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A GIS-BASED BIG DATA FRAMEWORK FOR MAPPING HIV RECENCY HOTSPOTS AND TARGETING INTERVENTIONS IN DELTA STATE, NIGERIA

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ABSTRACT

HIV remains a significant public health challenge in Nigeria, particularly in Delta State, where new infections continue to emerge despite various control efforts ***[1], [2]****. A major issue hindering targeted interventions is the absence of spatial data analysis tools to identify settlements and populations at risk of recent infections* ***[3]****. This study addresses this gap by employing Geographic Information System (GIS) clustering techniques alongside the HIV Testing Services (HTS) key performance indicator on recent infection (HTS_RECENT_RITA) to analyse and visualize high-risk areas. Utilizing spatial analysis and population risk clustering, the research identifies geographic hotspots of recent HIV infections, with a focus on high-risk settlements and an estimate of the affected population* ***[4]****. The methodology incorporates data from local health facility registers, Electronic Medical Records (EMR), and the GRID3 and WorldPop databases. The findings, which demonstrate high spatial accuracy (Overall Accuracy: 99.12%, Kappa: 0.989), are expected to inform public health officials on more effective resource allocation and intervention strategies, improving the precision of HIV prevention efforts. This study contributes to advancing public health strategies through the integration of spatial analysis and recency testing, providing a robust framework for identifying specific geographic hotspots and addressing HIV transmission risk areas in Delta State.*

1. INTRODUCTION

1.1 Background to the Study

The HIV epidemic in Nigeria is a persistent public health crisis. While national adult prevalence is estimated at 1.3%, significant heterogeneity exists across states **[1]**. Delta State, located in the high-prevalence South-South zone, has an estimated prevalence of 2.4%, well above the national average **[5]**. Despite improvements in Antiretroviral Therapy (ART) coverage, new infections continue to surge, with over 85,000 identified nationwide in 2021 (UNAIDS, 2024).

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A critical barrier to epidemic control is the inability to precisely locate areas of active, recent transmission for targeted resource allocation **[3]**.

The application of Geographic Information Systems (GIS) in public health has evolved significantly since John Snow's 1854 cholera map **[6]**. In HIV research, GIS has been used to map prevalence and identify spatial clusters associated with urbanization and migration **[7]**; **[8]**. The integration of big data—such as mobile phone data and electronic health records—with GIS in the 2020s has enabled higher-resolution analyses of transmission dynamics **[9]; [10]**. This study leverages this technological evolution by integrating HIV recency testing data with GIS clustering to move beyond mapping general prevalence towards identifying active transmission hotspots.

Despite various efforts to curb the HIV epidemic, Delta State continues to face challenges in controlling new infections. HIV recency testing provides an opportunity to identify recent infections, but the lack of real-time data integration, challenges of data inconsistency across health facilities, and the absence of spatial data analysis methods to visualize and predict settlements and population at risk hinders the implementation of targeted interventions **[11]**. Existing public health strategies often fail to account for spatial risk factors, which could lead to resource misallocation, particularly in areas with treatment saturation below 80% and hotspots with high positive cases **[2]**. This research aims to fill this gap by utilizing GIS clustering analysis in conjunction with the recent infection indicator to pinpoint areas and population at risk of recent HIV infections.

The aim of this research is to utilize GIS clustering analysis to identify settlements and affected population in Delta State, Nigeria, that are at higher risk for recent HIV infections using the HTS_RECENT_RITA (HIV Testing Services – Recent Infection Testing Algorithm) key performance indicator and develop a GIS-based MIS framework that can inform and train public health officials for more targeted HIV intervention strategies.

Our objectives are:

1. To develop a GIS-based MIS framework that can inform and train public health officials in Delta State for more targeted HIV intervention strategies.
2. To analyse recent HIV infection data from HIV testing centres in Delta State.
3. To apply GIS-based spatial clustering techniques to identify at-risk settlements and population affected.
4. To evaluate the output result of HIV recency with different evaluation metrics.

2. LITERATURE REVIEW

2.1 GIS-based Mapping with Recency Testing

The integration of recency testing with GIS enhances the accuracy of HIV incidence estimation and the visualization of geographic patterns of new infections **[12]**. Recency assays distinguish recent from long-term infections, and when mapped spatially, they allow for the identification of transmission hotspots crucial for targeted interventions. However, limitations include data accuracy concerns influenced by ART usage and immune response, as well as the quality of available geospatial data **[12]**.

