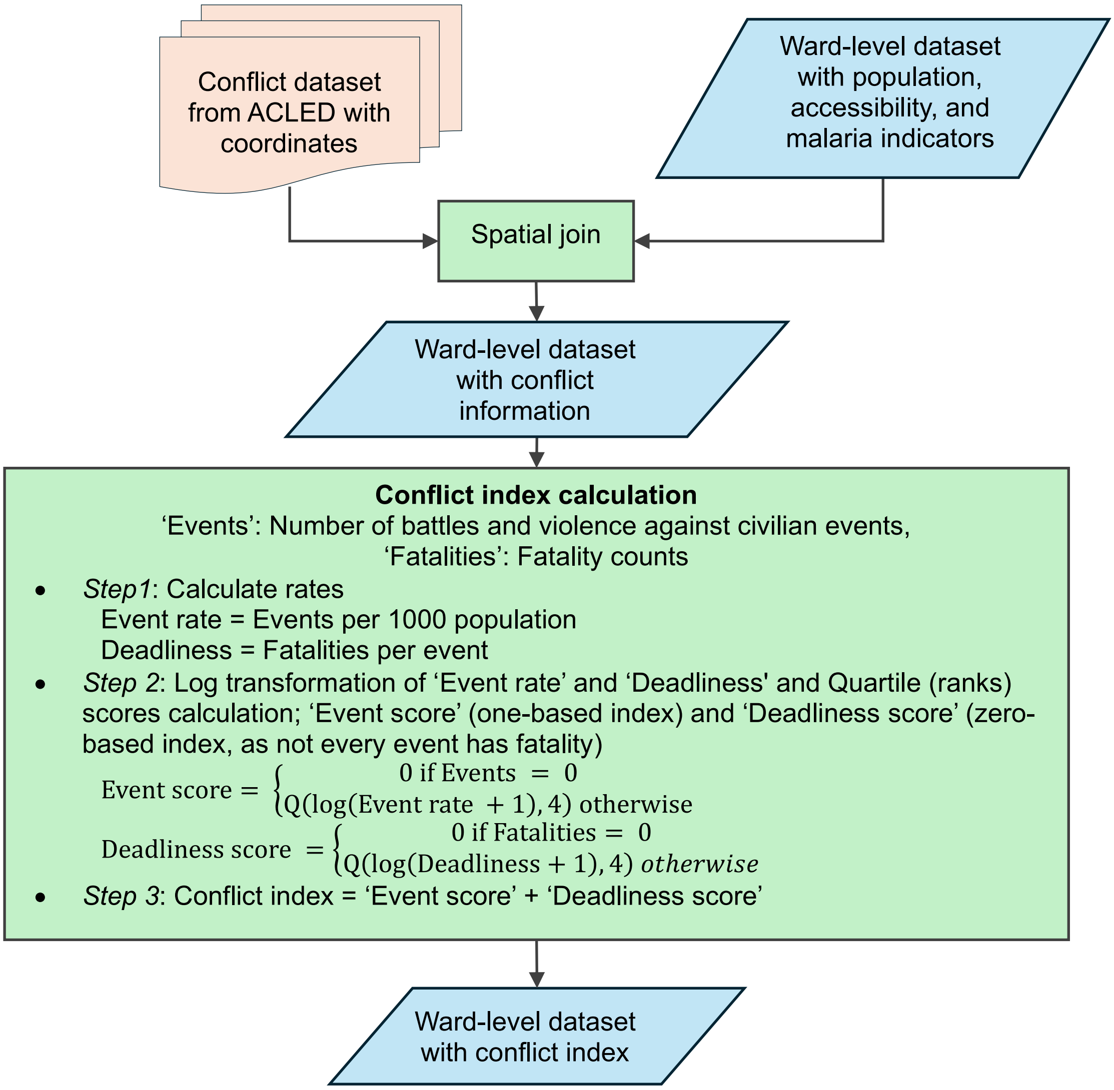


Figure 7. Data analysis workflow for conflict index calculation and integration into ward-level dataset

Stepwise approach of the project

An interactive dashboard is used to help stakeholders to conduct evidence-based rationale in stepwise approach to prioritize 300 wards and estimate number of CHW needed.

A comprehensive ward-level dataset

↓

Scenario setting page

Adjust importance level of different parameters to calculate vulnerability score

- Malaria: Define importance level of parasite prevalence rate, incidence rate and mortality rate of malaria
- Intervention: Choose one indicator among 'proportion of household with ITN'/'ITN usage', then define importance level
- Accessibility: Choose one indicator among 'proportion of people in remote area'/'median travel time to nearest facility', then define importance level

Choose a CHW expansion strategy

- 3 different options are available to choose on how to quantify number of CHWs needed
  1. 1 CHW per 1,000 population for total population in each ward
  2. 1 CHW per 1,000 population for total population beyond 1hr distance from facility
  3. 10 CHWs in each ward

Select states

- Either choosing input or clicking on map can be used to purposely select states.

↓

Ward selection page

This page is to further exclude wards according to ward-level parameters.

Ward parameters

- Vulnerability scores: To exclude wards according to their vulnerability scores as per set parameters in previous page.
- Proportion of population beyond 1hr distance: To exclude wards with fewer proportion of population in remote area.
- Travel time to PHC: To exclude wards which are less than the defined median travel time to nearest PHC.

Contextual parameters

- Maximum allowable conflict index: To exclude wards where conflict index is high according to number of conflict events and fatalities.
- Maximum driving hours from Abuja: To exclude wards according to their driving distance (in hours) from Abuja.

↓

CHW optimization page

This is a sample page where mathematical model can be applied using pre-defined parameters for the location-allocation analysis of CHWs within prioritized wards.

Select state for viewing

- Choose one state at a time to view where and how many CHWs are needed for theoretical CHW optimization

Optimization parameters (pre-defined as below in this project)

- PHC coverage area - 1 hour walking distance from PHC
- Catchment area by CHW - 1 hour walking distance from CHW location
- Number of CHW in urban area - 1 CHW for 2,500 rural population
- Number of CHW in rural area - 1 CHW for 1,000 rural population

Figure 8. Stepwise approach for prioritization and quantification of CHWs in dashboard

Ethical considerations

This analysis was done using aggregated data of malaria indicators, population density and conflict events at ward-level. There are no individual-level data or household addresses in the datasets. In the geospatial analysis results, names of geographic location are limited to ward-level, which is a broader administrative area encompassing multiple households. The survey datasets from DHS program were managed in accordance with 'DHS Datasets Authorization Letter' (acquired on 19 April 2024). The necessary cautions were taken to keep anonymity of reported data in the dashboard and in this report.

Ethical committee approval for this study was obtained from LSHTM Ethical Committee on 19 June 2024 with LSHTM MSc Ethics reference number: 30507.

4. Results

4.1 Descriptive analysis

Distribution of PHC facilities

Among the 21,329 PHC facilities, with a national average of 9.1 facilities per 100,000 people, there is significant variation across states. The Northeast zone had the lowest numbers, with Yobe having fewer than 100 facilities, resulting in the lowest coverage at 1.78 per 100,000 population. Southern states had more PHC facilities and Cross River in the South-South zone had nearly 30 facilities per 100,000 people.

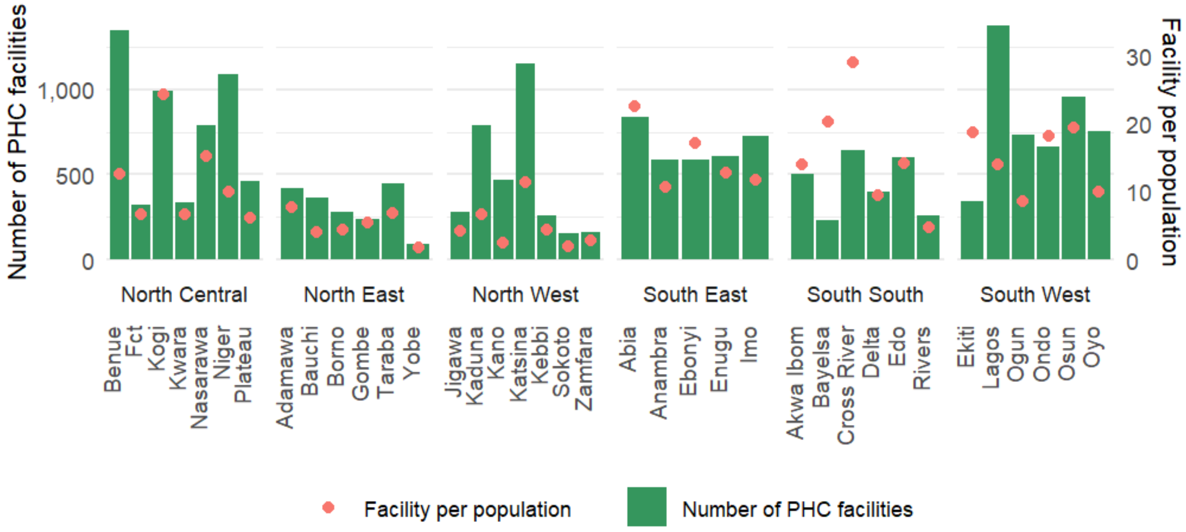


Figure 9. Number of PHC facilities and Number of PHC facilities per population of states in 2020 (GRID3 – Health facilities list, WorldPop - Population surface)

Most facilities (14,939, 70%) were MOH-owned, followed by other public and private sectors. In the North-West and North-East zones, the majority were MOH-owned, whereas southern zones had a higher proportion of non-MOH facilities. Notably, half of the facilities in Lagos were privately owned.

