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The spatial patterns of diabetes mellitus in Ghana: A spatial autocorrelation technique

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Abstract

Diabetes mellitus (DM) is an emerging health problem worldwide, and low- and middle-income nations like Ghana carry a considerable burden. However, DM spatial patterning in Ghana is largely under-researched, hence, effective interventions are difficult. This research analyses the spatial pattern of Type 1 (T1DM) and Type 2 (T2DM) in the Central Region of Ghana to identify DM clusters (hotspots and coldspots) for resource prioritization and management. A retrospective longitudinal design was employed to examine 8,992 DM cases retrieved from thirteen (13) hospitals over the period 2008 - 2019. The results revealed substantial temporal and spatial heterogeneity in DM distribution. Local Moran's I indicated statistically significant positive spatial autocorrelation for DM in most years ($p < 0.05$), while T1DM showed intermittent clustering. For T1DM, significant clustering varied annually, with persistent Low-Low clusters in southeastern MMDAs (e.g., Gomoa East) suggesting potential protective factors or under-diagnosis, and intermittent High-High clusters in urban centres like Cape Coast Metro, likely influenced by better healthcare access and urban lifestyles. The analysis for T2DM identified more stable patterns, with the Komenda Edina Eguafo Abirem (KEEA district consistently emerging as a significant Low-High outlier. Key hotspots for T2DM included KEEA, Cape Coast Metro, and Twifo Hemang Lower Denkyira. The study highlights the uneven distribution of DM in the Central Region, emphasizing the role of spatial analysis in public health planning. By identifying high-risk areas, the Ministry of Health, Ghana Health Service, and analogous agencies should strategically focus screening programmes, educational campaigns, and resource allocation on areas requiring intensive intervention.

Keywords: Diabetes mellitus, spatial patterns, spatial autocorrelation, hotspot, coldspot, interventions

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1 Introduction

Diabetes mellitus (DM) has emerged as a critical global health challenge, adversely affecting both social progress and economic growth. Its escalating prevalence strains healthcare infrastructures and social support systems across nations (Ogugua et al., 2024). In 1980, the global age-standardized prevalence was 4.7% in the adult population, rose to 8.5% in 2014 and 14% in 2024 among adults 18 years and older (WHO, 2024). Given its growing impact, DM remains a pressing public health priority and a key indicator within the Sustainable Development Goals (SDGs).

In Africa, DM accounts for the ailments of 24 million adults, aged 20 – 79 years. This figure is predicted to increase to 55 million by 2045, representing a 129% increase (WHO, 2023). Unfortunately, more than half of infected cases are undiagnosed, making DM more dangerous than expected. The increase may be driven by demographic, sociocultural, and economic metamorphosis, whereas the undiagnosed may be due to the unavailability of essential DM services in healthcare facilities, according to a 2019 WHO survey (WHO, 2023).

According to Ghana's Ministry of Health (MoH), on average, 200,000 new cases are recorded in their facilities annually. DM rate is between 2.6% - 9% across the population (MoH, 2022). The increase in DM burden is attributed to increased life expectancy, rapid urbanization, bad eating habits and adoption of a sedentary lifestyle (MoH, 2022). Ghana has made significant efforts in combating DM through initiatives like the NCD Project and the D-Card program are driving this transformation, focusing on strengthening governance, advancing workforce training, and leveraging innovative technologies (WHO, 2024).

However, it still poses an immense threat with regional patterns and variations. The Central region has a prevalence of 6.7% (Cape Coast Teaching Hospital [CCTH], 2022), while the Greater Accra and Ashanti regions have 6% and 10%, respectively. Unfortunately, the Central Region has the lowest attendance rate of 8% but among the top ten OPDs (CCTH, 2022). Geographic patterns of DM, if well established, will elicit high-priority areas and determine areas that need direct healthcare interventions. Despite the uneven spatial distribution of DM across the Central Region and Ghana, only one study has used geospatial techniques to document patterns using Ghana Health Service data (Oti-Boateng et al., 2016).

Spatial epidemiology, particularly Local Indicators of Spatial Association (LISA), has proven effective in identifying disease clusters in resource-limited settings (Xie et al., 2022). Applying these tools to subnational Ghanaian data can reveal heterogeneity invisible to aggregate national statistics, guiding targeted resource deployment. This study sought to analyse the geospatial patterns of diagnosed DM cases in the Central Region of Ghana from 2008 to 2019. The specific objectives are to (1) Analyse the spatial distribution of DM across MMDAs in Central Region of Ghana (2008-2019) and (2) Assess the temporal dynamics and persistent clustering patterns across MMDAs in Central Region of Ghana.

The significance of the study is the ability to spatially identify MMDAs with higher rates of Type 1 DM (T1DM) and Type 2 DM (T2DM) prevalence for effective resource allocation. Also, to understand why certain MMDAs are high cluster zones to inform MOH staff on developing strategist measures.

