MamaCare AI: A GeoAI Framework for Maternal Healthcare Accessibility Analysis in Underserved Communities

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Abstract

Maternal mortality remains a critical public health challenge in Northern Nigeria, where geographic barriers significantly delay access to essential healthcare services. In Kebbi State, approximately 62% of women of reproductive age reside more than 5 km from the nearest health facility, representing a severe and measurable accessibility gap. This paper presents MamaCare AI, a GeoAI framework integrating geospatial intelligence and machine learning to support maternal healthcare accessibility analysis and evidence-based intervention planning in underserved communities. Using GRID3 facility data (1,207 facilities), WorldPop population estimates, and Nigeria DHS-derived indicators, we conduct a spatial accessibility analysis across 1,510 grid points in Kebbi State. DBSCAN spatial clustering (silhouette score: 0.83) identifies priority underserved population zones, and a composite risk scoring model across all 21 Local Government Areas identifies Argungu, Augie, and Dandi as critical intervention priorities. Based on these findings, we propose a phased AI-assisted mobile clinic deployment strategy targeting 310,000 women across three priority LGAs. This work demonstrates how GeoAI methods can translate spatial health data into actionable intervention frameworks for low-resource maternal healthcare environments.

1. Introduction

Maternal mortality disproportionately affects women in low-resource settings, particularly in Sub-Saharan Africa. Nigeria accounts for approximately 34% of global maternal deaths, with an estimated national maternal mortality ratio (MMR) of 512 per 100,000 live births (World Health Organization, 2023). Within Nigeria, Northwestern states bear the heaviest burden: Kebbi State records an MMR exceeding 1,000 per 100,000 live births, with skilled birth attendance as low as 18% in some Local Government Areas (LGAs) (National Population Commission (NPC) Nigeria and ICF, 2019). These disparities are closely tied to geographic inaccessibility: rural populations face long travel distances to the nearest health facility, particularly in the absence of reliable transportation infrastructure.

Recent advances in geospatial intelligence and machine learning offer promising tools for addressing healthcare accessibility challenges in low-resource settings. Geographic Information Systems (GIS) and spatial analysis techniques can model healthcare facility coverage, identify underserved population clusters, and support evidence-based resource allocation (Mushore et al., 2021; Tanser et al., 2006). Integrating AI-based risk assessment with geospatial analysis creates a GeoAI pipeline capable of prioritizing intervention zones and informing deployment decisions in data- sparse environments (Delamater et al., 2012).

This paper presents MamaCare AI, a GeoAI framework for maternal healthcare accessibility analysis applied to Kebbi State, Nigeria. Using publicly available geospatial datasets and machine learning methods, the framework identifies underserved population clusters and generates a composite maternal health risk ranking across all 21 Kebbi LGAs. Building on these findings, we propose a phased mobile clinic deployment strategy designed for feasible implementation in low-resource environments.

The contributions of this work are:

1. A spatial accessibility analysis of 1,207 health facilities against 1,510 populated grid cells in Kebbi State, revealing that approximately 62% of women of reproductive age reside beyond 5 km of the nearest facility.
2. Application of DBSCAN spatial clustering to identify and characterize contiguous underserved population zones across priority LGAs, with clustering quality validated via silhouette analysis (score: 0.83).
3. A multi-component composite risk scoring model in-

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tegrating distance, facility density, population burden, and historical MMR across all 21 Kebbi LGAs, with sensitivity analysis confirming ranking robustness.

4. A proposed phased GeoAI-guided mobile clinic deployment strategy targeting 310,000 women across three critical-priority LGAs, with discussion of AI-assisted triage integration.

2. Related Work

GIS in Healthcare Accessibility. Spatial analysis has been widely applied to model healthcare facility accessibility in Sub-Saharan Africa. Tanser et al. (2006) demonstrated that geographic proximity to facilities is a primary predictor of maternal healthcare utilization in rural settings. Noor et al. (2003) applied travel-time modeling to predict malaria treatment access across Kenya, establishing a precedent for grid-based accessibility analysis. Delamater et al. (2012) provides a comprehensive review of accessibility measures in health geography, distinguishing distance-based from gravity-based models. Our work employs Haversine straight-line distance as an approximation appropriate for regions with limited road network data.

