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Distribution and Environmental Drivers of Mosquito Larvae in Rural Communities of Asa Local Government Area, Nigeria

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ABSTRACT

Background: Mosquito-borne diseases continue to pose a significant public health challenge in Nigeria, particularly in rural areas where environmental conditions favour persistent mosquito breeding and routine vector surveillance is limited. This study integrated field-based larval surveys with remotely sensed environmental variables to examine mosquito larval abundance, habitat productivity, and species-specific spatial risk in Asa Local Government Area (LGA), Kwara State, Nigeria.

Methods: Larval sampling was conducted across sixty-one aquatic habitats, and specimens were morphologically identified. Landsat 8 OLI imagery was used to derive vegetation, moisture, soil, and built indices, which were analyzed alongside entomological data using appropriate regression models and geographic information systems. Statistical significance was evaluated at $p<0.05$. Predictive risk maps were generated using QGIS.

Results: A total of 1,516 mosquito larvae were collected, yielding a mean larval abundance of 25.3 larvae per habitat. Two genera were identified: *Culex* spp. accounted for 59.3% of the total larvae, while *Anopheles* spp. constituted 40.7%. Larval productivity was highly heterogeneous across habitat types, with used tyres contributing the largest proportion of larvae (40.0%) while the least occurred in open water bodies (12.5%). Habitat positivity was highest in used tyres and buckets (100%) and lowest in open water (66.7%). Regression analyses revealed that remotely sensed vegetation and surface-moisture indices were significant predictors of larval dynamics. *Anopheles* larval abundance was significantly associated with LSWI ($p=0.014$), MNDWI ($p=0.015$), NDWI ($p=0.013$), MSAVI ($p=0.004$), and NDVI ($p=0.006$). *Culex* larval occurrence was significantly influenced by LSWI ($p=0.002$), MNDWI ($p=0.002$), MSAVI ($p<0.001$), and NDVI ($p=0.002$). Predictive risk maps showed spatial clustering of *Anopheles* larvae in moist, vegetated zones, whereas *Culex* risk was more widespread across peri-domestic and stagnant-water environments.

Conclusion: The pronounced heterogeneity in larval distribution and the strong associations between vegetation, surface-moisture indices, and larval dynamics underscored the value of satellite-derived metrics for identifying high-risk habitats and guiding targeted vector surveillance.

Keywords: Mosquito, Remote sensing, QGIS, Environmental variables

1.0 INTRODUCTION

Mosquito-borne diseases constitute a major public health concern globally and particularly across sub-Saharan Africa, where ecological suitability, climate variability, land-use change, and limited vector-control coverage facilitate persistent transmission [1, 2]. In addition to malaria, mosquitoes are responsible for the transmission of a wide range of pathogens, causing diseases such as lymphatic filariasis [3], yellow fever [4], dengue [5], chikungunya [4], Zika virus infection [6], West Nile fever [7], and various forms of viral encephalitis [8]. These diseases impose substantial health and socioeconomic burdens, especially in rural communities where environmental conditions favour mosquito proliferation and access to sustained vector surveillance and control is limited.

Nigeria remains highly vulnerable to multiple mosquito-borne diseases due to its diverse ecological zones, rapid landscape transformation, expanding agricultural activities, and variable water-management practices. Rural areas are particularly affected, as they often contain a complex mix of natural and artificial larval habitats, including seasonal streams, wetlands, irrigation channels, and water-holding containers associated with domestic and agricultural activities. Such environments support the breeding of multiple mosquito genera, notably *Anopheles*, *Culex*, and *Aedes*, each of which is associated with distinct disease transmission cycles [9, 10].