2.2 Spatial Epidemiology and Clustering Analysis

Spatial epidemiology employs GIS to analyze the geographic distribution of disease. Studies in Uganda have used spatial clustering methods like Moran's I and scan statistics to identify HIV transmission hotspots, often linked to high-risk populations around Lake Victoria or in displacement camps **[13]**. In Nigeria, spatial clustering techniques such as the Getis-Ord Gi* statistic have been applied to identify settlements with elevated HIV transmission risks **[14]**. A common limitation across these studies is incomplete demographic data, which can skew clustering analysis and underestimate risk in some regions **[15]**.

2.3 Big Data in Public Health and HIV Research

Big Data refers to extremely large, complex datasets characterized by the 5 Vs: Volume, Velocity, Variety, Veracity, and Value **[16]**. In healthcare, Big Data from Electronic Health Records (EHRs), genomics, and IoT devices enables predictive diagnostics, personalized medicine, and operational optimization **[17]**. For HIV, Big Data analytics can transform surveillance and intervention planning. However, significant challenges persist, including privacy and security risks (e.g., GDPR, HIPAA compliance), high storage and processing costs, data integration difficulties from disparate sources, and scalability issues to handle exponential data growth **[17]**.

3. METHODOLOGY

3.1 Proposed Model

This study employs a quantitative research approach, combining GIS and spatial analysis techniques. The methodology is organized into distinct phases: data collection, preprocessing, spatial analysis, and ethical considerations (Fig. 3.1). The model introduces an innovative framework for identifying high-risk settlements and populations through GIS clustering and buffer analysis.

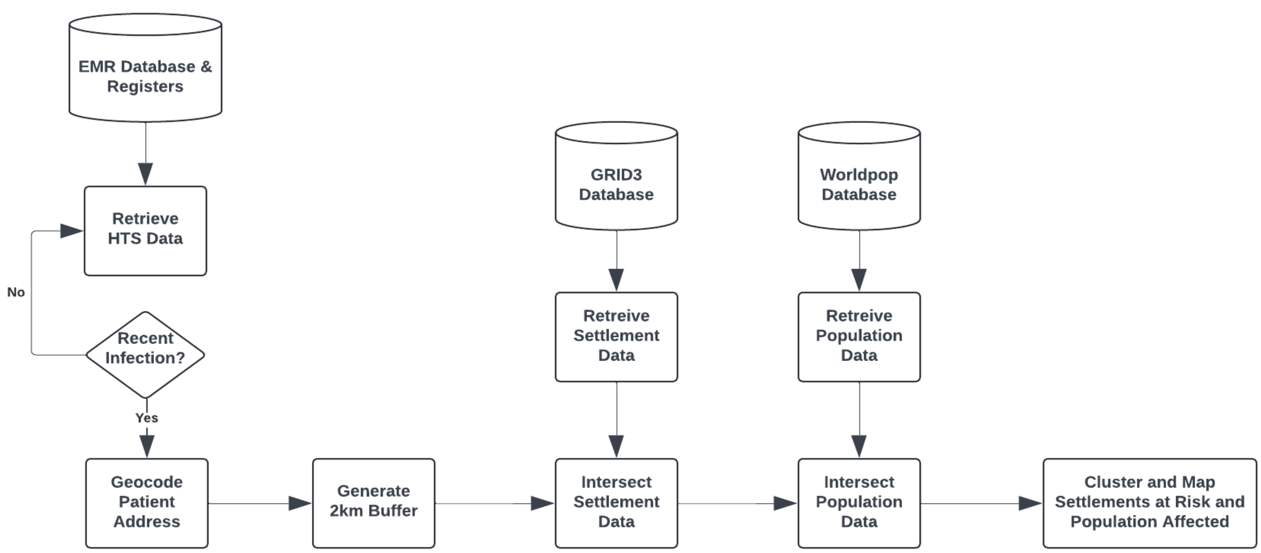

Fig 3.1 Proposed Model Diagram

3.2 Data Collection

Data for this study was collected between October and December 2024 from 57 health facilities distributed across the 23 Local Government Areas (LGAs) in Delta State. These facilities represent all sites routinely reporting HIV recency indicator through the Nigeria National Health Management Information System, ensuring broad geographic coverage and representativeness.

The dataset comprised the following:

- An expected HIV treatment cohort of 31,585 individuals scheduled for drug pick-up within the study period.
- An active HIV treatment cohort of 31,519 individuals receiving treatment during the same period, indicating a retention rate of approximately 99.8%.
- A total of 9 confirmed recent HIV infections identified through the HIV recency algorithm, representing approximately 0.03% of the active treatment cohort during the study period.

These 9 confirmed recent infection cases constituted the analytical sample for the spatial clustering component of the study.