2 Methodology

2.1 Study site

The study was carried out in Ghana's Central Region on the prevalence of DM among its MMDAs. The Region is located on latitude 5.6444° N, and longitude 1.2891° W. The Central Region of Ghana lies on the southern edge of Ghana, bounded by the Gulf of Guinea in the south and five other regions inland. It possesses a mixture of coastal plain, lagoon, and forest. The tropical climate of the region favours agriculture but promotes susceptibility to climate-related health dangers such as flooding and malaria. According to the GSS (2021), the region is fast transitioning into an urbanized one, which can influence disease patterns like DM. The region's economy is driven by agriculture, fishing, manufacturing, service industries, and tourism due to its historical sites like Cape Coast Castle and the eco-tourism of Kakum National Park (GSS, 2021). However, poverty and unemployment persist in rural areas, limiting access to nutritious food and healthcare, which are key factors in DM prevention and management (GSS, 2021).

The Central Region has notable health institutions, including the Cape Coast Teaching Hospital, the Trauma and Specialist Hospital in Winneba and several district and mission hospitals. Despite this, rural areas face shortages of medical staff and DM screening facilities. Limited healthcare access contributes to undiagnosed or poorly managed DM cases. The region hosts the University of Cape Coast (UCC), a leading institution in health research, the University of Education, Winneba, a leading institution in teacher training and host vibrant senior high schools. However, literacy rates vary, with rural areas lagging. Low health literacy affects DM awareness, diet choices, and treatment adherence. The study area is shown in Figure 1.

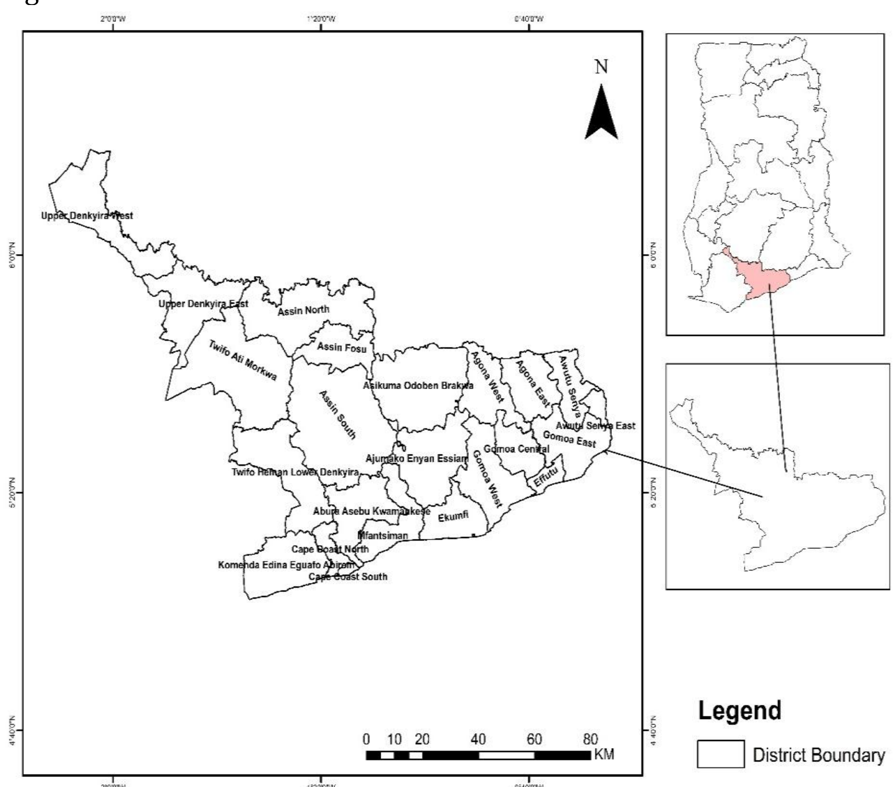

Figure 1: Metropolitan, Municipal and Districts Assemblies (MMDAs) in Central Region

2.2 Study design

The study employed a retrospective longitudinal design, performing secondary analysis of DM health data over 12 years from 2008 to 2019. The design allowed for consideration of temporal trends in DM prevalence and ongoing spatial focus at district level. The design was useful in determining persistent hotspots and coldspots over time and facilitating comparisons of areas across different years (Kengne et al., 2013).

A quantitative spatial epidemiology approach was also utilized, integrating geographic information systems (GIS) and spatial statistics to identify patterns of clustering. The study employed the macrolevel analysis whereby the study grouped the cases at the MMDA level to identify larger geographic trends that are suitable for public health intervention and not individual-level information (Anselin & Rey, 2014). It also employed the exploratory Spatial Data Analysis (ESDA) that helped identify spatial autocorrelation, clusters, and outliers in DM distribution (Xie et al., 2022).

2.3 Sampling and data processing

The study employed a multi-stage sampling approach. The first stage involved the selection of hospitals across the MMDAs. About 13 hospitals were selected from the 45 hospitals and polyclinics in the study area. The hospitals selected were those that provide DM services. The second stage involved purposive sampling of patients' folders (cases) with residential MMDAs outside the Central Region of Ghana. The remaining folders of patients were then considered as the target population, that is, 14,350 folders (cases) from 2008-2019. The year range chosen reflects the two years into the inception of World Diabetes Day in 2006 (UN, 2024), which may have had enough education to prompt individuals to act on their DM status. The year 2019 also marks the transition from the manual filing of patients' data onto the digital platform.