Maternal Health in Northern Nigeria. Nigeria's Northwest geopolitical zone consistently records the highest maternal mortality ratios in the country (National Population Commission (NPC) Nigeria and ICF, 2019). Studies by Okonofua (2010) and Adewole (2012) identify delayed care access, low antenatal coverage, and inadequate skilled birth attendance as principal drivers of preventable maternal deaths in this region. The GRID3 initiative (GRID3, 2020) has enabled high-resolution health facility mapping across Nigeria, creating a data infrastructure for spatial health analysis.

ML for Healthcare in Low-Resource Settings. Recent work has explored machine learning for health equity in resource-constrained environments (Wahl et al., 2018; Obermeyer & Emanuel, 2016). Cluster-based spatial methods including DBSCAN have been applied to identify disease burden hotspots and optimize mobile health resource deployment (Ester et al., 1996; Earnest et al., 2005). Composite risk scoring frameworks have been used in humanitarian contexts to prioritize intervention zones where granular individual-level data is unavailable (Tatem et al., 2013).

3. Methodology

3.1. Study Area and Data Sources

Kebbi State, located in Northwestern Nigeria (approximately 3.3°E–6.2°E, 10.0°N–13.4°N), comprises 21 LGAs with a total population of approximately 4.4 million. The state records some of Nigeria's most severe maternal health indicators, making it a critical case for spatial intervention analysis.

Three primary data sources were used:

- **GRID3 Health Facilities (v2.0):** A georeferenced dataset of 1,207 functional health facilities in Kebbi State, including primary healthcare centers, general hospitals, and specialist facilities (GRID3, 2020).
- **WorldPop Population Grid:** 100m resolution gridded female population estimates, aggregated to identify cells with female density ≥ 50 women/km^2 (WorldPop, 2020).
- **Nigeria DHS 2018:** LGA-level indicators including skilled birth attendance, facility delivery rates, and proxy MMR estimates (National Population Commission (NPC) Nigeria and ICF, 2019).

3.2. Spatial Accessibility Analysis

A regular analysis grid of 1,510 points at 5 km resolution was generated across the Kebbi State boundary, filtered to retain only cells meeting the female population density threshold (≥ 50 women/km^2). For each grid cell, the Haversine distance to the nearest GRID3 facility was computed. Cells were classified into four accessibility zones: optimal (0–2 km), acceptable (2–5 km), challenging (5–10 km), and severe constraint ($>$10 km). The proportion of grid cells exceeding the 5 km threshold (approximately 62%) was used as the primary accessibility deprivation indicator.

3.3. DBSCAN Spatial Clustering

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996) was applied to grid cells identified as severely underserved ($>$5 km from the nearest facility). The algorithm was parameterized with $\epsilon = 5$ km (converted to degrees: $\epsilon = 5/111 \approx 0.045$) and `min_samples` = 50, chosen to identify contiguous population zones suitable for mobile clinic routing. Clustering quality was assessed using the silhouette score, yielding a value of 0.83, indicating well-defined spatial separation between clusters. DBSCAN was selected over centroid-based methods such as K-Means due to its ability to identify arbitrarily shaped clusters without requiring a pre-specified cluster count — a critical advantage in rural settlement contexts where population distributions are irregular and spatially dispersed. Noise points (isolated settlements below the density threshold) were retained for visualization but excluded from intervention prioritization.

3.4. Composite Risk Scoring

A composite maternal health risk score was constructed for each of the 21 Kebbi LGAs using four normalized indicators on a 0–100 scale:

1. **Distance score (weight: 0.30):** Mean Haversine distance from LGA grid cells to nearest facility, normalized across all LGAs.

2. **Facility density score (weight: 0.25):** Inverse of health facilities per 10,000 women of reproductive age, normalized.

3. **Population burden score (weight: 0.20):** Female population at risk within the LGA, normalized to quintile ranks.

4. **Historical MMR score (weight: 0.25):** Proxy MMR estimates derived from Nigeria DHS 2018 LGA-level indicators, normalized.

The composite score was computed as the weighted sum of normalized indicator scores. Robustness was assessed via sensitivity analysis: $\pm 10\%$ variation in individual component weights produced only minor changes in the top three LGA rankings, confirming the stability of priority identification.

4. Results

4.1. Accessibility Analysis

Figure 1 presents the facility accessibility heatmap across Kebbi State. The analysis reveals a highly uneven distribution of healthcare coverage: while central and northern LGAs show clusters of green (optimal) zones around existing facilities, large portions of the southern and western areas exhibit orange-to-red accessibility zones, indicating severe constraints. Approximately 62cells reside more than 5 km from the nearest health facility, substantially above the WHO recommended 5 km access threshold — suggesting the majority of Kebbi's female population faces potentially unsafe healthcare access delays that compound obstetric risk.