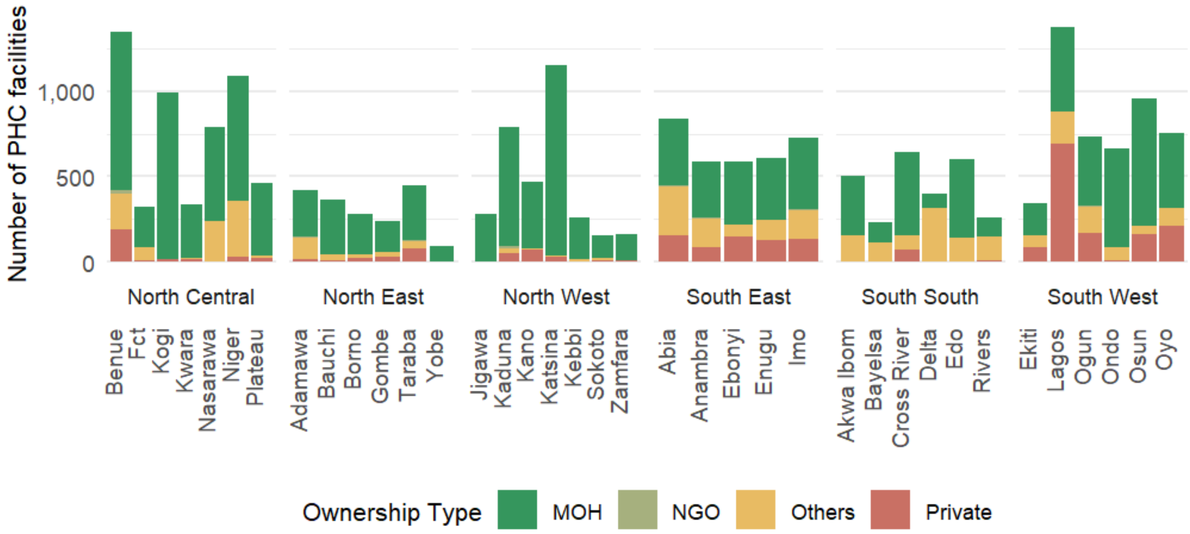
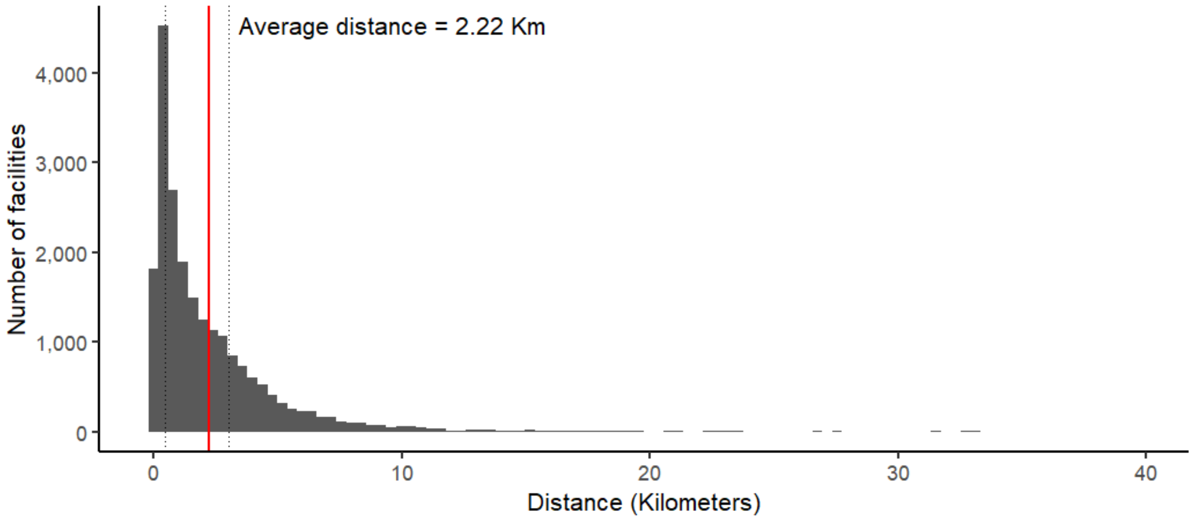


Figure 10. Ownership type of PHC facilities in states in 2020 (GRID3 – Health facilities list)

The average distance between the two nearest PHC facilities was 2.2 km, with significant difference between southern and northern states. In the North-East and North-West zones, notable variations existed among states. In Borno and Yobe, some facilities were over 20 km apart.



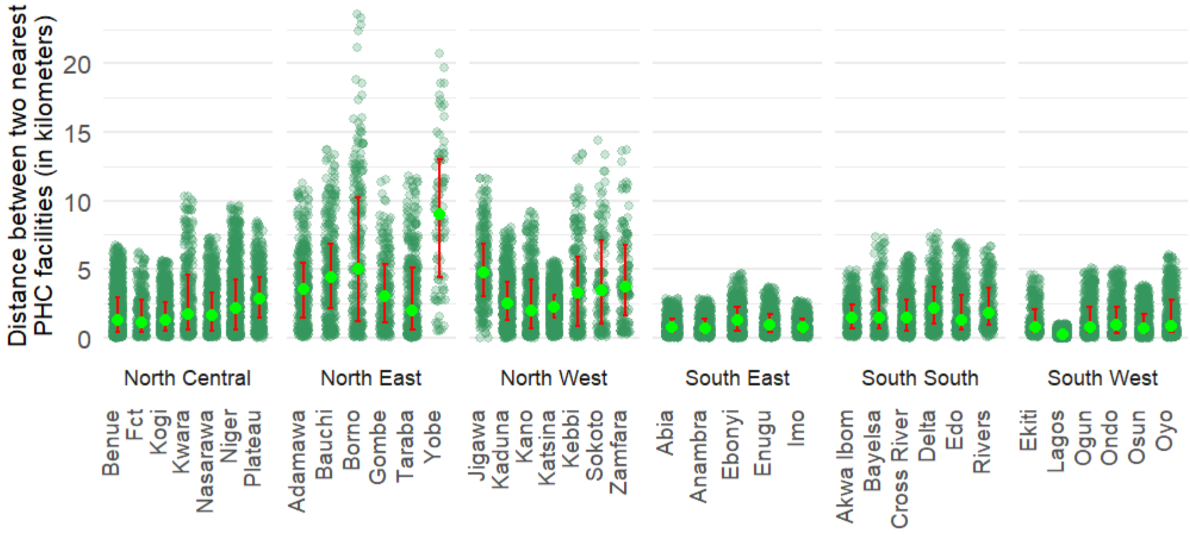


Figure 11. Distance between the two nearest PHC facilities in states (GRID3 – Health facilities list)

Spatial accessibility

Outside the North-East and North-West zones, people usually walked less than an hour to the nearest PHC facility. In Yobe, Zamfara, Sokoto, Borno, and Kebbi, the median travel time was over 60 minutes. In contrast, it was under 15 minutes in Lagos, Abia, Imo, and Anambra.

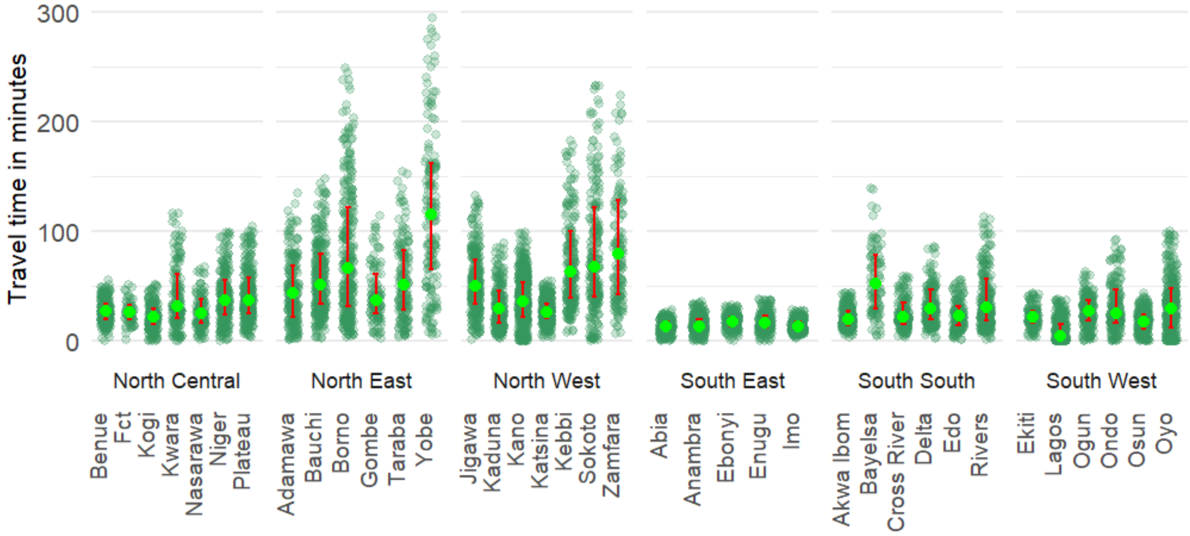


Figure 12. Travel time (minutes) by walking to the nearest PHC facility (GRID3 – Health facilities list, WorldPop – Population surface, and MAP – Friction surface)

About 20% of the population (46,462,130 people) lived more than an hour's walk from the nearest PHC facility, with nearly 90% of them residing in northern states.

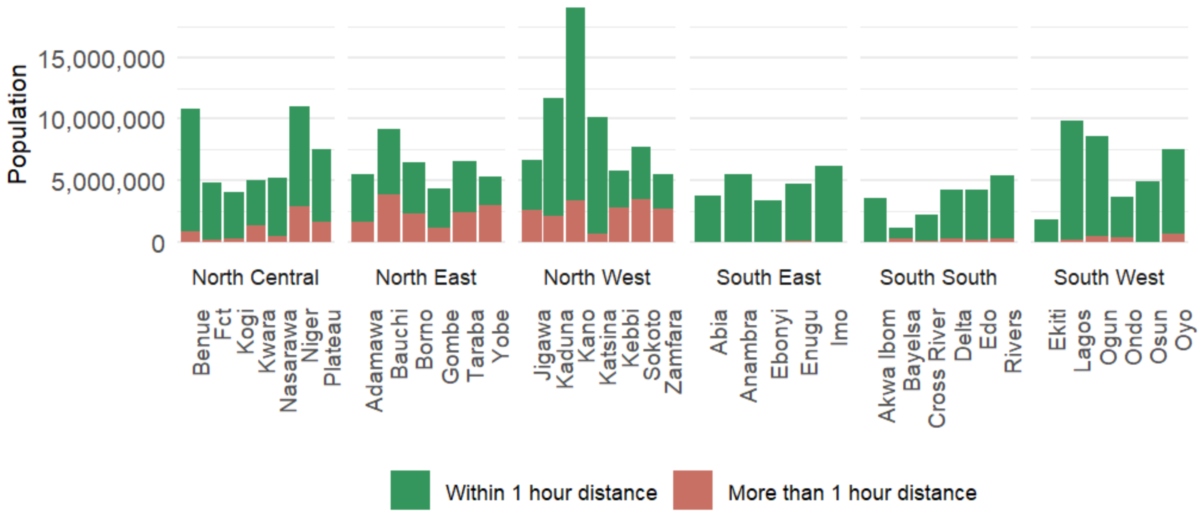


Figure 13. Population size with distance to the nearest PHC facilities (GRID3 – Health facilities list, WorldPop – Population surface, and MAP – Friction surface)

In most wards, fewer than half of the population lived more than an hour from the nearest health facility. Nevertheless, many wards had substantial populations of over 10,000 people living beyond accessible distances.