Patient folders that had more than one indicator missing were excluded. These indicators included demographic variables (age, sex, marital status, ethnicity, occupation, educational level and religion), district of residence, diagnosis variable (date of diagnosis), risk factors, management variables (deteriorating, follow-up, deceased), year of death and cause of death. After the exclusion criterion was applied, a total of 8,992 folders remained.

DM case counts per MMDA were converted to age-standardized rates per 10,000 population using the Ghana Statistical Service 2010 inter-censal population estimates, with linear interpolation for intervening years.

2.4 Data analysis

The analysis comprised Local Moran's I and Anselin Moran's I spatial autocorrelation analysis from ArcGIS Pro 3. The Local Moran's I involved examining the general clustering pattern of DM cases across the region and determining whether the cases were random in nature or were represented as significant clustering (Anselin & Rey, 2014). Significant hotspots (High-High cluster) and coldspots (Low-Low cluster) of the rates of DM, and spatial outliers (i.e., Low-High or High-Low cluster), were determined using the Local Moran's I (LISA) (Heppenstall et al., 2021; Anselin & Rey, 2014). Anselin Local Moran's I is as follows (Eqs.(1) and (2)

$$I_i \frac{x_i - \overline{X}}{S_i^2} \sum_{j-1, j \neq i}^{n} x_{i,j}(x_i - \overline{X}) \quad (1)$$

where:

x_i equates attribute of feature i.
$\overline{X}$ mean of corresponding attributes.
w_{ij} the spatial weight of i and j.

$$S_i^2 = \frac{\sum_{j=1,j\neq i}^{n} x_j - \overline{X})^2}{n-1} \qquad (2)$$

where:
n is the total features.

At a 95% confidence level ($p < 0.05$), clustering was determined so as to identify robustness (Ngesa et al., 2014). Temporal trend analysis was used as a way of determining the changing patterns over time so as to be employed when evaluating the stability of DM hotspots and coldspots (Kengne et al., 2013).

Spatial weights were defined using first-order Queen contiguity, whereby MMDAs sharing any boundary or corner point were considered neighbours. The weights matrix was row-standardised prior to analysis. To assess sensitivity to the weights specification, analyses were repeated using Rook contiguity and k-nearest neighbours (k=3). Results were consistent across specifications, supporting robustness of reported clusters.

3 Results

3.1 Spatial autocorrelation of DM from 2008-2019

Most years show statistically significant spatial autocorrelation ($p < 0.05$) from Table 1. Exceptions are 2010 ($p = 0.156$), 2012 ($p = 0.28$), indicating no significant clustering those years. From 2014 onward, p-values drop consistently to ≤0.001–0.044, suggesting increasingly strong spatial clustering of T1DM over time.

As presented in Table 1, results are more mixed. Significant years include 2008, 2010, 2012, 2014-2016, and 2019. Non-significant years (2009, 2011, 2017, 2018) have p-values ranging from 0.059-0.158, suggesting weaker or inconsistent spatial patterns. Overall, T1DM shows a stronger and more consistent spatial clustering trend than T2DM across the study period.

Table 1: Local Moran's I for T1DM and T2DM

T1DM					T2DM				
Year	**Moran's I**	**z-score**	**p-value**	**Sig.**	**Year**	**Moran's I**	**z-score**	**p-value**	**Sig.**
2008	0.142	2.31	0.021	s	2008	0.182	2.41	0.016	s
2009	0.188	2.84	0.005	s	2009	0.094	1.76	0.079	n.s.
2010	0.071	1.42	0.156	n.s.	2010	0.138	2.12	0.034	s
2011	0.155	2.48	0.013	s	2011	0.109	1.89	0.059	n.s.
2012	0.044	1.08	0.28	n.s.	2012	0.121	2.04	0.041	s
2013	0.161	2.53	0.011	s	2013	0.076	1.52	0.128	s
2014	0.234	3.42	0.001	s	2014	0.115	1.97	0.049	s
2015	0.278	3.91	0.001	s	2015	0.143	2.18	0.029	s
2016	0.119	2.01	0.044	s	2016	0.127	2.08	0.037	s
2017	0.207	3.08	0.002	s	2017	0.098	1.81	0.07	n.s.
2018	0.221	3.24	0.001	s	2018	0.062	1.41	0.158	n.s.
2019	0.245	3.61	0.001	s	2019	0.154	2.25	0.024	s

Note: *S= significant & n.s. = not significant*
Source: Field data, 2020

3.2 Spatial Distribution of T1DM across MMDAs (2008-2019)

Local Moran's I was used in identifying Metropolitan, Municipal, and District Assemblies (MMDAs) with higher clustering and statistical scores for T1DM, encircled by those with lower scores. Figure 2 indicates the year 2008 observed three significant clusters. T1DM clusters were highly intermittent, with significant spatial autocorrelation detected in 9 of 12 years. Cape Coast Metro was the most consistent hotspot (High-High in 2008, 2011, 2019), while Gomoa East was the most persistent coldspot (Low-Low in 2008, 2011, 2013–2015)