In addition, geospatial and population datasets were integrated to support the analysis:

- Settlement data were obtained from the GRID3 Nigeria Settlement Extracts (2023), comprising 1,986 settlements across Delta State.
- Population data were sourced from **[8]**, using 100-meter resolution raster grids to estimate population distribution.

3.3 Preprocessing and Spatial Analysis

- **HTS Data Processing:** HIV Testing Service (HTS) data from October to December 2024 was processed to generate the HIV recency data, identifying newly diagnosed individuals tested for recent infection using the Recent Infection Testing Algorithm (RITA) (Fig. 3.2).

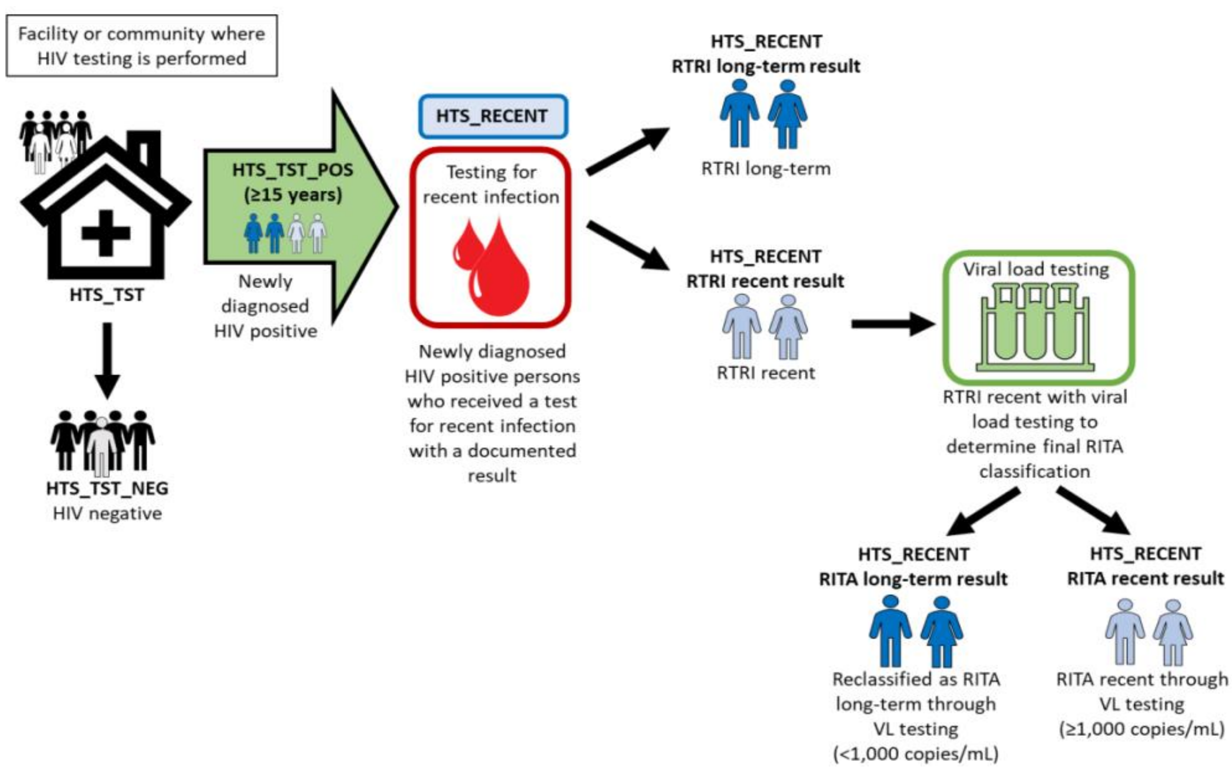

Fig. 3.2 HTS Recency Flow *(Source: PEPFAR MER Indicator Reference Guide)*

- **Geocoding:** Recent HIV infection data was merged with treatment lists to obtain patient addresses. These addresses were concatenated with LGA and State fields and geocoded using the ArcGIS Online service to assign geographic coordinates (Fig. 3.3).