4.2. DBSCAN Clustering of Underserved Populations

Figure 2 shows DBSCAN clustering results for the three identified priority LGAs. In Bagudo LGA, five distinct contiguous underserved clusters were identified, encompassing approximately 85,000 women of reproductive age. Augie LGA yielded four clusters covering approximately 125,000 women, while Argungu LGA contained three clusters covering approximately 180,000 women. The high silhouette score (0.83) indicates strong spatial cohesion within clusters, supporting the feasibility of zone-based mobile clinic routing. The prevalence of noise points (yellow) across all panels reflects the dispersed settlement pattern characteristic of rural Northern Nigeria.

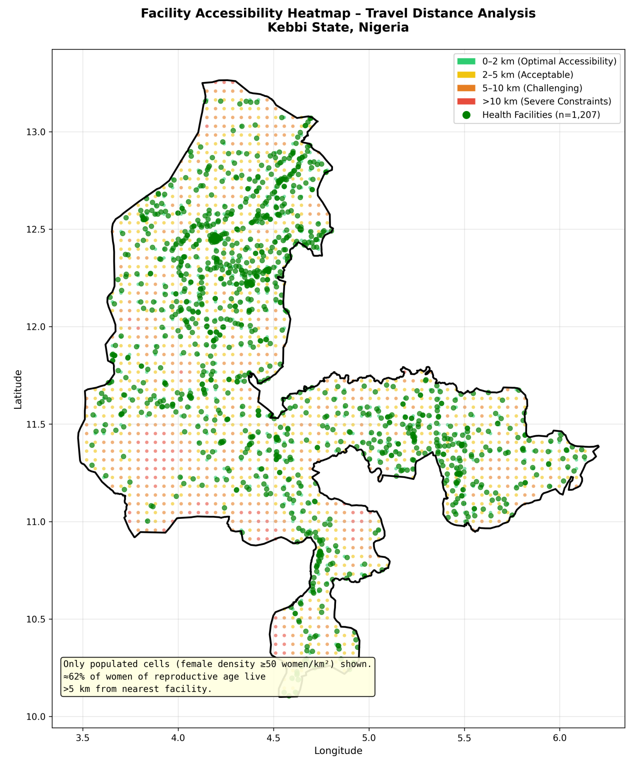

Figure 1. Facility accessibility heatmap for Kebbi State. Dot colors indicate distance to nearest health facility: green (0–2 km, optimal), yellow (2–5 km, acceptable), orange (5–10 km, challenging), red (>10 km, severe constraint). Green markers indicate GRID3 facility locations ($n = 1{,}207$). Approximately 62% of populated cells exceed the 5 km access threshold.

4.3. Composite Risk Ranking

Figure 3 presents the composite risk score breakdown across all 21 Kebbi LGAs. Argungu, Augie, and Dandi consistently ranked in the critical tier (composite score >80) across all four component indicators. Argungu scored highest on distance (100/100) and historical MMR components, reflecting both extreme geographic inaccessibility and severe historical mortality outcomes. The sensitivity analysis confirmed that the top three LGA rankings remained stable under $\pm 10\%$ weight variation, indicating robustness of the prioritization framework.

5. Proposed Intervention Framework

Building on the spatial analysis results, the MamaCare AI framework proposes a phased mobile clinic deployment strategy guided by GeoAI outputs. The deployment sequence follows the composite risk ranking, targeting critical-priority LGAs first:

Phase 1 (Months 0–3, Bagudo LGA): Deploy 3–4 mobile clinics across five identified underserved clusters, targeting approximately 85,000 women. Each clinic operates on

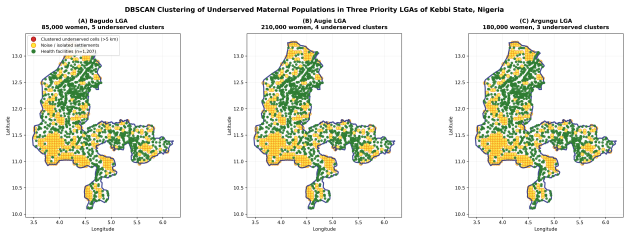

Figure 2. DBSCAN clustering of underserved maternal populations across three priority LGAs. Red points indicate clustered underserved cells (>5 km from facility); yellow indicates noise/isolated settlements. Green markers show facility locations. Silhouette score: 0.83 ($\epsilon = 5$ km, `min_samples`=50).