Asa Local Government Area (LGA) of Kwara State was selected as a representative study site due to its ecological and epidemiological characteristics typical of the Guinea savannah zone of North-Central Nigeria. The area experiences a tropical wet-and-dry seasons [11], with mean annual rainfall of approximately 1,000-1,300 mm and a distinct rainy season from April to October, followed by a dry season from November to March. Mean annual temperatures range between 25°C and 34°C, with relative humidity exceeding 70% during the peak rainy season [11]. These conditions promote the seasonal formation of temporary and semi-permanent water bodies, including pools, irrigation ditches, and lowland depressions, which serve as productive mosquito breeding habitats. Land-use patterns are predominantly agrarian, with over 60–70% of the area under cultivation (e.g., maize, cassava, and yam farming), interspersed with rural settlements characterized by low housing density (<500 persons/km²) [12]. Such environments have been associated with increased human-vector contact due to the proximity of households to breeding sites. These ecological characteristics promote the coexistence of malaria vectors (*Anopheles* spp.) and other medically important mosquitoes such as *Culex* spp., which are implicated in the transmission of lymphatic filariasis, West Nile virus, and other arboviruses. Epidemiological evidence indicates a high burden of malaria in the LGA, with a prevalence estimate of up to 57% [11], alongside filarial infection rates ranging from 1.6% to 17% [13]. Understanding the spatial distribution, productivity, and environmental drivers of larval habitats in such settings is therefore essential for designing integrated and locally appropriate vector-control strategies.

Recent advances in remote sensing and geographic information systems (GIS) have provided powerful tools for studying mosquito ecology by enabling the detection and monitoring of environmental variables that influence larval habitat suitability across large spatial extents. Satellite platforms such as Landsat, Sentinel-2, and SPOT offer repeated observations from which vegetation indices, surface-water indicators, soil moisture proxies, land surface temperature, and terrain attributes can be derived. Several studies have demonstrated that indices such as the Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), Land Surface Water Index (LSWI), and vegetation-adjusted indices are strongly associated with mosquito breeding habitats and larval densities [14–16].

Empirical evidence from diverse geographic settings supports the use of remote sensing to map larval habitats and predict mosquito abundance. Studies in West and Southern Africa have shown that satellite-derived environmental metrics can successfully identify productive larval habitats and delineate spatial hotspots of vector presence [15, 17, 18]. Similar approaches have been applied in North Africa and other regions to map areas vulnerable to mosquito-borne disease transmission, including diseases beyond malaria [19–21]. These methods are particularly valuable in rural environments, where larval habitats are often spatially dispersed, seasonally dynamic, and difficult to monitor using conventional field-based surveillance alone.

More recently, high-resolution remote sensing, including drone-based imagery, has further enhanced the detection of small and ephemeral larval habitats, demonstrating high accuracy in identifying mosquito breeding sites [22, 23]. However, moderate-resolution satellite data such as Landsat remain highly relevant for operational vector surveillance due to their free availability, long temporal coverage, and suitability for landscape-scale analyses in resource-limited settings [17, 24].

Despite the growing body of literature on the use of remote sensing for mosquito ecology, empirical studies applying these techniques in Kwara State and similar rural Nigerian settings remain limited. Environmental conditions, land-use practices, and mosquito species composition vary considerably across regions, limiting the direct transferability of findings from other ecological settings. There is therefore a need for locally grounded studies that quantify larval abundance, habitat productivity, and species-specific responses to environmental variables using remotely sensed data.

Against this backdrop, the present study integrates field-based larval surveys with Landsat-derived environmental variables and GIS-based spatial modeling to map mosquito larval densities and assess the influence of environmental factors on larval survival in rural communities of Asa LGA, Kwara State, Nigeria. By focusing on mosquito species, the study aims to (i) characterize larval habitat types and productivity, (ii) identify key remotely sensed predictors of larval abundance and occurrence, and (iii) generate spatially explicit risk maps to support integrated vector management. This approach contributes to a broader understanding of mosquito-borne disease ecology and provides an evidence base to strengthen vector surveillance and control strategies in rural Nigerian settings.