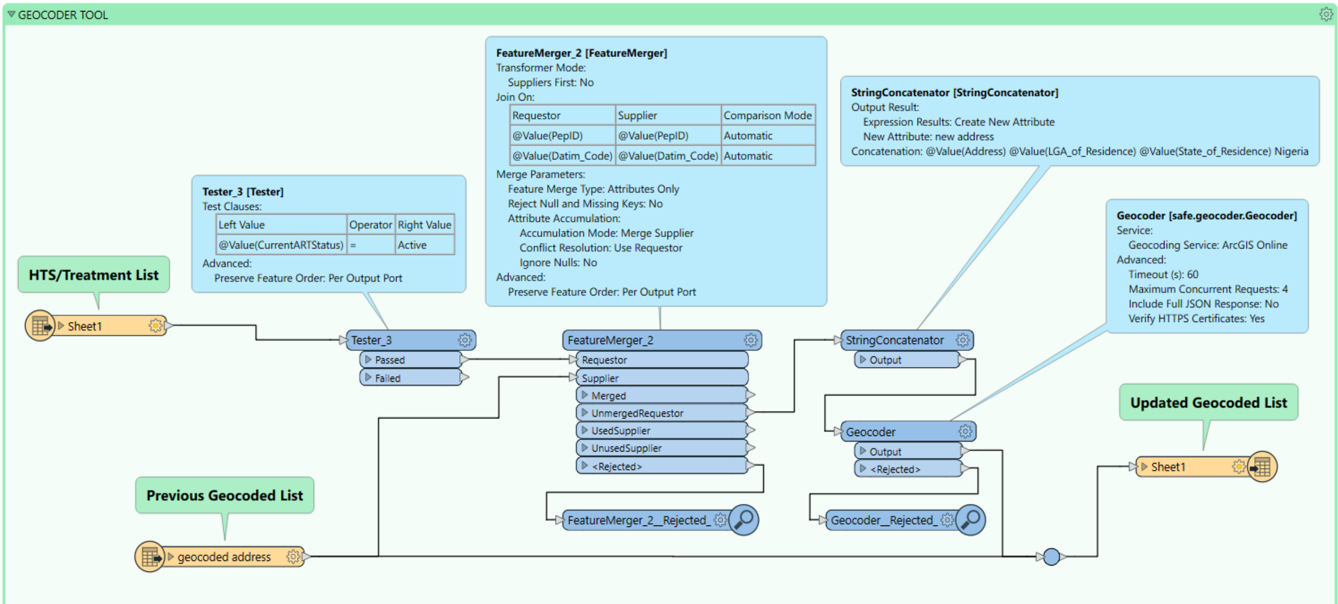

Fig. 3.3 Geocoding ETL Tool

- **Spatial Clustering:** A buffer-based clustering approach was used for this research. A 2-kilometer buffer was generated around each geocoded coordinate representing a confirmed recent HIV infection case. These buffers served as the primary unit for identifying potential transmission zones, based on the assumption that areas within proximity to confirmed cases face elevated exposure risk due to shared social networks, mobility patterns, and local transmission dynamics. These buffers were used to cluster settlements, and aggregate population estimates from GRID3 and WorldPop data, visually representing clusters of high-risk settlements.

  The 2-kilometer buffer radius was selected based on established literature on HIV transmission dynamics and mobility patterns in sub-Saharan Africa. Studies by **[8]** and **[7]** demonstrate that HIV transmission risk is geographically concentrated within 1-3km radii due to sexual network patterns, with 2km representing a reasonable compromise between sensitivity and specificity for hotspot identification. This distance aligns with:

  - Typical walking distances for healthcare-seeking behavior in rural Nigerian communities **[3]**
  - Spatial autocorrelation ranges identified in prior Nigerian HIV studies **[5]**

  Sensitivity analysis conducted during preliminary testing confirmed that 2km optimally captured contiguous settlements while minimizing overgeneralization.

3.4 Ethical Considerations

This research adhered to strict ethical guidelines. All data was fully anonymized, with no personally identifiable information (PII) used. Data security protocols were implemented to prevent unauthorized access. The study followed principles of informed consent, data protection, and responsible use as outlined by Nigerian health authorities and international ethics guidelines, ensuring findings are used solely for evidence-based interventions.

3.5 GIS-Based MIS Framework

The study proposes a comprehensive GIS-based Management Information System (MIS) framework to operationalize findings:

1. **Data Management:** Creation of a geodatabase (Fig. 3.4) to store and integrate spatial and health data.