Firstly, a High-High cluster in Cape Coast Metro, Mfantsiman, Abura Asebu Kwamankese (AAK) and Twifo Hemang Lower Denkyira (THLD) MMDAs, indicating a hotspot of high T1DM incidence. Again, one Low-High outlier in the northwest, that is Twifo Ati Morkwa (TAM) district and one Low-Low cluster in Gomoa East, reflecting a pocket of consistently low T1DM incidence. The spatial pattern shifted in 2009, shows a High-High cluster in the south again for Mfantsiman district, a Low-High outlier in THLD district, and a High-Low outlier in Gomoa West district, that is the central-eastern portion. This mix reflects contrasting spatial conditions with some areas showing local high incidence surrounded by low, and others with the inverse.

Only one Low-High outlier appeared in the centre in 2010 in Gomoa West Municipal, with the rest of the map being statistically not significant. This suggests a relatively uniform spatial distribution of T1DM incidence during this year. The year 2011 had more spatial structure. Two High-High outliers were identified in Upper Denkyira East municipal and Upper Denkyira West districts, alongside one High-Low outlier in Gomoa Central district in the eastern portion. One Low-Low was found in Gomoa East district and there Low-High clusters emerged in Assin North, South districts and Assin Foso MMDAs. The combination of oppositional clusters suggests transitional or shifting dynamics. In 2012, no significant clusters were detected. All MMDAs were classified as Not Significant, indicating a lack of strong spatial autocorrelation resulting from either the T1DM rates were more evenly distributed or there was not a strong enough signal for clustering.

Clustering re-emerged in 2013 with one Low-High outlier in THLD) in the northwest and two High-Low outliers in the east, Agona East and Effutu municipalities. Additionally, two Low-Low cluster appeared in the far eastern part of the map, occurring in Agona West and Awutu Senya West districts. The spatial pattern shows that while some areas consistently maintained low incidence, others showed mismatches with their surroundings. The year 2014 saw a return of all cluster types. A High-High cluster appeared in Upper Denkyira East municipal. A High-Low cluster emerged in Asikuma Odoben Brakwa and Effutu MMDAs. The Low-High cluster occurred in Upper Denkyira West and THLD districts, while a Low-Low cluster reemerged in the eastern part, namely, Gomoa East and Gomoa West districts. This wide spread of patterns suggests a highly heterogeneous spatial distribution of T1DM incidence.

One of the most spatially complex years, 2015 as shown in Figure 2, had one cluster or outlier of each type similar to 2014. Three central High-High cluster in Twifo Ati Morkwa (TAM), Assin North and Assin Foso MMDAs. Three High-Low clusters emerged in Asikuma Odoben Brakwa, Awutu Senya East and Awutu Senya West districts. Low-Low cluster occurred in Gomoa West, Gomoa Central, and Gomoa East MMDAs and a Low-High in Assin South and THLD MMDAs. The clustering pattern indicates highly localized spikes and depressions in T1DM incidence, with potential epidemiological significance. In 2016, only one High-Low outlier was observed in Gomoa East district. The rest of the MMDAs was Not Significant, suggesting that only isolated high-incidence zones stood out amid low-risk neighborhoods.

The pattern shifted again in 2017 and 2018 with similar clusters. Two Low-High clusters appeared in Upper Denkyira East municipal and Assin North district respectively. Two High-Low clusters appeared in AAK and Awutu Senya West districts. No Low-Low or High-High clusters appeared, indicating a more fragmented spatial relationship. In 2018, spatial structure remained similar to 2017 as shown in Figure 2. The same two Low-High outliers and one High-Low outlier persisted, with most other areas remaining Not Significant. The year 2019, showed renewed clustering. A High-High cluster emerged in Cape Coast Metro, THLD, AAK and Komenda Edina Eguafo Abirem (KEEA) districts. There is a Low-High outlier occurring in TAM and Mfantsiman districts. This suggests a return to strong local patterns of high incidence surrounded by either high or low values.

Aggregated spatial analysis across the entire period of 2008–2019 indicates variability in clustering. The analysis portrayed Low-High clusters in Upper Denkyira East municipal and Assin North district. Low-Low clusters emerged in TAM and THLD and Assin Foso MMDAs whereas Agona East and Effutu MMDAs recorded Low-Low clusters. Other MMDAs that recorded Low-Low clusters include Agona West, Gomoa East, Gomoa West, Gomoa Central, Awutu Senya East and Awutu Senya West MMDAs.