2.0 METHODOLOGY

2.1 Study Area

The study was conducted in the Asa Local Government Area (LGA) of Nigeria. The LGA is one of the sixteen administrative LGAs in Kwara State, situated in the North Central geopolitical zone. It covers an estimated land area of about 1,286 km² and had a recorded population of approximately 126,435 according to the 2016 census [25]. Geographically, Asa LGA is located between longitude 4° 12′00″E and 4°48′00″E and latitude 8°12′00″N and 8°36′ 00″N, defining its spatial extent within the region. Asa LGA is predominantly rural, encompassing dispersed settlements, seasonal rivers, wetlands, farmlands, and temporary pools that serve as potential mosquito breeding habitats. The area experiences a tropical climate characterized by distinct wet and dry seasons, with peak rainfall between May and October [11]. The landscape is a mosaic of agricultural fields and natural vegetation, providing diverse ecological niches for mosquito larval development.

2.2 Study Design

A cross-sectional, spatially explicit ecological study was employed to investigate mosquito larval densities and their environmental determinants. The study integrated field larval surveys with remotely sensed environmental variables derived from satellite imagery and GIS analysis. This design allowed for simultaneous assessment of larval abundance and mapping of potential high-risk habitats across the LGA.

2.3 Data Sources

2.3.1 Field Data

Mosquito larvae were sampled from sixty-one identified aquatic habitats across multiple rural communities in Asa LGA, including ponds, temporary pools, drainage channels, and farm irrigation sites. Habitat selection was conducted using a purposive sampling approach, targeting water bodies with visible characteristics conducive to mosquito breeding (e.g., stagnant or slow-moving water, organic matter, and vegetation cover). Sampling was carried out during both the early and wet season periods to capture temporal variation in larval abundance. Larval collections were conducted between 08:00 and 11:00 hours, when larval activity is typically highest, and visibility is optimal. At each habitat, larval sampling was performed using a standard 350 mL dipper in accordance with World Health Organization (WHO) guidelines [26]. A fixed number of 10–20 dips per habitat was taken, depending on habitat size and accessibility, with dips systematically distributed along the perimeter and across microhabitats. For small habitats (<1 m²), all accessible water was sampled, while for larger habitats (>10 m²), dips were taken at regular intervals (approximately 1–2 m apart) [26]. The approximate surface area of each habitat was estimated and categorized as small (<1 m²), medium (1–10 m²), or large (>10 m²) to standardize sampling effort. Collected larvae were preserved and transported to the laboratory, where they were identified morphologically to genus level using standard identification keys [27].

2.3.2 Satellite and Environmental Data

Landsat 8 Operational Land Imager (OLI) imagery was used to derive remote sensing variables to characterize environmental conditions associated with mosquito larval habitats across Asa LGA. Multispectral Landsat 8 OLI data were processed to derive a suite of vegetation, surface-moisture, soil, and built-up spectral indices relevant to mosquito larval ecology.

2.4 Statistical Analysis

Larval habitat and entomological data were entered into Microsoft Excel 365 and analyzed using R (version 4.5.2) and STATA (version 17). Descriptive statistics were computed to summarize larval abundance and species composition. Continuous variables were summarized using means and standard deviations, while categorical variables were summarized using frequencies and percentages. Larval survival was defined as the presence of at least one larva in a habitat, and positivity rates were calculated as the proportion of positive habitats expressed as percentages. Habitat productivity was assessed using a productivity index, calculated as the proportion of total larvae contributed by each habitat type. Species composition was determined from morphologically identified larvae. Species frequency was calculated as the number of habitats in which each species occurred, while relative species abundance was expressed as a percentage of the total larval count. Larval density was calculated as the number of mosquito larvae collected per standard dipping effort across each sampled habitat type, while larval abundance was defined as the total number of mosquito larvae collected from each habitat type and sampling location during the study period.

2.5 Remote Sensing Processing

Pre-processing of satellite imagery was conducted to ensure radiometric consistency and minimize atmospheric effects before analysis. Landsat 8 Operational Land Imager (OLI) data were subjected to standard radiometric and atmospheric correction procedures using established preprocessing workflows to obtain surface reflectance products suitable for environmental analysis. All images were spatially referenced and clipped to the boundary of Asa LGA to ensure consistency across datasets.