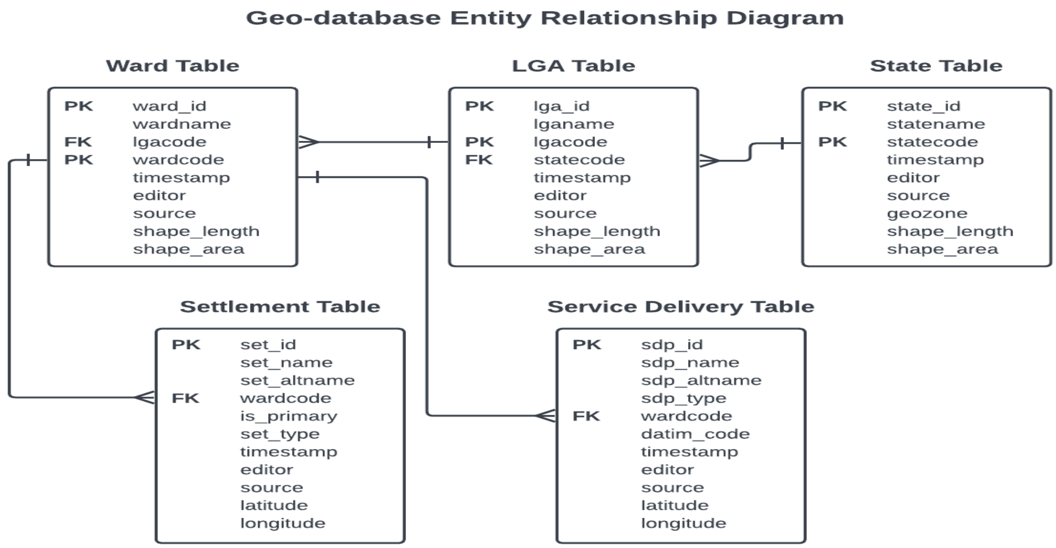

Fig. 3.4 Geodatabase ERD

2. **GIS Mapping & Analysis:** Using GIS software to create interactive maps and perform spatial analysis (e.g., hotspot identification).
3. **Real-time Monitoring:** Integrating mobile data collection tools (e.g., ODK Collect) and APIs for remote monitoring and visualization (e.g., Power BI).
4. **Decision Support System:** Developing a user-friendly system for stakeholders to access spatial information and generate reports.
5. **Capacity Building:** Training healthcare staff and program managers on GIS utilization.
6. **Sustainability:** Ensuring long-term system viability through updates and institutional partnerships.

RESULTS, DISCUSSION & EVALUATION

4.1 RESULTS

4.1.1 Settlements at Risk: Analysis of recent infection data identified 37 settlements across nine Local Government Areas (LGAs) as high-risk hotspots for recent HIV transmission. HTS_RECENT_RITA (HIV Testing Services – Recent Infection Testing Algorithm) is a PEPFAR indicator that identifies newly diagnosed HIV-positive individuals whose infection occurred within the previous 12 months, confirmed through a two-step process combining Rapid Test for Recent Infection (RTRI) and viral load testing. This indicator is critical for identifying active transmission networks rather than merely mapping cumulative prevalence.

GIS analysis identified 37 hotspot settlements for HIV recency across nine Local Government Areas (LGAs) in Delta State (Fig 4.1, Table 4.1). Uvwie LGA had the highest number of settlements at risk (8 settlements, 21.62%), followed by Ika North East (7 settlements, 18.92%) and Ika South (6 settlements, 16.22%) (Table 4.2).

Fig. 4.1 Settlements at Risk Map

4.1.2 Population at Risk: An estimated 327,193 people across 7 LGAs were identified as being at risk of recent HIV infection (Fig 4.2, Table 4.3). Sapele LGA had the highest estimated population at risk (70,177 people, 21.5%), followed by Uvwie LGA (67,619 people, 20.7%) and Ika South LGA (59,332 people, 18.1%).