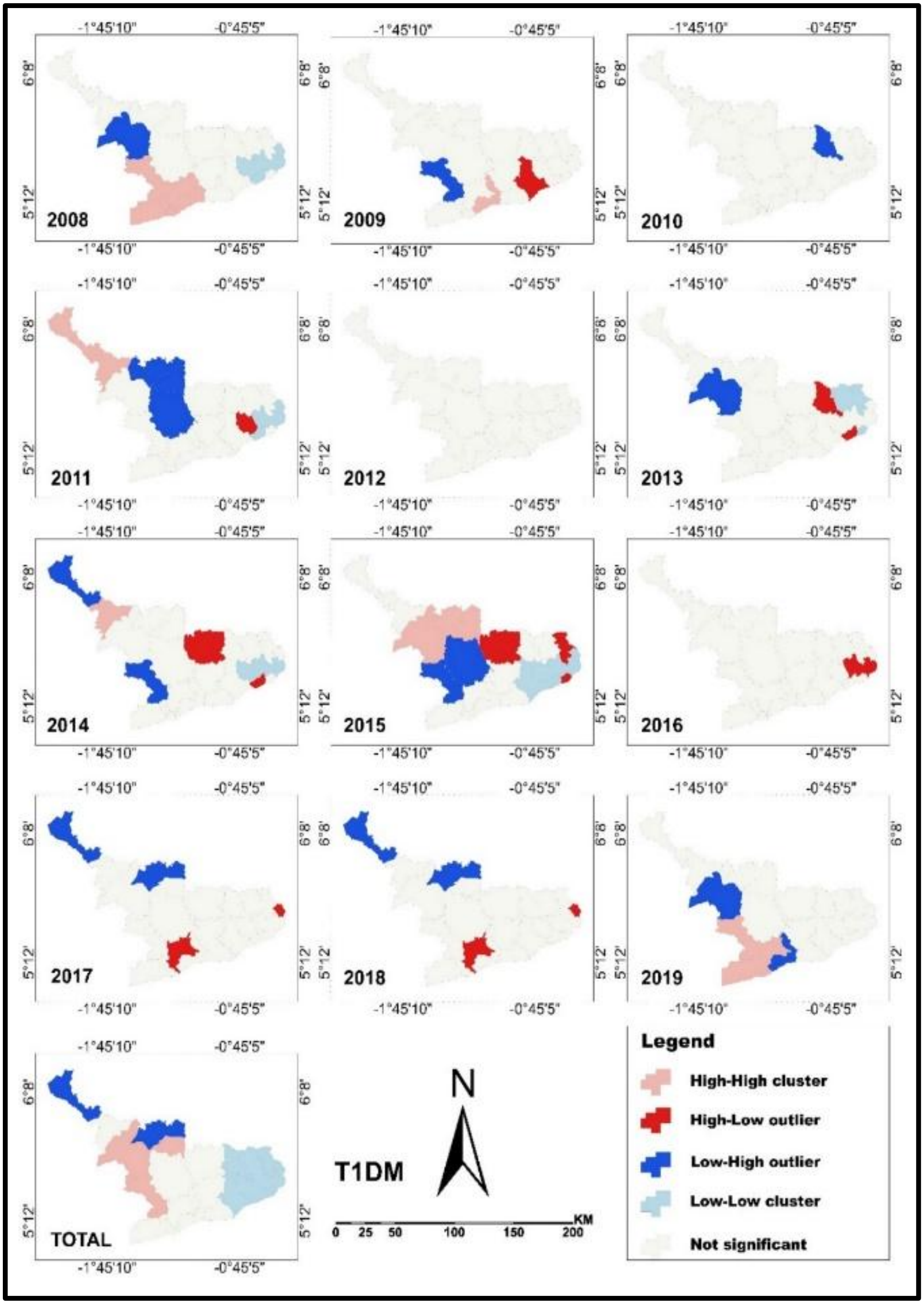

Figure 2: Anselin Moran's I for T1DM, 2008 – 2019
Source: Field data, 2020

3.3 Spatial Distribution of T2DM across MMDAs (2008-2019)

The analysis for T2DM is presented in Figure 3. The year 2008 begins with a notable mix of spatial clusters as shown in Figure 3. A Low-High cluster area dominates the TAM, suggesting a low T2DM prevalence amidst higher-rate of High-High neighbors in THLD, KEEA, and AAK districts, Cape Coast metro and Mfantsiman municipal. The significant High-High cluster indicates a concentration of high T2DM rates. A smaller Low-Low cluster is seen in Gomoa Central and Gomoa East districts and Effutu municipal. In 2009, the clustering becomes more subdued, with only a single Low-High outlier remaining in the southwestern part of the region, that is, KEEA district. The rest of the map shows no significant spatial patterns, pointing to a temporary dissipation in clustering.

A shift occurs 2010 with the emergence of two High-Low outliers in Awutu Senya East and Awutu Senya West districts. These areas exhibit high T2DM values while being surrounded by lower-rate neighbours, indicating isolated spikes in T2DM prevalence. In 2011, a High-High cluster in KEEA district in the south coincides with a nearby Low-High outlier in AAK, reinforcing the spatial heterogeneity of T2DM across short distances. The year 2012 sees the presence of a Low-High outlier zone in THLD district.