Following pre-processing, a suite of spectral indices relevant to mosquito larval habitat characterization was derived from the Landsat imagery. These indices were selected for their established relevance to vegetation structure, surface moisture, soil exposure, and built-up features that influence mosquito breeding and larval survival. Vegetation indices included the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Modified Soil-Adjusted Vegetation Index (MSAVI). Surface water and moisture conditions were characterized using the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Land Surface Water Index (LSWI). Indices related to soil and built-up surfaces, including the Surface Reflectance Brightness (SRB), Built-up Index (BI), and Normalized Difference Built-up Index (NDBI), were also computed. All spectral indices were calculated using standard formulations and extracted at larval sampling locations for subsequent statistical analysis. These remotely sensed variables were then integrated with field-collected larval data to examine environmental determinants of larval abundance, survival, and spatial distribution across Asa LGA.

2.6 GIS and Spatial Modeling

Field Geographic coordinates of all larval sampling locations were recorded in the field and imported into a QGIS (Version 3.44.3) for spatial analysis. Field-collected larval data were georeferenced and overlaid with satellite-derived environmental layers to examine spatial relationships between larval distribution and environmental conditions across the Asa Local Government Area. All spatial datasets were projected to a common coordinate reference system to ensure spatial consistency.

Statistical modeling was applied to quantify environmental determinants of mosquito larval dynamics. Logistic regression models were used to evaluate predictors of larval presence or absence. Model selection was guided by likelihood-based criteria and information-theoretic measures, including Akaike Information Criterion (AIC), and model diagnostics were used to assess goodness of fit. Statistical significance was assessed at $p < 0.05$.

The fitted regression models were subsequently integrated into the GIS environment to generate spatially explicit predictions of larval suitability across the study area. Environmental raster layers were used as inputs to the final models, and predicted probabilities and expected larval densities were calculated using raster-based map algebra. These outputs were classified into risk categories to delineate areas of low, moderate, and high larval risk. Spatial prediction surfaces were validated using field survey observations, and model performance was assessed using standard accuracy metrics, including Receiver Operating Characteristic (ROC) curves. The resulting predictive maps were used to visualize spatial heterogeneity in mosquito larval risk and to identify priority areas for targeted larval source management.

2.7 Ethical Considerations

Ethical approval (KW/MOH/ERC/2024/06/312-1) for this study was obtained from the Kwara State Ministry of

Health Ethical Review Committee before the commencement of field activities. In addition, permission to conduct the study was granted by relevant local authorities, and community leaders within Asa LGA provided consent for larval sampling to be carried out in their respective communities. Community engagement activities were conducted before fieldwork to explain the study's purpose and to ensure residents' acceptance and cooperation.

3.0 RESULTS

A total of 1,516 mosquito larvae were collected from 61 habitats, while larval counts ranged from 0 to 86. Of the habitats surveyed, 88.5% were positive for mosquito larvae. Two mosquito species groups were identified during the larval survey: *Anopheles* spp. and *Culex* spp. *Culex* larvae were the most frequently encountered, occurring in 32 habitats, representing approximately 59% of the total larval population. *Anopheles* larvae were recorded in 22 habitats, totaling 618 larvae and contributing about 41% of the overall larval abundance (Table 1). Larval occurrence varies substantially across habitat types (Table 1), while larval positivity rate was 88.5% (Table 2). Used/abandoned tyre habitats consistently supported high larval densities (25.3±15.2) larvae per habitat), with all sites positive for larvae.

Table 1. Relative Species Abundance

Species	No. of habitat (+)	No. of larvae	Relative abundance (%)
Culex spp.	32	898	59.3%
Anopheles spp.	22	618	40.7%
Total	54	1,516	100

Table 2. Larval Positivity

Measure	Value
Positive habitats (≥1 larva)	54
Number of habitats sampled	61
Total larval positivity rate	88.5%

Open water habitats exhibited the highest mean larval occurrence, but a lower positivity rate (66.7%) (Table 3). Similarly, habitat productivity analysis revealed that used tyre habitats were the most productive, contributing 40.0% of all mosquito larvae collected during the study period while Pot habitats accounted for 23.8% (Table 4).