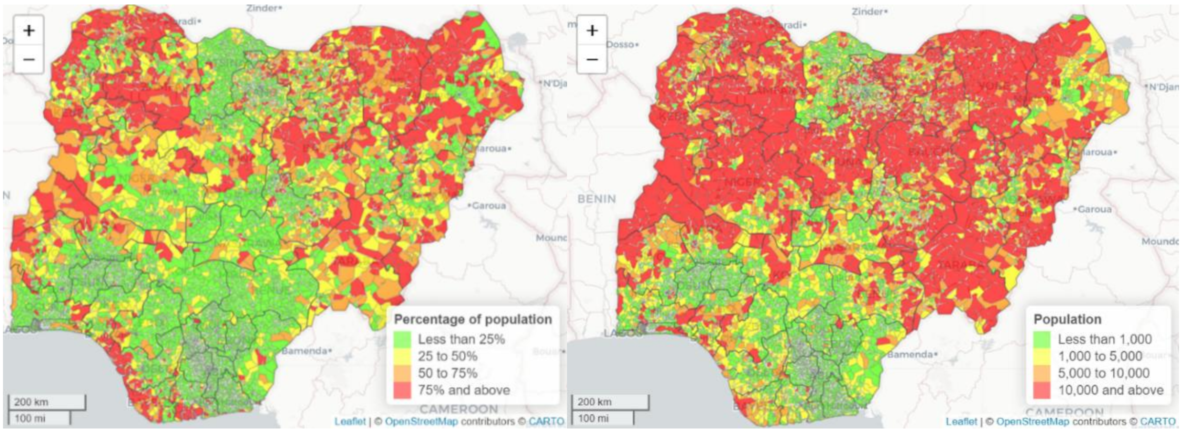


Figure 14. Percentage of population (left) and population size (right) at wards, who are living beyond 1 hour distance from the nearest PHC facilities (GRID3 – Health facilities list, WorldPop – Population surface, and MAP – Friction surface)

Malaria indicators

In 2022, there were 300 expected malaria cases per 1,000 people in all states (except Kaduna) in the North-East and North-West zones. The estimated mortality rate varied significantly within states, with no notable differences among zones. Zamfara had the highest malaria incidence rate, while Kano reported the highest mortality rate, and both are from North-West zone.

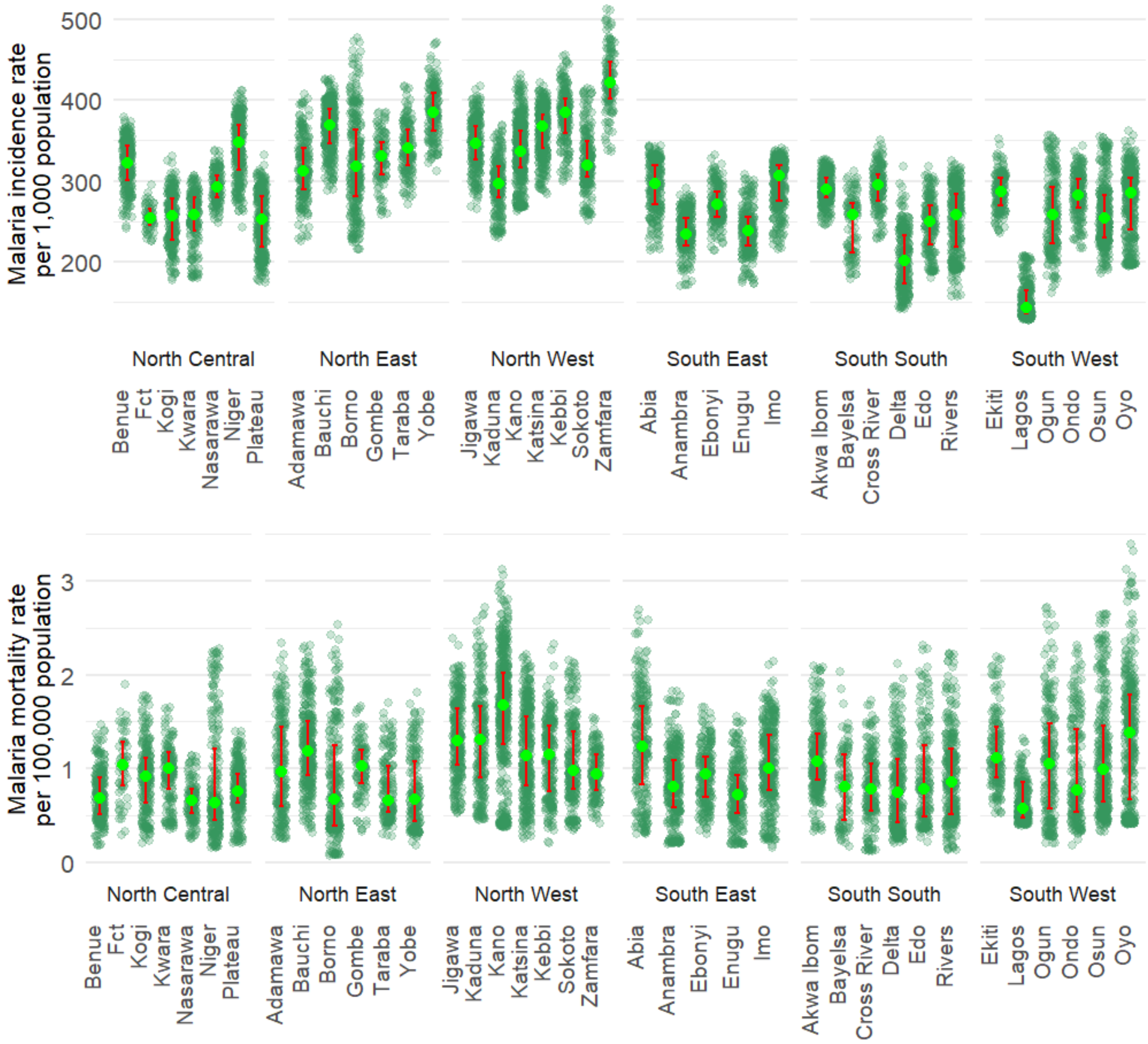


Figure 15. Estimated ward-level Malaria incidence rate and mortality rate in 2022 (MAP – Malaria surfaces, WorldPop – Population surface)

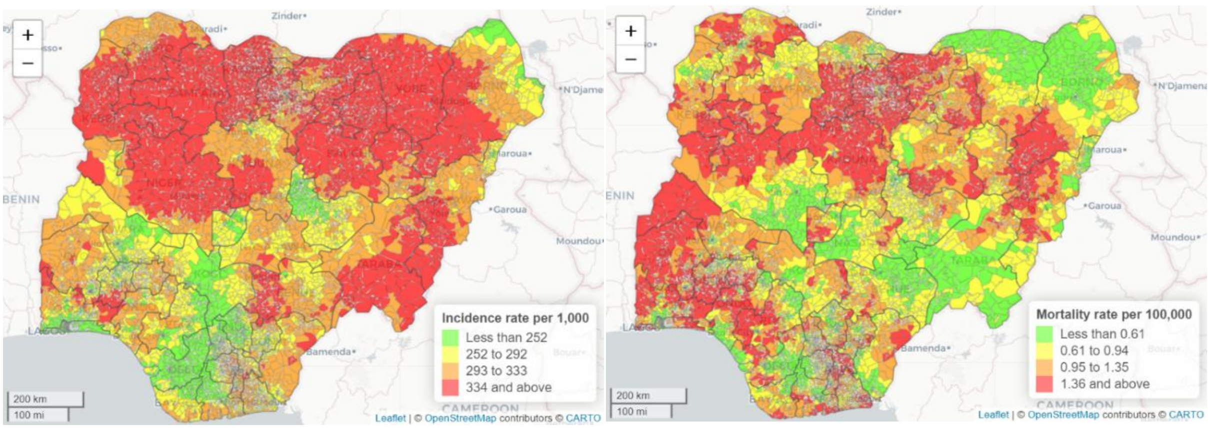


Figure 16. Estimated Malaria incidence rate (left) and mortality rate (right) at wards in 2022 (MAP - Malaria surfaces)

More than one in three children under 5 years of age in all states in the North-East and North-West zones had Pf malaria parasite in blood, with little variation across LGAs. In contrast, states in South-East zone had the lowest prevalence, but with significant disparities across LGAs.

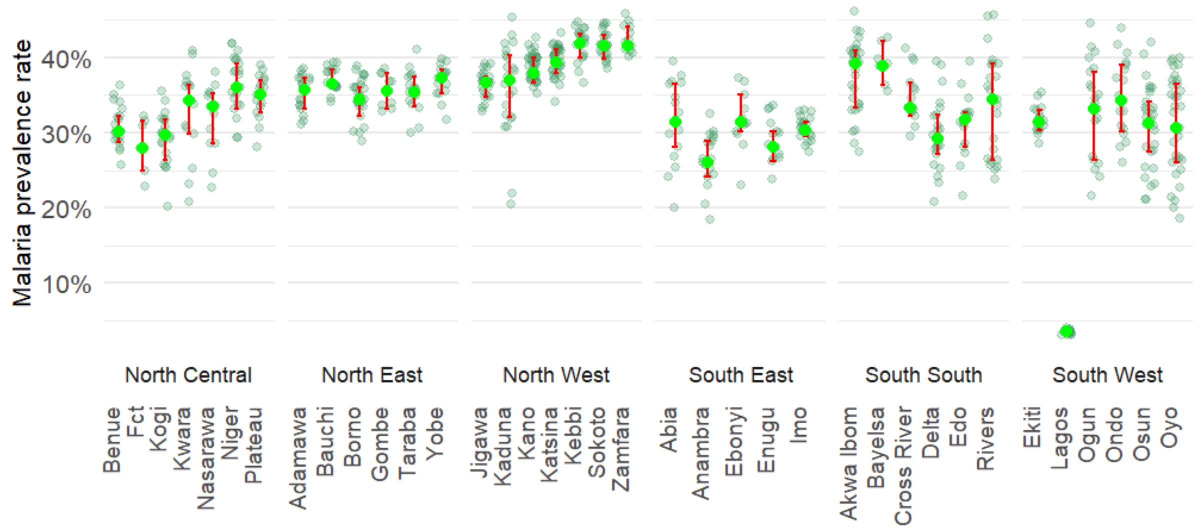


Figure 17. LGA-level Malaria prevalence among under children 5 years of age in states in 2021 (MAP, 2024)

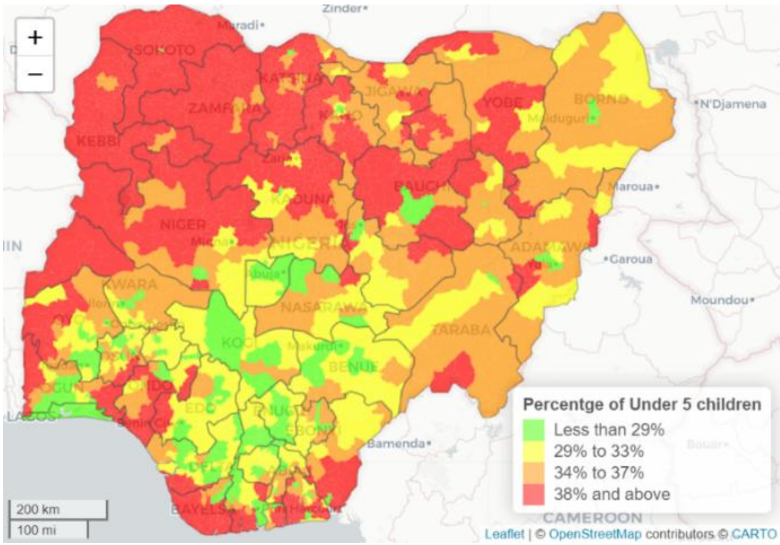


Figure 18. Malaria prevalence at LGAs in 2021 (MAP, 2024)

In the North-East and North-West zones, over half of population (excluding Borno) owned an insecticide-treated bed net (ITN) in their households. Conversely, fewer than one in four people in Anambra, Enugu, and Rivers in the South-East and South-South zones owned an ITN. Most households with ITNs reported regular use.