Only one High-High cluster appears in the southern tip in 2013 in KEEA, indicating a localized concentration of high T2DM burden, without any surrounding clusters. Again in 2014, a Low-High outlier is visible in the south, AAK district, reaffirming the persistence of this pattern in that locale. A more complex spatial picture unfolds in 2015. A Low-High outlier remains in AAK district, while a High-High cluster emerges again in the south, KEEA district. Additionally, a single Low-Low cluster appears in the north, Upper Denkyira East municipal indicating a rare but statistically significant cold spot. The clustering pattern simplifies with a single Low-High outlier in KEEA district in 2016, indicating some stability in spatial autocorrelation.

The year 2017 features a solitary Low-High outlier in KEEA, continuing the pattern of spatial persistence in specific locations. Interestingly, no significant clusters are detected in 2018, suggesting a year of spatial randomness or transition in T2DM distribution. This lack of clustering may reflect either improvements in uniformity of healthcare access or anomalies in the data. However, clustering surges again in 2019 with the most extensive Low-High outlier grouping spanning three distinct MMDAs, THLD, AAK and KEEA. This reinforces the idea of a recurring local pattern of T2DM weight and neighbouring relations.

The aggregated map combines the spatial analysis for the whole period, 2008–2019. One persistent, extended Low-High outlier remains the most prominent in KEEA in the south, highlighting the long-term consistency of this spatial process.

3.4 Spatiotemporal Trends and High-Cluster Zones

Temporal Dynamics and Persistent Clustering Patterns

The temporal analysis revealed substantial year-to-year variation in clustering patterns. For T1DM, certain years (2010, 2012, 2016) displayed no significant clustering, suggesting either uniform spatial distribution or data collection challenges (see Fig. 2). The southeastern MMDAs (particularly Gomoa East) emerged as persistent Low-Low clusters across multiple years, while urban centres like Cape Coast Metro showed intermittent High-High clustering.

For T2DM as shown in Figure 3, the KEEA district consistently emerged as a significant Low-High outlier throughout the study period, demonstrating remarkable spatial persistence. Key hotspots for T2DM included KEEA, Cape Coast Metro, and THLD. Notably, no significant clusters were observed in 2018, suggesting dynamic epidemiological changes.

3.5 Aggregated Spatial Analysis (2008-2019)

The aggregated analysis across the entire study period (Fig. 2) revealed more stable long-term patterns. For T1DM, Low-High clusters persisted in Upper Denkyira East municipal and Assin North district, while multiple MMDAs in the eastern and southeastern portions showed consistent Low-Low clustering patterns, including Gomoa East, Gomoa West, Gomoa Central, Awutu Senya East and Awutu Senya West.

For T2DM, the aggregated map highlighted one persistent, extended Low-High outlier in KEEA in the south (Fig. 3), demonstrating the long-term consistency of this spatial pattern and identifying it as a priority area for targeted interventions.