Table 3. Larval Abundance and Positivity by Habitat Type

Habitat type	Mean ± SD	Median	Positivity (%)
Bucket	13.5 ± 3.5	13.5	100
Drum	25.0 ± 20.4	16.5	72.7
Open water	31.7 ± 31.7	32.5	66.7
Pot	22.6 ± 17.9	18.5	87.5
Rice field	0	0	0
Used tyre	25.3 ± 15.2	19.5	100

Note: "Other container types were excluded from density analysis due to insufficient sample size, but were included in productivity estimates to account for their total contribution to larval output."

Table 4. Habitat Productivity Rate

Habitat type	Total larvae collected	Productivity rate (%)
Used tyre	607	40.04
Pot	361	23.81
Drum	250	16.49
Open water	190	12.53
Other containers	81	5.34
Bucket	27	1.78
Rice field	0	0
Total	1,516	100.0

Table 5 presents spectral indices derived from Landsat 8 OLI imagery at mosquito larval sampling points in Asa LGA. Vegetation-related indices exhibited positive mean values across the study sites. NDVI recorded a mean value of 0.16±0.08, while EVI averaged 0.20±0.11. Among the vegetation indices, MSAVI showed the highest mean value, 0.27±0.11. SAVI exhibited a distribution comparable to EVI, with similar central tendency and dispersion across sampling locations. Water-related indices were predominantly negative, with mean values of –0.20 for NDWI, –0.22 for MNDWI, and –0.03 for LSWI (Table 5). Indices associated with soil and built-up characteristics recorded low mean values. The Soil Reflectance Band (SRB) had a mean of 0.16±0.01, while the Normalized Difference Built-up Index (NDBI) averaged 0.03±0.07. Across all indices, the observed minimum and maximum values indicate spatial variability in land surface characteristics within the study area.

Table 5. Distribution of Environmental Indices across Mosquito Larval Sampling Locations

Variable	Mean ± SD	Min.	Max.
SRB	0.163 ± 0.013	0.131	0.198
BI	0.058 ± 0.054	−0.109	0.126
EVI	0.204 ± 0.113	0.089	0.547
LSWI	−0.028 ± 0.071	−0.105	0.192
MNDWI	−0.223 ± 0.023	−0.292	−0.166
MSAVI	0.270 ± 0.114	0.135	0.568
NDVI	0.162 ± 0.082	0.073	0.397
NDWI	−0.196 ± 0.060	−0.364	−0.118
SAVI	0.204 ± 0.113	0.089	0.547
NDBI	0.028 ± 0.071	−0.192	0.105

Note: Min. = minimum; Max. = maximum

3.1 Species-Specific Regression Analysis of Larval–Environmental Relationships

Regression analyses revealed that remotely sensed environmental variables were significant predictors of larval dynamics for both *Anopheles* and *Culex* species, although the strength and significance of individual predictors varied between species. For *Anopheles* larvae, several vegetation- and surface-moisture–related indices were significantly associated with larval abundance. LSWI, MNDWI, NDWI, MSAVI, and NDVI all showed significant associations (p<0.05), with NDVI and MSAVI exhibiting stronger levels of significance (p<0.01). The Soil Reflectance Band (SRB) demonstrated a marginal association with larval abundance. Model diagnostics indicated

an adequate fit, with an Akaike Information Criterion (AIC) value of 113.44 (Table 6). In contrast, the logistic regression model for *Culex* species identified a slightly different pattern of environmental associations. LSWI, MNDWI, MSAVI, and NDVI were all strongly associat-