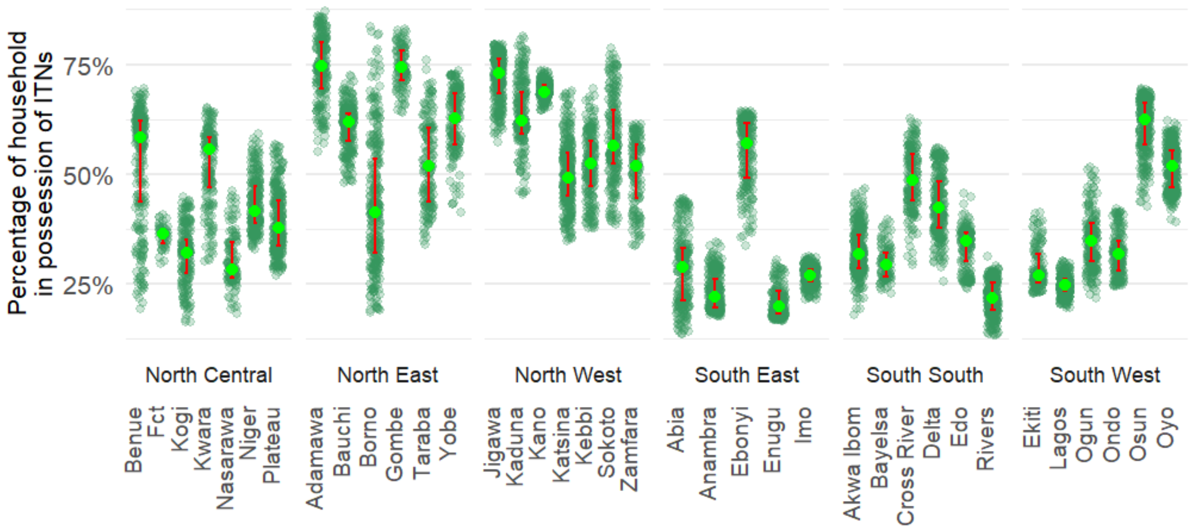


Figure 19. Percentage of household in possession of ITNs in states in 2022 (MAP – Malaria surfaces, WorldPop – Population surface)

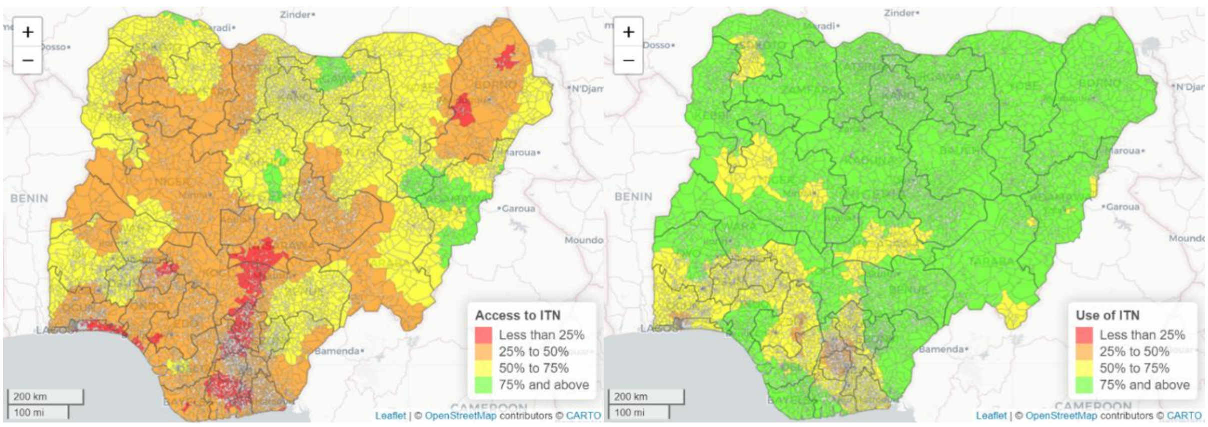


Figure 20. Percentage of household with access to ITN (left) and use of ITN (right) at wards in 2022 (MAP – Malaria surfaces, WorldPop – Population surface)

Conflict index at ward-level

Most wards did not report conflicts in the first quarter of 2024. However, wards with high levels of conflict were concentrated in Borno (North-East), Kaduna, Zamfara, and Katsina (North-Central), Benue, Niger, and Plateau (North-West), and Rivers (South-South).

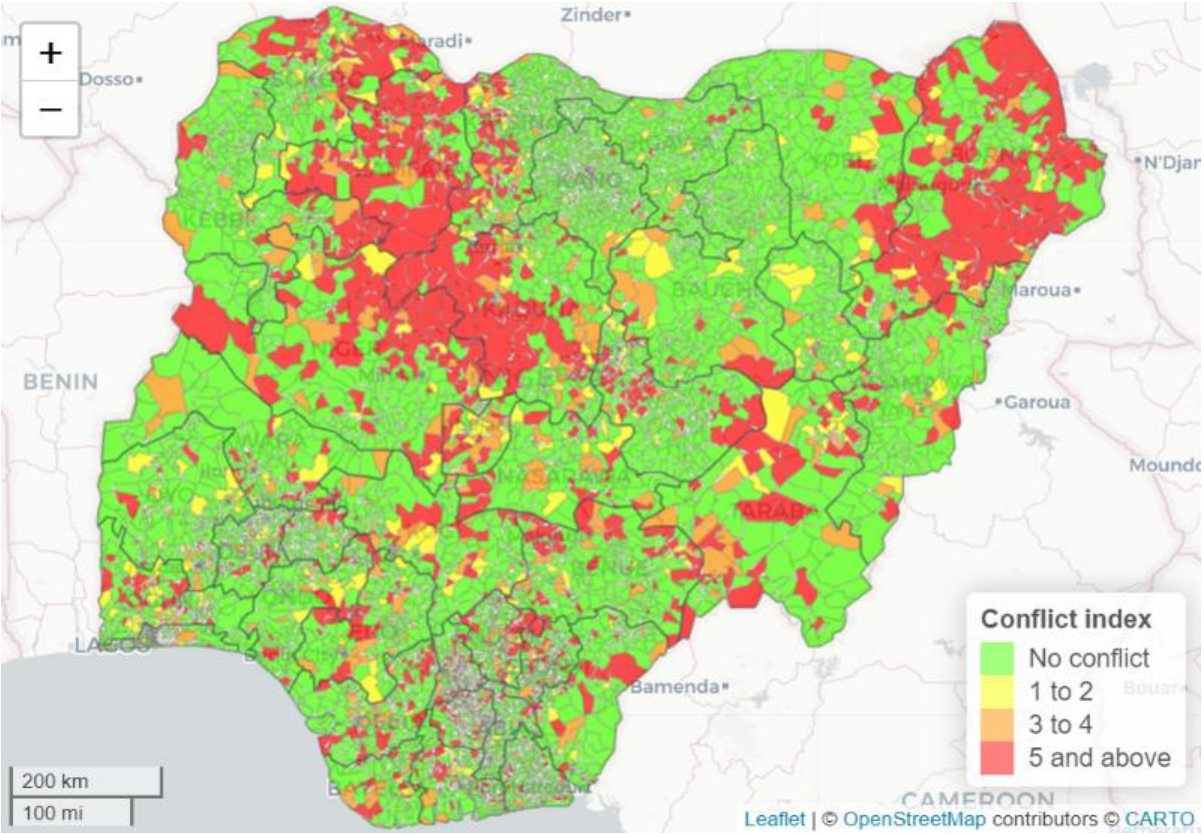


Figure 21. Conflict index of wards in 2024 (ACLED)

4.2 Prioritization of wards

We employed a stepwise approach with subjective decision-making to demonstrate how the objectives could be met.

Step 1: Scenario setting

We defined an algorithm for vulnerability score, CHW expansion strategy and selection of states.

Algorithm for vulnerability score

We selected indicators and assigned respective importance level for vulnerability score calculation. The tool designed allows users to select the importance level for each parameter, but here we present an example scenario.

Parameters	Indicators	Importance level
Disease burden	Estimates of newly diagnosed Plasmodium falciparum cases per 1,000 population	Low
	Estimates of death of Plasmodium falciparum cases per 100,000 population	Medium
	Percentage of children under 5 years of age who have PF parasitaemia with RDT test	Medium
Intervention coverage	Proportion of population with access to an ITN	Low
	Proportion of population with use of an ITN	Not selected
Accessibility	Proportion of population who are living beyond 1 hour distance from nearest PHC facilities	High
	Ward-level median travel time to the nearest PHC facilities	Not selected

CHW expansion strategy

We defined a CHW expansion strategy to have an estimated figure for planning purpose. We set '1 CHW per 1,000 population for total population beyond 1hr distance from facility' as the expansion strategy meaning that CHWs would only be placed in remote populations.

Identification of states

In this example, we selected Delta, Edo, Kogi, FCT, Niger and Zamfara states. In the screenshot of the scenario setting page, we included two plots to compare selected states.

- The bubble plot allows for plotting various indicators from MIS 2021 at the state-level and vulnerability scores.
- The box plot in the bottom right corner compares vulnerability scores between selected states, with an interactive feature to view ward-level scores.