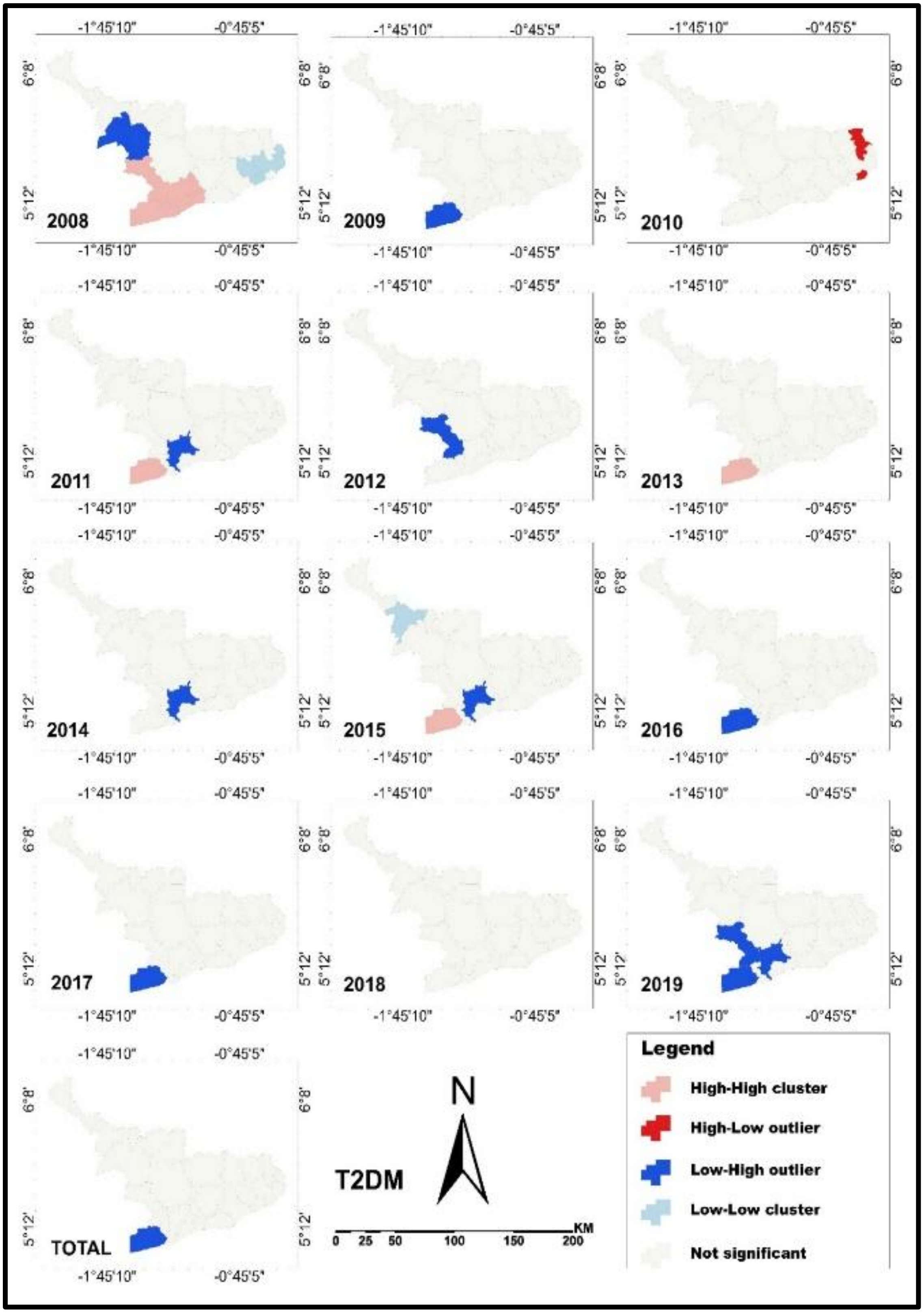

Figure 3: Anselin Moran's I for T2DM, 2008 – 2019
Source: Field data, 2020

4 Discussions

The geographic distribution of T1DM in Ghana's Central Region from 2008-2019 shows substantial spatial and temporal variation, reflecting broader patterns observed across sub-Saharan Africa. Low-Low clusters in southeastern districts and Low-High clusters in Assin North and Upper Denkyira West indicate reduced DM prevalence in rural areas. Studies suggest this pattern stems from traditional fiber-rich diets with vegetables and legumes that lower glycemic load (Adjei et al., 2024; Ofori-Asenso et al., 2016), alongside increased physical activity among rural populations (Addo et al., 2009). Additional contributing factors include limited access to processed foods due to fewer retail outlets (Steyn & McHiza, 2014), possible genetic adaptations conferring metabolic resilience (Chen et al., 2017), and underdiagnosis resulting from inadequate healthcare infrastructure (Danquah et al., 2012). These rural characteristics collectively create environments less conducive to DM development.

High-High clusters, particularly in Cape Coast Metro appearing in 2008 and 2019, align with urban epidemiological patterns throughout West Africa, representing what Barker (1981) termed "disease of civilization." Patterson et al. (2019) documented similar urban T1DM aggregation in Nigerian cities, attributing to enhanced diagnostic capabilities and healthcare access rather than true incidence differences. The persistent clustering in Cape Coast Metro likely reflects concentration of specialized diagnostic facilities, creating surveillance bias rather than genuine epidemiological hotspots (Ogle et al., 2022). Temporal fluctuations present methodological challenges, with some years (2010, 2012, 2016) showing no discernible patterns. In resource-limited settings, DM surveillance faces obstacles including inconsistent case detection and variable diagnostic capacity (Bahendeka et al., 2019). The disrupted patterns in 2017-2018, featuring Low-High and High-Low outliers without homogeneous clusters, may reflect changes in monitoring approaches or healthcare system disruptions rather than actual epidemiological shifts.

The persistent Low-Low clustering in Gomoa East, Gomoa West, and Awutu Senya MMDAs across multiple years presents an intriguing epidemiological pattern. Current evidence suggests T1DM prevalence in sub-Saharan Africa may correlate with genetic heterogeneity patterns, creating differential population vulnerability (Motala et al., 2022). However, in regions with weak healthcare infrastructure, Low-Low clustering may instead indicate systematic case under-ascertainment, requiring cautious interpretation (Mayer-Davis et al., 2018). The exceptionally heterogeneous 2015 pattern, displaying all cluster categories simultaneously, reinforces observations from the SWEET World Diabetes Registry documenting significant intra-country variation in African T1DM trends (Danne et al., 2017). This regional diversity likely results from converging influences including genetic predisposition differences, environmental triggers, infectious disease patterns, and healthcare access disparities, creating complex epidemiological landscapes that defy simple explanation.

The aggregated 2008-2019 analysis provides valuable long-term geographical insights but faces important limitations. T1DM case detection in West Africa struggles with diagnostic capacity issues, likely misclassifying many cases as T2DM (Motala et al., 2022). Additionally, observed clustering may partially reflect healthcare-seeking behavior trends rather than true incidence variation. Future research should integrate genetic epidemiology data, environmental exposure assessments, and healthcare utilization patterns with these spatial findings. The complex temporal dynamics identified suggest static spatial analysis cannot fully capture epidemiological reality. Longitudinal cohort studies incorporating regional and temporal elements, similar to European studies (Stahl-Pehe et al., 2024; Harjutsalo et al., 2008), would provide more robust epidemiological understanding of T1DM in Ghana and inform development of region-specific surveillance systems accounting for healthcare constraints.