Table 6. Effects of Environmental Indices on *Anopheles* Larval Presence

Variable	Estimate	Std. Error	p-value
(Intercept)	18.658	8.642	0.031*
SRB	-53.173	28.48	0.062
LSWI	-2867.533	1162.513	0.014*
MNDWI	2989.966	1223.623	0.015*
MSAVI	-378.016	131.187	0.004**
NDVI	502.285	184.497	0.006**
NDWI	-3051.031	1222.36	0.013*

** p < 0.01, * p < 0.05, ns = not significant

Table 7. Effects of Environmental Indices on *Culex* Larval Presence

Variable	Estimate	Std. Error	p-value
(Intercept)	-24.25	9.172	0.008**
EVI	69.411	46.41	0.135
LSWI	4420.877	1421.87	0.002**
MNDWI	-4622.216	1491.921	0.002**
MSAVI	596.6	180.627	<0.001***
NDVI	-944.576	300.572	0.002**

*** p < 0.001, ** p < 0.01, * p < 0.05, ns = not significant

ed with *Culex* larval presence (p<0.01), with MSAVI showing the highest level of statistical significance (p<0.001). Unlike the *Anopheles* model, EVI was not significantly associated with *Culex* larval occurrence (p=0.135) (Table 7).

3.2 Spatial Distribution and Predicted Risk of Anopheles and *Culex* Larvae in Asa LGA

There was a marked spatial heterogeneity in predicted *Anopheles* larval risk within the LGA. Areas of high predicted risk are concentrated primarily in the central to southeastern portions of the LGA, where contiguous zones of elevated suitability are evident. Several settlements, including Panpo, Alapa, Afon, and Ogbondoko, are located within or adjacent to these high-risk zones. Moderate-risk areas are distributed across much of the LGA's central corridor, forming transitional zones between high- and low-risk areas. In contrast, low-risk areas are predominantly observed in the northern and northwestern sections of Asa LGA, where predicted larval suitability is relatively limited (Figure 1).

Figure 2 reveals a widespread distribution of moderate to high predicted risk for *Culex* larvae throughout much of the LGA. Areas with high predicted risk are prominent across the central and southern portions of Asa LGA, forming relatively continuous zones of elevated suitability. Areas classified as moderate risk are widely distributed across the LGA, particularly within the central belt. In