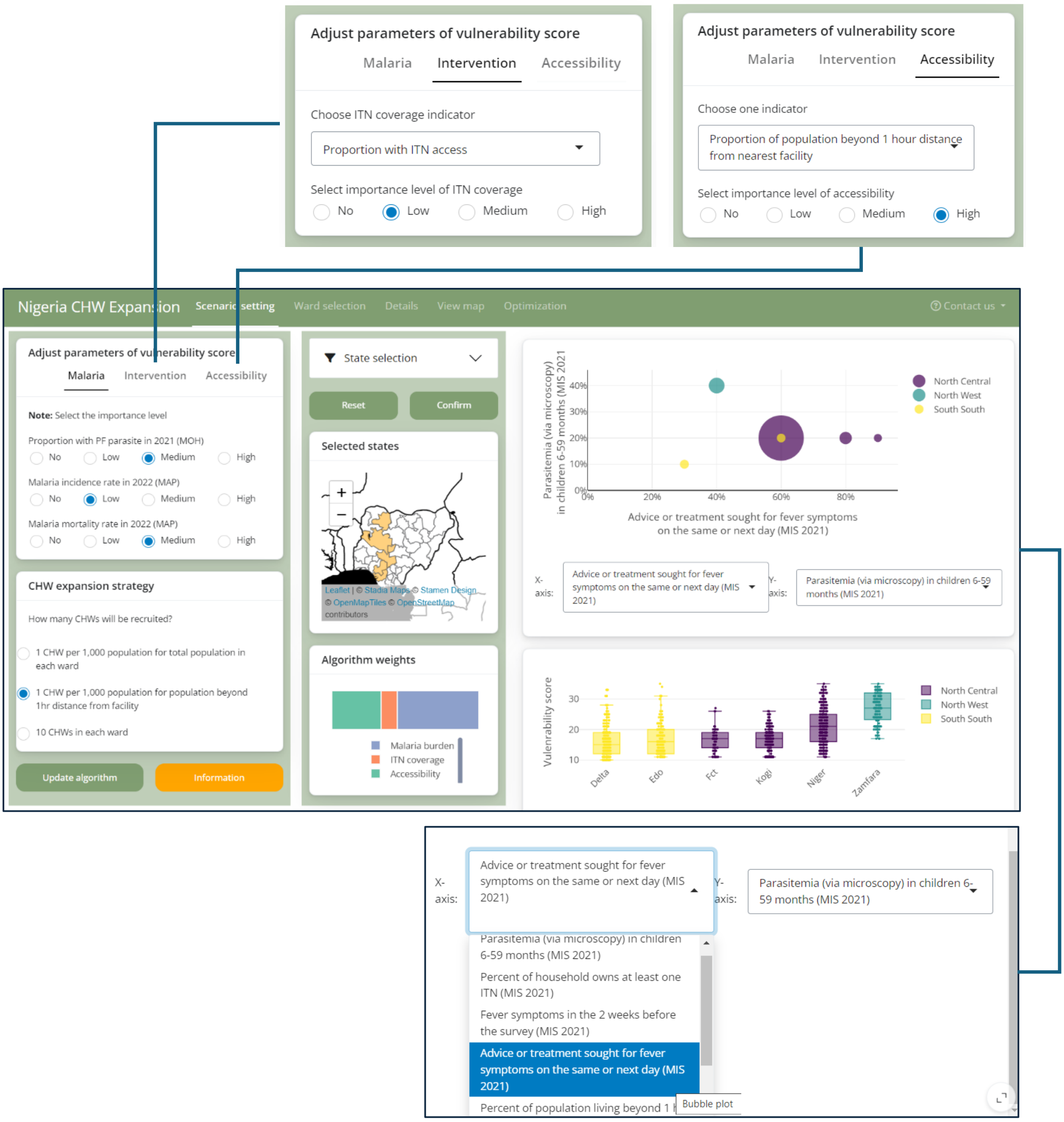


Figure 22. Screenshots of **'Scenario setting'** page with defined parameters and selected states. (In 'Adjust parameters of vulnerability score' box at top left corner, there are three tabs for three parameters: 'Malaria' - Disease burden, 'Intervention' – Intervention coverage and 'Accessibility' – Accessibility to PHC facilities. At each tab, selected indicators and their importance levels are displayed. In bubble plot, different indicators can be displayed on x and y axis.)

Step 2: Ward selection

Among total of 1,181 wards from 6 selected states, we wanted to prioritize approximately 300 wards as per objectives.

Ward parameters

Following parameters were set to prioritize wards.

Parameters	Setting	Excluded wards*
Vulnerability scores	18 to maximum	561 wards with lowest vulnerability scores
Minimum proportion of population who are living beyond 1 hour distance from nearest PHC facilities	25%	838 wards with less than 25% of its population living beyond 1 hour distance
Ward-level median travel time to the nearest PHC facilities	30 minutes or greater	621 wards with median travel time of less than half-an-hour to nearest PHC facilities

** Numbers for individual parameter only. Total 864 wards were excluded, leaving 317 prioritized wards.*

Contextual parameters

We further excluded wards according to following contextual parameters.

Parameters	Setting	Exclusion*
Maximum allowable conflict index	7	14 wards with highest conflict index of 8
Maximum driving hours from Abuja	12 hours	11 wards with more than 12 hours driving distance from the capital city

** Numbers for individual parameter only. Total 25 wards were excluded, leaving 292 prioritized wards.*

Interactive dashboard allows us to adjust ward-level parameters while monitoring the summary table in the bottom right corner. We tuned the parameters until the number of wards was close to 300.

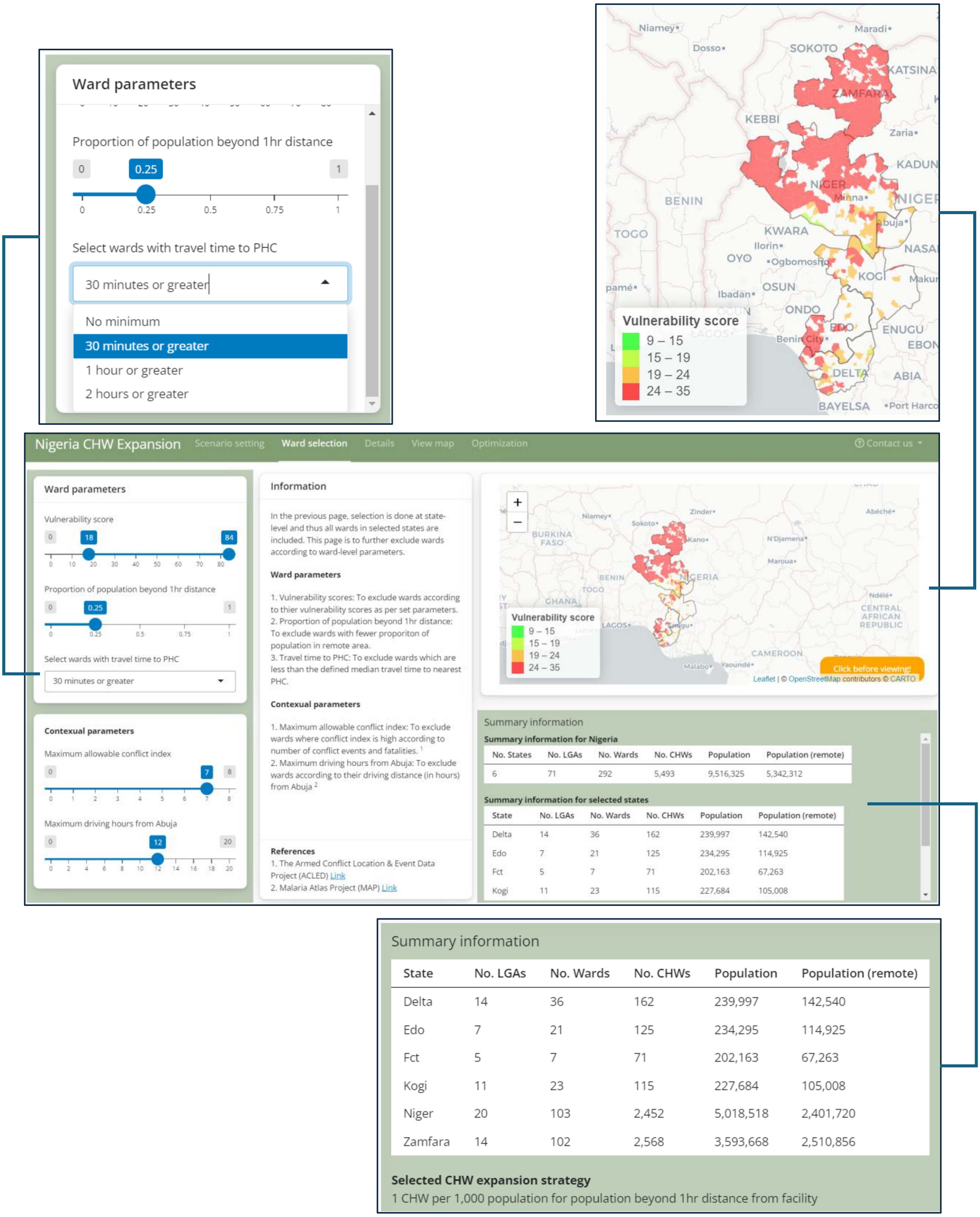


Figure 23. Screenshots of **'Ward selection'** page with set parameters. (In 'Ward parameters' box at top left corner, there are 4 options to select regarding median travel time to nearest PHC facilities to filter wards. While tuning the parameters, summary information about each state and selected CHW expansion strategy could be seen simultaneously in the 'Summary information' box at right bottom corner)

Summary of prioritized wards

A total of 292 wards from 71 LGAs across 6 states were selected for expansion of CHWs. Approximately 5,500 CHWs were needed to cover more than 5 million population who are living beyond 1 hour walking distance from the PHC facilities.

State	No. LGAs	No. Wards	No. CHWs[1]	Population (all)	Population (remote)[2]
Delta	14	36	162	239,997	142,540
Edo	7	21	125	234,295	114,925
FCT	5	7	71	202,163	67,263
Kogi	11	23	115	227,684	105,008
Niger	20	103	2,452	5,018,518	2,401,720
Zamfara	14	102	2,568	3,593,668	2,510,856
Total	**71**	**292**	**5,493**	**9,516,325**	**5,342,312**

[1] *1 CHW per 1,000 population for population beyond 1hr distance from facility*
[2] *Population living beyond 1 hour distance from the nearest PHC facilities*

Table 3. Summary information of prioritized wards as result of ward selection

In the dashboard, different disease burden and contextual indicators of prioritized wards and their geographical distribution could be observed.