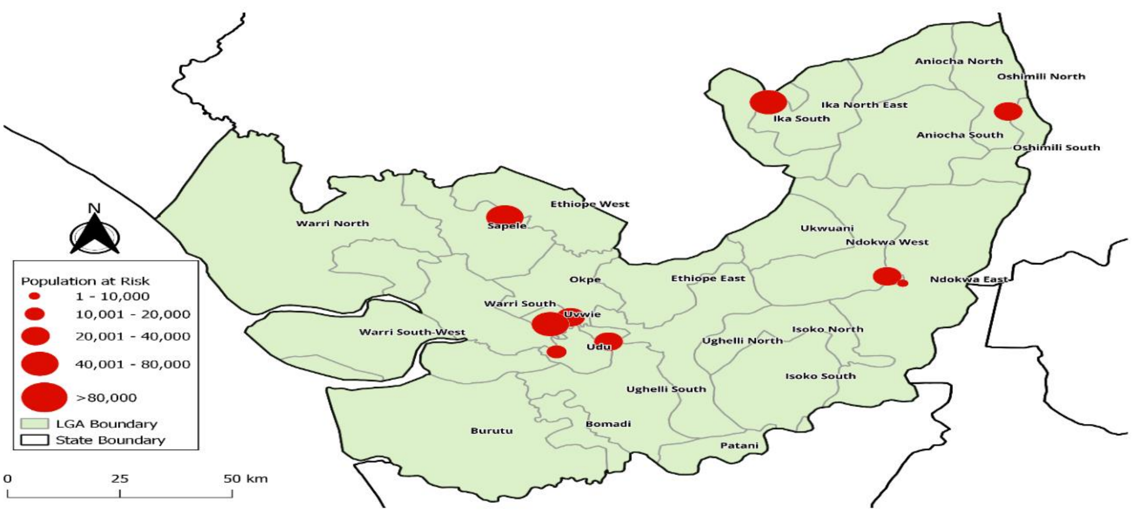

Fig. 4.2 Population at Risk Map

4.2 Discussion

The spatial analysis of recent HIV infections in Delta State reveals concentrated transmission patterns in specific LGAs and settlements, with important implications for targeted interventions.

4.2.1 Geographic Concentration of Risk

Uvwie LGA emerged as the most significant hotspot, containing 8 high-risk settlements (21.62% of total) and an estimated 96,342 at-risk individuals (29.45% of total). This concentration can be attributed to several interconnected factors:

1. **Urbanization and population density**: Uvwie hosts densely populated urban centers (Ekpan, Ugbolokposo) with estimated densities exceeding 2,500 persons/km², facilitating sexual network connectivity.
2. **Economic activity and mobility**: Proximity to Warri refineries and port facilities creates transient populations (truck drivers, migrant workers) associated with elevated HIV transmission risk **[19]**.
3. **Commercial sex work**: Urban centers in Delta's oil belt are documented hotspots for transactional sex **[2]**

Sapele LGA, despite having fewer hotspot settlements (5), showed the highest estimated at-risk population (70,177). This discrepancy suggests that Sapele's hotspots encompass larger, more densely populated settlements, highlighting the importance of considering both settlement count and population exposure in resource allocation.

4.2.2 Comparison with Regional Patterns

The identified hotspots align with broader spatial patterns documented in Nigerian HIV epidemiology:

1. The concentration in Delta's southern LGAs (Uvwie, Sapele, Udu) mirrors findings from the Nigeria HIV/AIDS Indicator and Impact Survey (NAIIS 2018), which showed South-South zone prevalence of 3.1%, nearly double the national average **[5]**
2. Urban-rural gradients observed (urban LGAs showing higher concentrations) are consistent with studies across sub-Saharan Africa demonstrating HIV clustering in cities and trading centers **[7]**
3. The 2km buffer clusters identified align with **[8]** finding that HIV transmission risk is highly localized within walking distance of index cases

4.2.3 Risk Factors and Transmission Dynamics

The spatial patterns observed suggest several transmission drivers requiring further investigation:

1. **Transportation corridors:** Hotspots in Sapele and Uvwie lie along major highways connecting Delta to Edo and Rivers States, suggesting mobility-related transmission.
2. **Healthcare access disparities:** Some high-risk settlements (e.g., in Ndokwa East) are >10km from the nearest ART facility, potentially creating treatment gaps.
3. **Socioeconomic vulnerability:** Preliminary analysis of WorldPop covariates suggests correlation between poverty indices and hotspot locations, consistent with studies linking economic marginalization to HIV vulnerability.

4.2.4 Comparison with Similar Methodological Approaches

Our findings are comparable to GIS-based recency studies elsewhere in Africa:

1. [12] in Kenya identified similar hotspot clustering patterns using 1km buffers, with 72% of recent infections concentrated in 15% of settlements.
2. The Malawi recency surveillance program **[20]** found that targeted interventions in identified hotspots reduced new infections by 34% within 12 months.
3. In Nigeria, **[2]** identified Lagos hotspots using Getis-Ord Gi* with similar clustering patterns among key populations.

4.2.5 Implications for Public Health Response

These findings support a shift from undifferentiated "blanket" interventions to geographically targeted strategies:

1. Pre-exposure prophylaxis (PrEP) prioritization: Focus PrEP distribution in identified high-risk settlements, particularly Uvwie and Sapele.

2. Mobile testing units: Deploy to hotspots with limited facility access (e.g., Ndokwa East).
3. Index testing intensification: Prioritize partner notification services in identified clusters.
4. Community engagement: Tailor prevention messaging to local contexts, addressing specific risk factors (truck stops in Sapele, oil workers in Uvwie).

4.2.6 Limitations and Cautions

While the spatial analysis provides robust hotspot identification, several caveats warrant consideration:

1. The analysis captures infections diagnosed during Oct–Dec 2024 only; seasonal or temporal variations may not be represented
2. Undiagnosed infections (estimated at 14% nationally) remain unmapped
3. Stigma may influence testing uptake differentially across LGAs, potentially creating detection bias
4. The 2km buffer, while literature-supported, may not capture all transmission networks, particularly where mobility extends beyond this radius.