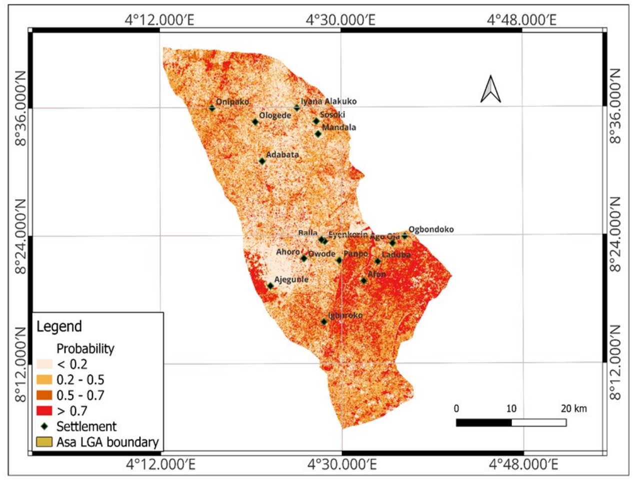

Figure 1. Predictive Risk Map for *Anopheles* species

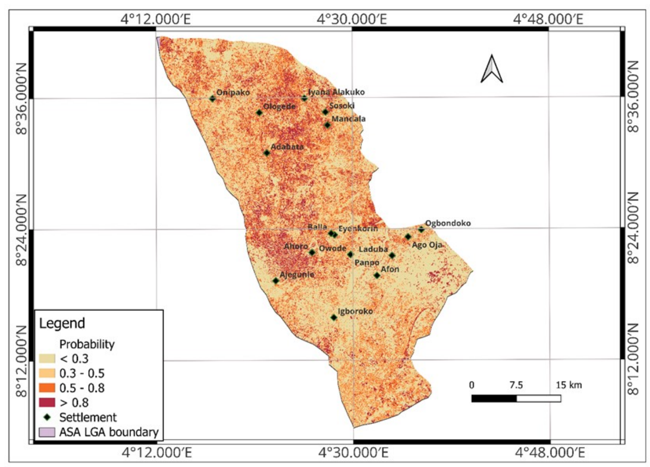

Figure 2. Predictive Risk Map for *Culex* species

contrast, lower-risk areas (p<0.3) are more limited in extent and are mainly observed as scattered patches toward the northern and northwestern sections of the LGA, where predicted larval suitability appears comparatively reduced (Figure 2).

4.0 DISCUSSION

This study demonstrates the utility of remotely sensed environmental variables for mapping mosquito larval abundance, habitat productivity, and species-specific risk in rural communities of Asa Local Government Area, Kwara State, Nigeria. By integrating field-based larval surveys with Landsat 8 OLI–derived spectral indices and spatial modeling, the study provides a spatially explicit assessment of larval habitat suitability for both *Anopheles* and *Culex* species. The findings reinforce the growing body of evidence that satellite-derived vegetation and surface-moisture indicators are robust predictors of mosquito larval ecology in heterogeneous rural landscapes.

The observed heterogeneity in larval abundance and habitat productivity across Asa LGA is consistent with earlier studies demonstrating that mosquito larvae are not uniformly distributed but are concentrated in a limited number of highly productive habitats [28, 29]. In this study, artificial container habitats, particularly used tyres, pots, and drums, accounted for a disproportionately large share of total larval production, highlighting their importance as key larval sources. Similar dominance of container habitats has been reported in both African and non-African settings, underscoring their epidemiological relevance for vector control [21, 30].

The spatial clustering of productive habitats, as reflected in the overdispersed larval counts, further supports targeted larval source management approaches rather than blanket interventions. This pattern aligns with findings from The Gambia and western Kenya, where a small proportion of habitats contributed most of the larval population [28, 29]. The strong spatial heterogeneity observed in Asa LGA therefore reinforces the feasibility of spatially targeted larval control strategies.

The coexistence of *Anopheles* and *Culex* larvae across multiple habitat types reflects the ecological diversity of larval environments in the study area. While *Culex* species were more abundant and widely distributed, *Anopheles* larvae were also present in substantial numbers, indicating the potential for persistent malaria transmission. Similar overlap of larval habitats has been reported in Egypt, South Africa, and Burkina Faso, where environmental conditions supported multiple mosquito genera simultaneously [15, 17, 19]. The presence of both genera within close proximity to settlements highlights the dual public health burden posed by nuisance mosquitoes and malaria vectors in rural Nigerian settings. This finding shows the importance of integrated vector management approaches that address multiple mosquito species rather than focusing exclusively on adult-stage interventions.

Regression analysis for *Anopheles* larvae identified vegetation and surface-moisture indices as significant predictors of larval abundance. The strong associations observed for NDVI, MSAVI, NDWI, MNDWI, and LSWI are consistent with established ecological understanding that *Anopheles* larvae are closely linked to moisture availability, vegetation structure, and water persistence [9]. Similar relationships have been documented in Zambia, Senegal, and Swaziland, where terrain and moisture-related indices were key determinants of *Anopheles* breeding habitats [14, 18, 31]. The marginal association observed for surface reflectance brightness (SRB) suggests that exposed or sparsely vegetated surfaces may indirectly influence larval habitat suitability, possibly through effects on water temperature and evaporation. Adeola and other colleagues [12] reported comparable findings in South Africa, where soil and vegetation indices jointly influenced the spatial distribution of mosquito breeding sites.

The *Culex* logistic regression model revealed a slightly different environmental sensitivity profile, with strong associations for moisture- and vegetation-related indices such as LSWI, MNDWI, MSAVI, and NDVI, while EVI was not significant. This distinction between *Anopheles* and *Culex* responses is consistent with previous studies showing that *Culex* species are more tolerant of a wider range of environmental conditions and are often associated with organically enriched or human-modified habitats [10, 32].