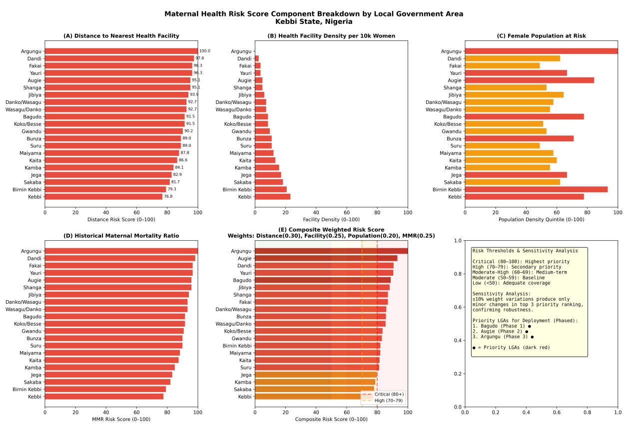

Figure 3. Composite maternal health risk score breakdown by LGA. Panels (A–D) show normalized component scores (0–100) for distance, facility density, female population burden, and historical MMR. Panel (E) shows the weighted composite score. Red dashed line indicates critical threshold (80+). Top 3 priority LGAs: Argungu, Augie, Dandi.

a rotating 2-week schedule aligned with cluster centroids identified by DBSCAN.

Phase 2 (Months 4–6, Augie LGA): Deploy 2–3 additional clinics across four clusters, extending cumulative coverage to approximately 210,000 women.

Phase 3 (Months 7–9, Argungu LGA): Deploy 2 clinics across three clusters, reaching full priority coverage of approximately 310,000 women across all three priority LGAs.

The AI-assisted component of MamaCare AI incorporates an SMS-based triage system enabling community health workers to submit symptom data for remote risk classification. A lightweight risk scoring model (logistic regression trained on DHS antenatal risk indicators) generates triage recommendations, routing high-risk cases to the nearest facility with referral capacity. This design is intentionally low-bandwidth and deployable on feature phones without internet connectivity, addressing infrastructure constraints in rural Kebbi.

6. Discussion

This work has several limitations that should be acknowledged. First, the accessibility analysis uses Haversine straight-line distance rather than network travel-time, which may underestimate true access barriers in areas with poor road infrastructure — a known characteristic of rural Kebbi. Second, the composite risk scores use LGA-level DHS-derived indicator estimates rather than individually geocoded patient records, which limits granularity. Third, the proposed deployment strategy and AI triage component remain at the conceptual stage pending clinical validation and regulatory approval. Impact projections (estimated preventable deaths) are not reported as findings of this study, but are discussed qualitatively in alignment with published intervention effectiveness literature (World Health Organization, 2023).

Despite these limitations, the framework demonstrates that combining publicly available geospatial datasets with standard ML methods (DBSCAN, composite scoring) can generate actionable, evidence-grounded prioritization outputs for maternal health intervention planning in low-resource settings. The approach is generalizable to other Northwestern Nigerian states and, with appropriate data adaptation, to similar low-resource settings in Muslim-majority regions globally.

7. Conclusion

This paper presented MamaCare AI, a GeoAI framework for maternal healthcare accessibility analysis in Kebbi State, Northern Nigeria. Spatial analysis of 1,207 GRID3 facilities and 1,510 population grid cells revealed that approximately 62% of women of reproductive age reside beyond the 5 km facility access threshold. DBSCAN clustering (silhouette score: 0.83) identified priority underserved zones across three critical LGAs, and composite risk scoring confirmed Argungu, Augie, and Dandi as highest-priority intervention areas. The proposed phased deployment strategy targets 310,000 women in the identified zones. This work contributes an open, reproducible GeoAI methodology for evidence-based maternal health resource allocation in underserved Muslim-majority communities and low-resource settings more broadly.

Impact Statement

This work addresses maternal mortality in Muslim-majority Northern Nigeria, where Kebbi State records an MMR more than double the national average. Transparent, reproducible ML methods applied to public geospatial data enable evidence-based resource prioritization without proprietary infrastructure. Ethical risks include potential misuse of geospatial targeting and false reassurance from AI triage — mitigated by population-weighted optimization and requiring community health worker confirmation for all triage outputs. Future deployment requires appropriate patient consent and data governance frameworks, consistent with UN SDG$\tilde{3}$.1.

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