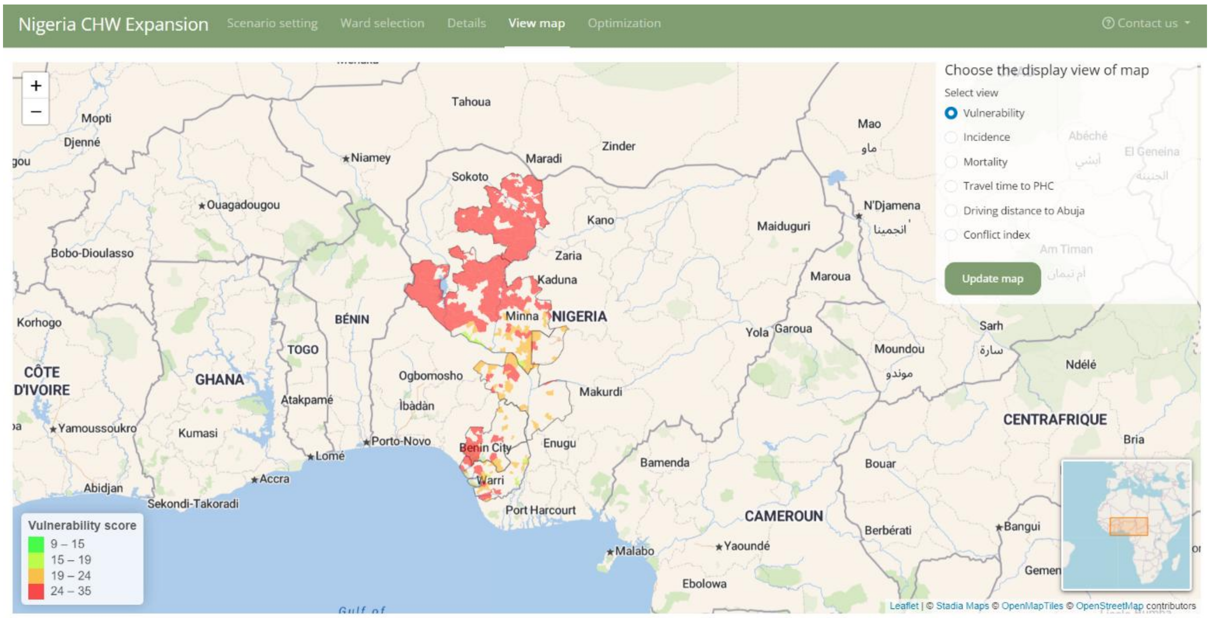


Figure 24. Screenshot of 'View map' page, displaying viewing options at right upper corner

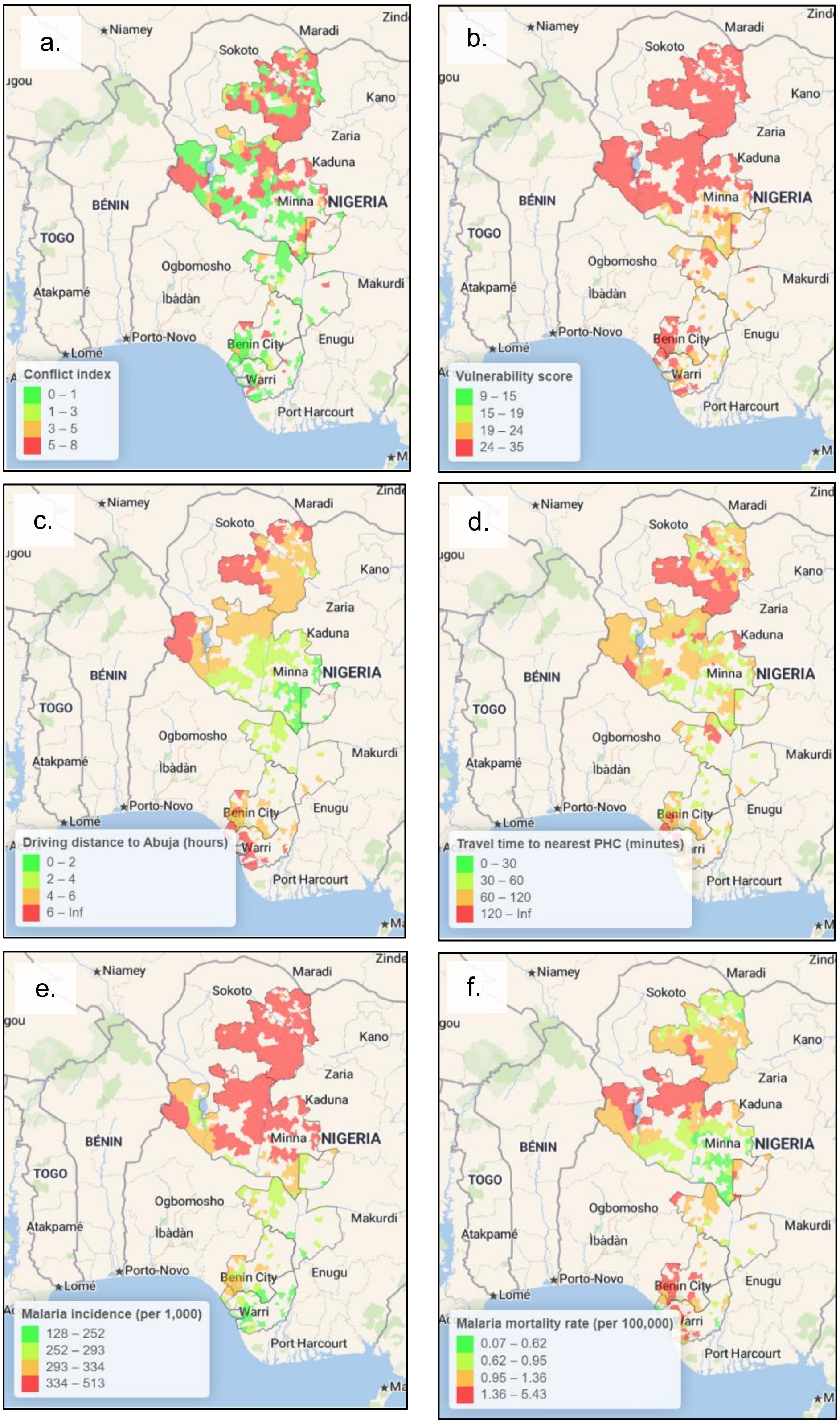


Figure 25. Screenshots of ward-level indicators at prioritized wards: (a) Conflict index, (b) Vulnerability index, (c) Driving distance in hours from Abuja, (d) Walking distance in minutes to nearest PHC facility, (e) Estimated malaria incidence rate, and (f) Estimated malaria mortality rate (ACLED – Conflict dataset, MAP – Malaria surfaces and Friction surface, WorldPop – Population surface, GRID3 – Health facilities list)

4.3 Quantification of CHWs – Delta state

We applied 2 methods to quantify the number of CHWs needed in Delta state: a simple approach and a geospatial optimization model.

Method 1: Ward-level estimate according to population

We simply assigned one CHW to every 1,000 population in each ward who are living beyond 1 hour distance from PHC facility. This approach is efficient for the interactive dashboard but does not account for the actual location of beneficiaries or CHWs.

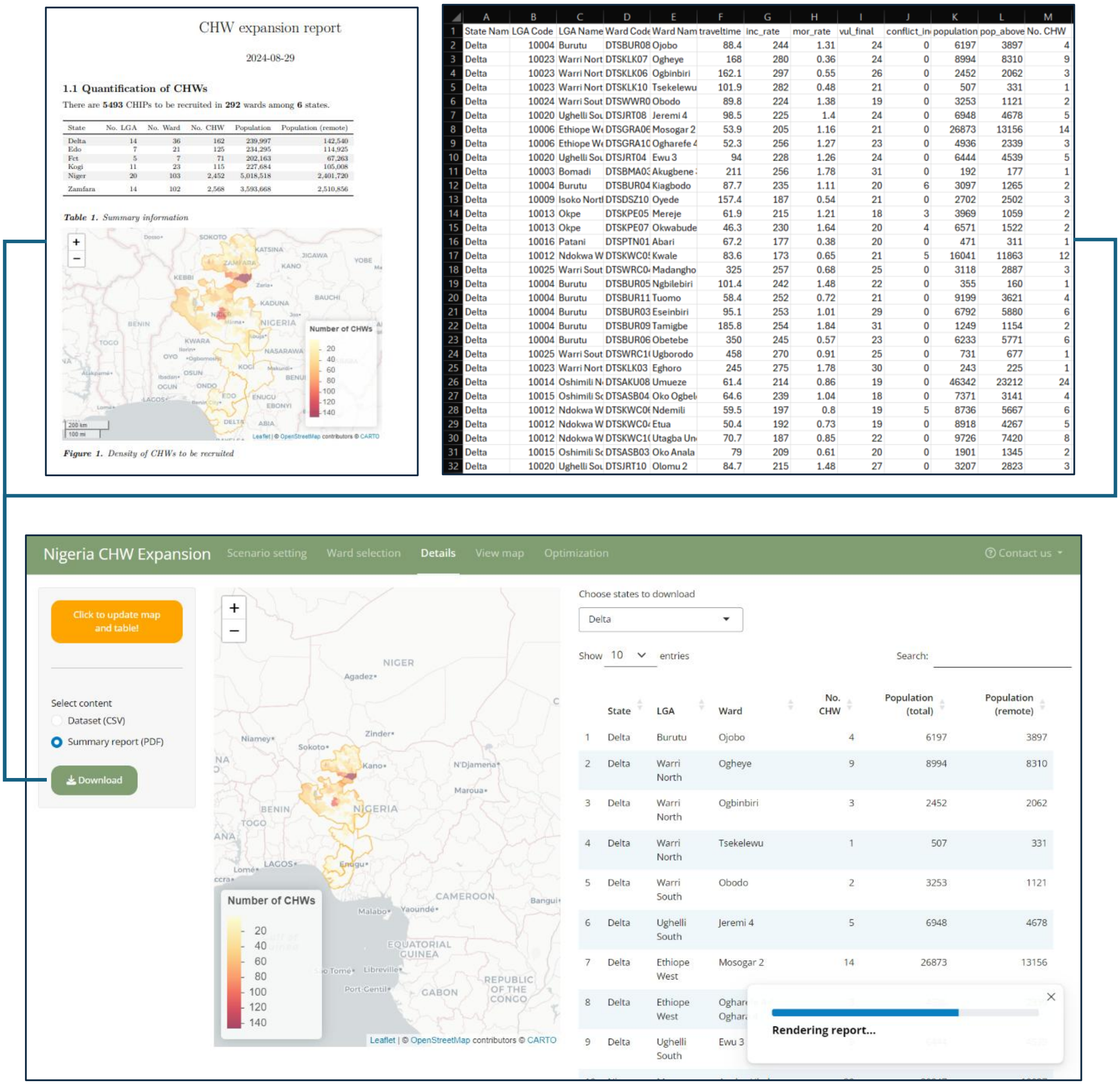


Figure 26. Screenshots of 'Details' page, displaying number of CHWs needed at prioritized wards and download options for Delta state.

162 CHWs are needed to cover a population of 142,540 across 36 wards in 14 LGAs.

Sr.	LGA name	No. Wards	No. CHWs	Population reached
1	Bomadi	1	1	177
2	Burutu	7	25	21,748
3	Ethiope West	2	17	15,495
4	Isoko North	1	3	2,502
5	Ndokwa East	2	11	9,452
6	Ndokwa West	4	31	29,217
7	Okpe	2	4	2,581
8	Oshimili North	1	24	23,212
9	Oshimili South	2	6	4,486
10	Patani	1	1	311
11	Ughelli South	3	13	12,040
12	Warri North	5	18	14,925
13	Warri South	1	2	1,121
14	Warri South-West	4	6	5,273
	Total	**36**	**162**	**142,540**

Table 4. Number of CHWs needed at ward-level according to population coverage

Method 2: Spatial optimization model

In the spatial optimization model approach, we firstly set parameters to define constraints for CHW expansion strategy. This approach allowed us to optimize the allocation of CHWs based on both geographic and demographic factors, optimizing effectiveness and efficiency.