The broader spatial distribution of predicted *Culex* risk across Asa LGA, as shown in the risk map, mirrors findings from urban and peri-urban studies in Dakar and Toronto, where *Culex* suitability surfaces were more diffuse than those of malaria vectors [31, 32]. This widespread suitability highlights the challenge of controlling *Culex* populations and reinforces the need for community-level environmental management.

The predictive risk maps generated for both mosquito genera illustrate the value of integrating regression outputs with GIS to produce actionable spatial products. High-risk *Anopheles* zones were spatially clustered and often coincided with specific settlements, whereas *Culex* risk was more broadly distributed across the LGA. These patterns are comparable to risk maps produced in Burkina Faso, Egypt, and South Africa, where remotely sensed predictors successfully delineated high-risk larval zones [15, 17, 20]. The spatial overlap between high-risk zones and human settlements observed in Asa LGA has important implications for vector surveillance and control. Similar studies have shown that such maps can be used to prioritize larval surveillance, guide targeted larviciding, and optimize allocation of limited control resources [23, 24].

The findings of this study support the growing consensus that remote sensing and GIS are valuable tools for enhancing larval surveillance in resource-limited settings. While high-resolution drone imagery has demonstrated superior accuracy in identifying small larval habitats [22, 23]. This study shows that freely available Landsat imagery remains effective for LGA-scale risk mapping. This is particularly relevant for routine surveillance programs in low- and middle-income countries, where cost and accessibility are critical considerations. Moreover, the integration of remotely sensed data with field observations aligns with WHO recommendations for evidence-based larval source management, particularly in areas where larval habitats are fixed, findable, and productive.

This study demonstrated the effectiveness of integrating field-based entomological surveys with remotely sensed environmental data and spatial modelling to map mosquito larval abundance, habitat productivity, and species-specific risk in rural communities of Asa LGA, Kwara State, Nigeria. The findings confirm that mosquito larval distribution in the study area is highly heterogeneous, with a small number of habitat types, particularly artificial containers such as used tyres, drums, and pots, contributing disproportionately to overall larval production. Remotely sensed vegetation and surface-moisture indices derived from Landsat 8 OLI imagery were significant predictors of larval abundance and occurrence for both *Anopheles* and *Culex* species, although species-specific differences in environmental sensitivity were observed. Predictive risk maps revealed distinct spatial patterns, with *Anopheles* larval risk occurring in more spatially clustered zones and *Culex* risk being more widely distributed across the landscape. The close spatial overlap between high-risk zones and human settlements highlights the continued vulnerability of rural communities to mosquito-borne diseases.

Besides, the study provides strong evidence that freely available satellite data, when combined with appropriate statistical models and GIS techniques, can generate reliable, spatially explicit information to support targeted larval surveillance and vector control. The approach presented is scalable, cost-effective, and well-suited to resource-limited settings, offering practical value for integrated vector management programs. Future work incorporating higher-resolution imagery, seasonal analyses, and climatic variables would further enhance predictive accuracy and support more dynamic risk assessment.

Limitations and Future Directions

Although the study provides robust insights, certain limitations should be acknowledged. The use of moderate-resolution satellite imagery may limit detection of very small or transient larval habitats, a challenge noted in earlier studies. The inclusion of sixty-one sampling sites also serves as a limitation to this study. Besides, the cross-sectional design captures environmental conditions at specific times and may not fully represent seasonal dynamics. Future studies incorporating multi-temporal imagery and higher-resolution sensors could further refine risk predictions.

Conflicts of Interest

The authors declare that there is no conflict of interests.

Authors' Contributions

YHO performed data collection and contributed to data analysis tools. **SOJ** conceived and designed the study, contributed to data analysis tools, analysis of data and manuscript writting. **OGO** contributed to study design, data analysis tools, analysis of data, and manuscript writing. All authors approved the final copy of the manuscript.

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