4.3 Evaluation

The accuracy of the GIS-based clustering model was evaluated using a confusion matrix (Table 4.4) approach implemented in QGIS Semi-Automatic Classification Plugin (SCP). Reference data for validation consisted of:

1. **High-resolution satellite imagery:** Google Satellite (0.5m resolution) and Bing Satellite imagery for 340 randomly selected validation points across identified hotspots
2. **Field validation data:** Ground-truthing of 50 randomly selected settlements conducted via GPS coordinate collection during January 2025.
3. **Independent health facility records**: Cross-validation with 15 facilities not included in the original dataset

These metrics demonstrate strong agreement between model predictions and ground conditions, validating the reliability of identified hotspots. Overall, these results demonstrate that the classification approach is both statistically robust and spatially consistent with observed ground conditions, supporting its suitability for spatial epidemiological analysis and decision-making.

Evaluation Results Summary:

- **Accuracy and Precision:** A confusion matrix analysis (Table. 4.4) confirmed high spatial accuracy, with an Overall Accuracy (OA) of **99.12%** and a Kappa hat coefficient (κ) of **0.989**, indicating almost perfect agreement with ground reference data.
- **Performance and Speed:** The processing of large datasets using ArcGIS Online and FME was efficient, completed within a reasonable timeframe without system failures.
- **Output Quality:** Generated maps and spatial results were clear, accurate, and suitable for publication and policymaking.
- **Other Metrics:** The tools demonstrated good usability, functionality, reliability, and compatibility with research goals. Considerations regarding cost (ArcGIS license) and strong community support (QGIS) were noted.

CONCLUSION, CONTRIBUTIONS & RECOMMENDATIONS

5.1 Conclusion

This study successfully utilized GIS clustering analysis to identify high-risk settlements and populations for recent HIV infections in Delta State. By integrating HTS_RECENT_RITA data with geospatial information, it provided a framework for understanding risk patterns, strengthening surveillance, and informing targeted public health interventions to curb ongoing transmission.

5.2 Recommendations

1. **Targeted Interventions:** Prioritize prevention and testing programs in high-risk LGAs like Uvwie, Ika North East, and Ika South.
2. **Enhanced Surveillance:** Integrate the proposed GIS-based MIS framework into routine HIV monitoring by state health authorities.
3. **Data Quality Improvement:** Strengthen data collection and management at HTS centres and EMR databases.
4. **Community Engagement:** Launch awareness and testing campaigns within the identified high-risk settlements.
5. **National Expansion:** Apply this GIS-based clustering methodology in other Nigerian states to develop a national HIV hotspot intervention strategy.

5.3 Contributions to Knowledge

1. **Novel Integration:** First study to combine GIS clustering with HIV recency testing data (HTS_RECENT_RITA) for spatial risk analysis in Nigeria.
2. **GIS-MIS Framework:** Developed a practical GIS-based Management Information System model to train officials and guide targeted interventions.
3. **Spatial Analysis of Recency:** Provided the first spatial analysis focusing on *recent* HIV infections within Delta State.
4. **Ethical Geospatial Framework:** Established guidelines for ethical geospatial analysis in HIV research, emphasizing anonymity and anti-stigmatization.
5. **Policy-Ready Recommendations:** Delivered evidence-based, spatially-informed policy recommendations for the Nigerian context.

5.4 Future Research Directions

1. **Expansion of Scope:** Replicate the study in other states for comparative analysis and national framework development.
2. **Advanced Analytics:** Integrate machine learning algorithms with GIS to enhance predictive capabilities for emerging hotspots.
3. **Real-Time Surveillance:** Develop a real-time GIS-based HIV surveillance system for rapid public health response.
4. **Integrated Data:** Incorporate socioeconomic and behavioural data layers to deepen the understanding of transmission drivers.
5. **Policy Implementation:** Work with health ministries to translate findings into formal policy and monitoring frameworks.