Parameters	Setting	Descriptions
PHC coverage area	1 hour walking distance from nearest PHC facility	As threshold set per NPHCDA, model attempts to place CHW for individuals who are living beyond 5km distance from nearest PHC facility. Thus, geographic coverage of a PHC facility is assumed as 1 hour walk (approximately 5km distance).
Catchment area by CHW	1 hour walking distance from CHW location	A CHW is expected to provide services to individuals living within 1 hour walk (approximately 5km distance) from its location.

CHW in urban area	1 CHW for 2,500 urban population	Within the catchment area, a CHW is expected to provide services to a defined population size. In urban areas, one CHW is assigned to 2,500 individuals, but in rural, only 1,000 individuals. (Urban/rural classification was done by define_urban function of PATHtools package in R)
CHW in rural area	1 CHW for 1,000 rural population	

Table 5. Parameters of spatial optimization model

First, 'PHC coverage area' parameter was used to define individuals who are living in proximities (within 5km distance) to existing PHC facilities. Within this geographic coverage of a PHC facility, individuals are assumed to be covered by facility-based services and they are excluded when required number of CHWs is estimated.

We then implemented operational constraints to ensure that CHWs can effectively deliver iCCM services to their assigned populations within a feasible walking time. The 'CHW catchment area' parameter was designed to limit the area within which a CHW could reasonably walk and provide iCCM services within one hour. To determine this, we utilized a walking-only friction surface to estimate the time required for CHWs to travel on foot from their location. Additionally, we calibrated the 'population coverage' parameter based on the urbanization level of the area where a CHW is expected to serve. Urban areas were defined according to the European Commission's "degree of urbanization" approach, as outlined in the 2017 World Bank report. Using WorldPop's population density raster data, we identified adjacent 1km² pixels with populations exceeding 300 individuals. Clusters containing more than 2,000 individuals were then categorized as urban areas.

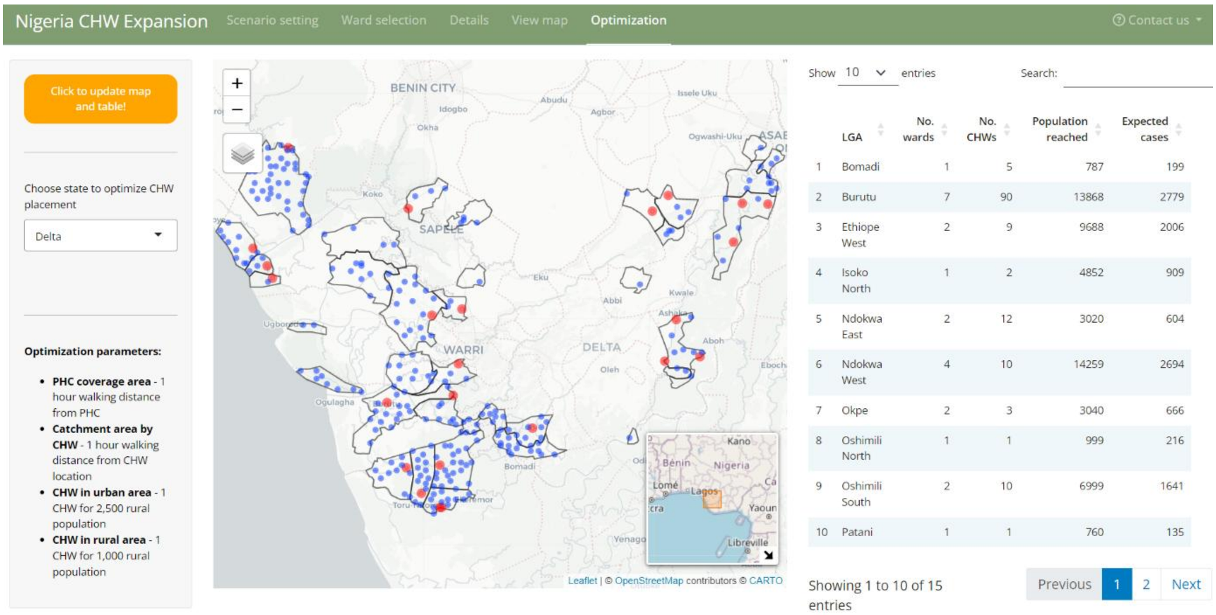


Figure 27. Screenshot of dashboard, displaying location and allocation of CHWs needed at prioritized wards (Red dots – PHC facilities, Blue dots – Optimized locations of CHWs)

273 CHWs are needed to cover 85,395 people across 36 wards in 14 LGAs.

Sr	LGA name	No. Wards	No. CHWs	Population reached	Estimated malaria cases
1	Bomadi	1	5	787	199
2	Burutu	7	90	13,868	2,779
3	Ethiope West	2	9	9,688	2,006
4	Isoko North	1	2	4,852	909
5	Ndokwa East	2	12	3,020	604
6	Ndokwa West	4	10	14,259	2,694
7	Okpe	2	3	3,040	666
8	Oshimili North	1	1	999	216
9	Oshimili South	2	10	6,999	1,641
10	Patani	1	1	760	135
11	Ughelli South	3	31	8,370	1,853
12	Warri North	5	57	10,136	2,979
13	Warri South	1	16	2,262	527
14	Warri South-West	4	26	6,355	1,622
	Total	**36**	**273**	**85,395**	**18,830**

Table 6. Number of CHWs needed according to spatial optimization model

5. Discussions

With the aim of institutionalizing iCCM to end preventable child deaths, WHO and UNICEF set out the main principles of institutionalizing community health (1), including:

- *Prioritize populations and areas that are hardest to reach and implement community health interventions in a comprehensive manner with quality and equitable coverage, guided by national policy and local systems to ensure impact.*
- *Use practical and participatory learning and research to identify, sustain and scale up effective community interventions, while providing opportunities for sharing lessons among countries and globally.*

To be in line with these principles, this project demonstrated a stepwise decision-making process using the data-driven evidence and an interactive decision support tool.

Prioritization at different levels

We purposely selected states in this project for demonstration purpose. However, state-level representative data from MIS 2021 would be helpful to make evidence-based rationales in state selection. Because there were huge disparities in malaria burden, intervention coverage and treatment seeking behaviours across states.

Nigeria's nationwide CHW density has been reported to exceed the African regional average. (4, 25) Furthermore, 8,289 CHIPS Agents have been trained across 13 states. (26) Therefore, up-to-date information on the number and distribution of CHWs is a crucial factor in prioritizing states for health interventions.

As second step, we conducted prioritization at ward-level to be in line with Ward Health System Strategy (WHSS) and objectives of the project. Prioritization at LGA-level may be an administratively convenient approach because, according to PHCUOR implementation guidelines, LGHA is the responsible body for primary health care services at community level. (22)

Setting parameters for vulnerability score

We adopted MCDA approach to prioritize areas for CHW expansion based on malaria burden (incidence, prevalence, mortality rate) and access to equitable services. Following different strategies could be considered when setting importance level of malaria burden parameters.

- **Efficient and overarching approach:** Deploying CHWs in high-prevalence areas, malaria hotspots, can have a substantial impact by reducing the parasite reservoir within the community and overall burden of disease, when resources are used more efficiently. Testing, treatment, and education on preventive measures are crucial in bringing down transmission rates.
- **Reactive and preventive deployment:** In high-incidence areas, malaria transmission is ongoing and possibly increasing if there is no immediate action. CHWs can quick respond to prevent outbreak or further transmission by conducting early diagnosis and treatment, as well as engaging in vector control efforts and community education in areas with seasonal spikes.
- **Strengthening case management:** High mortality suggests inadequate access to effective treatment or associated health problems, such as malnutrition. CHWs are critical to reduce deaths by ensuring timely diagnosis, treatment, referral and awareness raising on treatment seeking behaviours. This approach is applicable in areas with limited access to healthcare.

Efficient and impactful CHW deployment can be achieved by leveraging the importance level these indicators based on local epidemiological trends. During this project, we raised importance level of prevalence and mortality to ‘medium’. Because we emphasize to ensure efficiency while focusing more on case management rather than responding to outbreaks.

Accuracy of modelled surfaces on Malaria burden

Along with geospatial covariates and other predictor datasets on intervention coverage, Malaria prevalence (parasite rate) in Nigeria was modelled from cross-sectional survey (DHS 2018) data, rather than routinely surveillance data. Bayesian space-time geostatistical model was used to predict parasite rate for every 5 ×5 km pixel. From the modelled parasite rate, malaria incidence was subsequently developed using mechanistic transmission models, adjusted for adjustments for effective treatment rate and transmission pattern. On the other hand, mortality estimates were subsequently developed from parasite rate using case fatality rate (CFR) model for sub-Saharan Africa. (44)

Incorporating routinely reported data could significantly enhance the accuracy of model estimates. (44) Survey datasets on parasite rates may be skewed due to overrepresentation of clusters from high malaria burden areas or surveys conducted during peak transmission seasons, which can inflate estimates. Conversely, data from lower burden settings or off-peak seasons might lead to underestimation. Regularly reported data would help balance these variations and provide a more accurate reflection of the actual malaria burden. However, adjustments for routine surveillance data would be needed due to disparities in treatment seeking behaviour and proportion treated in non-reporting private facilities.

Non-malaria indicators for prioritization in an integrated approach

We acknowledged that iCCM approach is a core component of integrated management of childhood illness (IMCI) which intends to improve access to life-saving interventions for both malaria and non-malaria diseases, such as pneumonia and diarrhoea. (19) Our approach could be improved by incorporating geospatial datasets for non-malaria diseases. In a study using Bayesian Markov Chain Monte Carlo logistic regression model, region of residence was a significant predictor of all pneumonia symptoms (cough, fever, short and rapid breath) and living in rural area was a significant predictor of fever. (47) Another study using routine health data on pneumonia during 2011-2018 identified LGAs (area councils) with FCT with higher rate of occurrence of pneumonia. (48) Spatial analysis of 2018 DHS datasets revealed that there were hotspots of diarrhoea among children under 5 years of age in Yobe, Bauchi, Gombe, Kano, Sokoto, Imo, and Taraba states. Multilevel logistic regression also showed that regions are significant predictors of diarrhoea. (49) However, we could not identify disease burden indicators of pneumonia or diarrhoea at desired granular (ward) level during this project.

Robustness of malaria indicators used in prioritization

Due to availability of high-resolution maps for malaria incidence, we used it as proxy indicator to identify areas which were disproportionately at risk of P falciparum malaria. Malaria serological markers, antimalarial antibody prevalence is also a robust indicator to measure malaria transmission intensity and to classify recent or historical malaria exposure. In the settings aiming for malaria elimination, serological surveillance indicators could provide information about recent transmission and help to identify priority areas to focus for elimination measures. (50, 51)

Additionally, we could build more comprehensive algorithm for vulnerability score by adding more contextual indicators of malaria. Because areas with persistence malaria burden are often linked to vector habitat changes, resistance to ITN and antimalarial drugs, and importation of cases due to migration. (44) Moreover, malaria vaccination coverage will be an important parameter to include in the future application of our approach. In early 2024, Accelerated Malaria Vaccines Introduction and Rollout in Africa (AMVIRA) initiative launched introduction of the two malaria vaccines, RTS,S/AS01 (RTS,S) and R21/Matrix-M (R21), into the routine immunization of 19 countries including Nigeria. (52) With efficacy of 75% against malaria episodes and 13% reduction in mortality among children, malaria vaccine will reduce burden of malaria, and consequently vulnerability to malaria. (53)

Geographic coverage of PHC facility and catchment area of a CHW

We used walking-only friction surface, which is a relative measure of how long it might take to walk across the surface of the globe, to calculate the accessibility to PHC facilities. (31, 33) According to NPHCDA's standard, people within a 5km walking distance are considered to have access to PHC facilities. Assuming an average walking speed of 5km per hour, we targeted the population living beyond 1-hour walking distance. (5) During a multi-country evaluation of iCCM by the Global Fund, the similar distance of 5km from the nearest facility was applied for mapping communities who have benefitted by iCCM. (9) Similarly, previous studies considered geographical coverage of health facility as 5km (35, 38) or 1 hour walking distance. (36) However, some studies suggest that care takers' perception of 1 hour travel to a health service is too long. (9) In Sierra Leone, hard-to-reach areas are beyond 5km distance, but a shorter distance of 3 – 5 km, if terrain is difficult. (34)

Quantification of CHWs

As per NPHCDA, CHIPs agents are defined as 'support staff' to ensure UHC at community level. Under PHC facility at ward-level, CHIPs agents work alongside other community health workers, such as CHOs, CHEWs and JCHEWs. (5, 25) So, if the primary purpose is to guide expansion of CHIPs program, we can simply adopt the threshold of 10 to 20 CHIPs per ward as defined by NPHCDA. (5, 25)

There is no defined population threshold for CHWs in Nigeria, so we implemented two simple strategies: one CHW per 1,000 people for those living more than an hour from the nearest PHC, and one CHW per 1,000 people for the entire ward population. However, we noticed several different thresholds in other countries, (9, 34, 35, 38) and a suggestion that population coverage can be reduced in areas with high malaria transmission. (36) Disaggregating the number of CHW per population according to urbanity (36) or distance from health facilities (38) was applied in the region. During spatial optimization in our project, we used different population coverage threshold for rural (1,000) and urban (2,500). Additionally, each CHW's catchment area was defined as a 60-minute walking distance from their station, so that CHW does not need to walk long to provide services. Previous studies used smaller catchment areas of 3–4 km, (38) and 30 minutes. (34) In a study in Haiti, multiple thresholds of 0, 30, and 60 minutes were used to simulate different scenarios. (36)

Some contextual factors may influence quantification of CHWs. Workload needed to provide minimum service package to the affected population can be used to quantify CHWs needed. In Madagascar, CHWs spent an average of 2.6 hours providing care for each child under 5 years of age diagnosed with malaria. (9)

High CHW turnover rates due to insecurity and migration should be considered. While there are more CHW demands in peri-urban or rural area, cities peripheries, and nearby rural areas have recently become zones of profound insecurity. (16) Also, healthcare workers prefer to work in the urban areas where facilities are owned more by the highest tier of government. (8) PHUOR guidelines encourages to recruit females for CHIPs, (22) but there is an increased likelihood of migration among 18–24 year old women. (14)

Enhancing utilization of iCCM services

Beyond the availability coverage, demand-side factors may pose further barriers to accessing services for malaria. (10) Some iCCM activities were lack of funding for behavioural change communication activities and demand creation strategies. (9) Demand creation is important as low utilization of health services increases the cost of iCCM programmes per capita, affects investments and sustainability, and limits reductions in morbidity and mortality rates. (1, 9, 23) In a multi-country evaluation study, reasons for not taking a sick child to the CHW were; not knowing the CHW (78% in urban; 33% in rural) and preferring facility services (23% in urban and 45% in rural). (9) In Nigeria, there was delay before seeking treatment or advice, suggesting weak evidence of access to CHWs. (6) Despite evidence-based strategies, institutionalization of iCCM requires community involvement. (1) increases use of iCCM by increasing trust in and support for CHWs. Community involvement in the CHW selection and CHW recruitment from local communities, creates a built-in retention strategy and increases community trust necessary for improving access to services. (9, 25)

There were recurrent concerns about insufficient supplies, especially in rural areas. (1, 8) This could affect community trust in the health system as CHWs could be undermined and uptake of iCCM will not be equitable or improved. (1, 9) Receiving facilities must be well-stocked and have sufficient trained staff to strengthen PHC services by CHWs. Moreover, one of recommendations for institutionalizing iCCM in PHC is classification of referral centres according to the severity of disease and being communicated to CHWs and caretakers. So that a child with danger signs is sent directly to a health facility that can manage the condition and not necessarily to the nearest health facility. (1)

Factors such as misalignment of timing of funding for non-malaria (pneumonia and diarrhoea) and malaria commodities, and gaps in financing the full iCCM package had a negative impact on iCCM extension and coverage. The gap in co-financing non-malaria iCCM components was an issue in Nigeria. (1) During CHW expansion, aligning to existing and potential funding for comprehensive iCCM package should be considered.

Limitations of the project

1. *Possible data quality problems with data sources*

In a study reviewing governance of iCCM in 47 countries, including Nigeria, revealed that one of the key challenges in success of iCCM is information-sharing across collaborators. (23) In this project, validity of the travel time calculation totally depends on quality of PHC facilities dataset. According to the latest available data from FMoH's health facility registry (HFR) database (access through PharmAccess), there were more than 34,076 PHCs in 2019. (54) But there is no georeferenced information from that source. Another WHO dataset (access through The Humanitarian Data Exchange - HDX) identified 4,697 primary healthcare facilities in 2019. But this is unrealistic as there were more than 9,000 political wards. In the dataset we used (access through GRID3), 648 (3%) out of 21,329 features were located within 100 meters from each other. These facilities may be overlapped or misplaced, but we were not able to conduct physical verification.

Moreover, PHC facility must be functional to supervise CHW activities at ward-level. (5) In this project, we assumed that 21,329 PHCs are functioning and providing mentioned essential services as defined by NPHCDA. But a recent report stated that only 20% of those facilities were identified as fully functional. (54) Even though we filtered 'functioning' PHC facilities in the analysis, the situation may have changed from 2019 when dataset was published.

During location-allocation analysis, we resampled the modelled estimates of malaria incidence and mortality rate from 5x5km to 1x1km resolution. In estimating CHWs needed at each 1km grid using spatial optimization model, we completely relied on the assumption that each 1km grid will have same malaria risk if they are within the same 5km grid.

The modelled surfaces for malaria disease burden and intervention coverage in this analysis heavily depend on parasite rates and predictor variables such as ITN access, Indoor residual spray (IRS) coverage, and effective antimalarial treatment coverage, derived from survey (DHS 2018). Although the DHS sampling methodology ensures representativeness, potential biases may arise due to survey locations being clustered in high-burden areas or the survey timeline coinciding with peak transmission seasons. These factors could skew the data, impacting the accuracy of the model's estimates.

2. Limitations with travel time calculation

Travel time calculation using modelled friction surface is believed to be a more realistic measure than Euclidean distance. But it does not account for seasonal variation and reflects the conditions when it was published in 2020. To account for factors affecting motorized travel, such as road infrastructure, cost and availability of motorized transportation, travel time by walking is a preferable option to calculate travel time in rural areas. (31) However, walking might not always be the most common mode of transportation. Additionally, there are changes that nearest PHC facility may not offer required services and people may choose further facilities to receive services. (31) So, we acknowledged that travel time surfaces should not be interpreted as the actual current travel time, (37, 55) though it is considered as a reliable proxy indicator of accessibility.

3. Evaluation of efficiency of proposed CHW expansion strategy

Despite comprehensive and updated HRIS is crucial to ensure equitable distribution and deployment of health workers, (21) unavailability of HRIS remains a big challenge in several countries. (20) During this project, we could not access information about current deployment of CHWs. Ahmat et al. stated that there were 116,454 CHWs in 2018 (4), but efficiency calculation was not possible without disaggregated and georeferenced data. Previous studies assessed efficiency using population coverage between current and theoretical scenarios. (34, 35, 38) In addition, temporal changes in access, i.e., improvement in treatment delays before and after deploying new CHWs, is also recommended as a robust indicator to measure the impact of expansion. (6)

4. Administrative barriers of service availability at PHC facilities

When calculating accessibility to PHC facilities, we assumed individuals could visit nearby facilities regardless of administrative boundaries. On the other hand, we constrained service availability so that people in border areas would not visit health facilities in neighbouring countries. In real-world settings, certain PHC facilities may accept patients only within the same ward. Also, National boundaries may be porous, allowing populations to access cross-border essential health care services.

6. Conclusions

We extracted ward-level estimates from modelled geospatial dataset of disease burden, intervention coverage, friction surface and population density, and publicly available health facility dataset. We found that lower proportion of non-MOH owned PHC facilities in North-East and North-West zones led to lowest number of PHC facilities. Consequently, there were huge variations in distance between PHC facilities, accessibility to them and size of population who were beyond 1 hour travel time among wards of northern zones. Disparities in malaria burden and intervention coverage were also detected across different states. Even though we purposely selected states during this project, we could use evidence-based rationale for state selection.

Within selected states, we introduced MCDA approach to prioritize wards according to the parameters of disease burden and accessibility. During the prioritization process, we introduced and web-based interactive dashboard as a decision support tool, and a stepwise approach. This could ensure the stakeholder engagement through bridging the knowledge gap between technical assistance parties and policy makers and allowing the stakeholders to see the results of different prioritization criteria. We also included options to prioritize according to contextual parameters such as health security (conflict index) and administrative concerns (driving distance from Abuja). During recent years, optimization models are being used to enhance the location-allocation of CHW. We introduced the optimization for Delta state as an example in the interactive dashboard. As the model accounts for actual location of population and CHWs, more estimated number of CHWs are needed.

The validity of estimates hugely depends on validity and granularity of geospatial and health datasets. We acknowledged the limitations of this project and there are opportunities to refine the process using more comprehensive, reliable and recent datasets. Moreover, efficiency calculation from coverage perspective and longer-term health impact, using existing HRIS could be beneficial for more efficient deployment. Ultimately, we could integrate stepwise prioritization and optimization model into HRH planning using updated NHWR.

This project provides geospatial insights into HRH planning using estimated disease burden, population size and accessibility to PHC facilities to identify prioritized wards, quantify the underserved population and guide decision making for CHWs expansion.

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