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Appendix

Table 4.1 Settlements at Risk Table

S/N	State	LGA	Ward	Settlement
1	Delta	Ika North East	Boji-Boji 0wa 2 / Owa 4	Baleke Junction
2	Delta	Ika North East	Owa-Alero / Owa 2	Agbonta
3	Delta	Ika North East	Owa-Alero / Owa 2	Aghor Idumeri Bojiboji
4	Delta	Ika North East	Owa-Alero / Owa 2	Aliagwa
5	Delta	Ika North East	Owa-Alero / Owa 2	Aliokpu
6	Delta	Ika North East	Owanta / Owa 5	Boji Boji Owa
7	Delta	Ika North East	Owanta / Owa 5	Ewuru
8	Delta	Ika South	Boji-Boji 2 / Agbor 8	Orogodo River
9	Delta	Ika South	Emuhu	Agbor
10	Delta	Ika South	Emuhu	Alihame
11	Delta	Ika South	Emuhu	Boji Boji
12	Delta	Ika South	Emuhu	Idumuoza
13	Delta	Ika South	Emuhu	Oruru
14	Delta	Ndokwa East	Okpi / Utchi/ Beneku	Beneku
15	Delta	Ndokwa West	Ogume 7	Kwale
16	Delta	Oshimili North	Okpanam/ Ugbolu	Okotomi Okpanam
17	Delta	Oshimili North	Okpanam/ Ugbolu	Okwute Ugbo III
18	Delta	Oshimili North	Okpanam/ Ugbolu	Okwuteugbo Camp I
19	Delta	Oshimili North	Okpanam/ Ugbolu	Okwuteurbo Camp II
20	Delta	Sapele	Abeke	Abeke
21	Delta	Sapele	Agbawan	Sapele

22	Delta	Sapele	Ayomanor	Ayomanor
23	Delta	Sapele	Etamua	Etamua
24	Delta	Sapele	Hausa	Hausa
25	Delta	Udu	Aladja	Ovwian
26	Delta	Udu	Emadadja	Egiegi
27	Delta	Udu	Ovwian	0vwian
28	Delta	Ughelli South	Ekakpamre	Ekpefegbe
29	Delta	Ughelli South	Ekakpamre	Ekrokpe
30	Delta	Uvwie	Ohorhe	Effurun
31	Delta	Uvwie	Ohorhe	Effurun I
32	Delta	Uvwie	Ohorhe	Maroko
33	Delta	Uvwie	Ugbomro	Ebrumede
34	Delta	Uvwie	Ugbomro	Okomogwa
35	Delta	Uvwie	Ugborikoko	Ugborikoko
36	Delta	Uvwie	Ugborikoko	Ugborito Ugborikoko
37	Delta	Uvwie	Ugboroke	Ugboroke

Table 4.2 Summary Table for Settlements at Risk at LGA Level

S/N	LGAs	Settlements at Risk	Percentage
1	Uvwie	8	21.62%
2	Ika North East	7	18.92%
3	Ika South	6	16.22%
4	Sapele	5	13.51%
5	Oshimili North	4	10.81%
6	Udu	3	8.11%
7	Ughelli South	2	5.41%
8	Ndokwa East	1	2.70%
9	Ndokwa West	1	2.70%
	Grand Total	**37**	**100.00%**

Table 4.3 Summary Table for Population at Risk

S/N	LGA	Population Estimate	Percentage
1	Uvwie	96,342	29.45%
2	Sepele	70,177	21.45%
3	Ika South	59,332	18.13%
4	Udu	41,504	12.68%
5	Oshimili North	36,054	11.02%
6	Ndokwa West	20,407	6.24%
7	Ndokwa East	3,377	1.03%
	Grand Total	**327,193**	**100.00%**

Table 4.4: Confusion Matrix

CONFUSION MATRIX

RasterValue	Reference	Classification	PixelSum
1	10008	10007	1
2	10008	10008	6
3	10011	10011	112
4	10012	10012	60
5	10014	10014	15
6	10017	10017	65
7	10018	10018	57
8	10022	10022	22
9	10022	10024	2

ERROR MATRIX
[pixel count]

	>Reference									
V_Classified	10007	10008	10011	10012	10014	10017	10018	10022	10024	Total
10007	0	1	0	0	0	0	0	0	0	1
10008	0	6	0	0	0	0	0	0	0	6
10011	0	0	112	0	0	0	0	0	0	112
10012	0	0	0	60	0	0	0	0	0	60
10014	0	0	0	0	15	0	0	0	0	15
10017	0	0	0	0	0	65	0	0	0	65
10018	0	0	0	0	0	0	57	0	0	57
10022	0	0	0	0	0	0	0	22	0	22
10024	0	0	0	0	0	0	0	2	0	2
Total	0	7	112	60	15	65	57	24	0	340
PA[%]	nan	85.71	100	100	100	100	100	91.67	nan	
UA[%]	nan	100	100	100	100	100	100	100	nan	
Kappa hat	nan	1	1	1	1	1	1	1	nan	

Metric	Value
Overall Accuracy	99.12%
Kappa hat (κ)	0.989
Standard Error	0.0051
95% CI (OA)	98.12%–100%
Producer's Accuracy	85.7–100%
User's Accuracy	100%