T2DM spatial patterns display similar complexity, with extensive temporal and spatial heterogeneity reflecting continental trends. KEEA's persistent Low-High clustering suggests complex interactions between local risk factors and regional healthcare dynamics warranting further investigation. High-High clusters in areas like KEEA and THLD during 2008-2011 coincide with Ghana's rapid economic development period, supporting the concept of diabetes transition in West African urban populations (Agyemang et al., 2016). Temporal anomalies in 2009 and 2018, when clustering disappeared, mirror patterns in Nigerian surveillance data (Uloko et al., 2018), potentially reflecting data quality issues or genuine epidemiological shifts. KEEA's continued Low-High outlier status demonstrates what Sankoh and Byass (2012) called "spatial stickiness" in health outcomes. The 2015 and 2019 concurrent clustering patterns exemplify geographical heterogeneity in DM risk factors across Ghana's ecological zones (Motala et al., 2022), challenging uniform public health approaches and supporting spatially sensitive interventions (Beaglehole et al., 2011).

5 Conclusion

The spatial analysis of T1DM and T2DM prevalence across Ghana's Central Region MMDAs over twelve years revealed distinct clustering patterns with significant public health implications. T1DM demonstrated consistent spatial clustering characterized by three primary patterns: Low-Low clusters in southeastern regions potentially influenced by genetic factors, favourable environmental conditions, or enhanced healthcare access; and Low-High clusters in Assin North and Upper Denkyira West, suggesting localized protective factors operating within high-prevalence environments. These patterns underscore the dynamic nature of T1DM distribution and highlight the necessity for geographically tailored interventions. For T2DM, substantial regional trends emerged, particularly in 2008 when eleven MMDAs displayed clustering. High-High clusters (hotspots) appeared in KEEA, Cape Coast Metro, THLD, Mfantsiman, and AAK, indicating areas with persistently elevated T2DM prevalence requiring intensive public health attention. TAM emerged as a Low-High outlier, representing a low-prevalence area surrounded by high-risk zones and warranting investigation into protective factors. Meanwhile, Low-Low clusters (coldspots) in Awutu Senya East, Awutu Senya West, Gomoa Central, and Gomoa East indicated sustained low prevalence, potentially attributable to healthier dietary patterns, increased physical activity, or other localized protective characteristics. The absence of statistically significant clusters in 2018 suggests a shifting epidemiological landscape, possibly driven by population migration, improved healthcare policies, or modifications in lifestyle and environmental risk factors. This temporal variability emphasizes the critical need for continuous surveillance systems to effectively adapt public health strategies to changing disease patterns.

These findings demonstrate the essential role spatial epidemiology plays in directing targeted interventions and informing evidence-based policy decisions. By identifying high-risk clusters, the Ministry of Health, Ghana Health Service and analogous agencies must implement can strategically focus screening programs, educational campaigns, and resource allocation in areas requiring intensive intervention. Conversely, low-prevalence regions offer valuable opportunities to investigate protective factors that might be replicated elsewhere to prevent disease occurrence. The study confirms that DM prevalence is not uniformly distributed but rather shaped by complex interactions among socioeconomic determinants, environmental exposures, genetic predispositions, and healthcare-related factors. Future research should incorporate granular data on these characteristics to refine intervention strategies and enhance predictive modelling capabilities. Public health practitioners can address Ghana's escalating DM burden by utilizing spatial analysis to move beyond broad generalizations toward precision-based approaches that account for local contexts and specific risk profiles. Given the dynamic nature of disease clusters, retrospective longitudinal research design remains essential for monitoring evolving trends and evaluating the impact of policy modifications. Such ongoing surveillance ensures that interventions remain responsive to changing epidemiological patterns, allowing for adaptive management strategies that can effectively reduce diabetes prevalence and improve population health outcomes across diverse geographic settings in Ghana's Central Region.

6 Ethical Approval

This study received ethical approval from the Ghana Health Service (GHS-ERC 002/03/19), and the Cape Coast Teaching Hospital (CCTHERC/EC/2019/090). These approvals were sought in order to access the health files of the DM patients in the various health facilities in the Central Region.

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8 Competing interest

No competing interest

9 Funding

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References

Addo, P. N., Nyarko, K. M., Sackey, S. O., Akweongo, P., & Sarfo, B. (2015). Prevalence of obesity and overweight and associated factors among financial institution workers in Accra Metropolis, Ghana: a cross sectional study. *BMC Research Notes*, *8*(1), 1-8.

Adjei A, Brightson KTC, Mensah MM, Osei J, Drah M, Narh CT, et al. (2024) Determinants of glycemic control among persons living with Type 2 diabetes mellitus attending a district hospital in Ghana. *PLoS ONE 19*(11): e0308046. https://doi.org/10.1371/journal.pone.0308046

Agyemang, C., Meeks, K., Beune, E., Owusu-Dabo, E., Mockenhaupt, F. P., Addo, J., ... & Stronks, K. (2016). Obesity and Type 2 diabetes in Sub-Saharan Africans–Is the burden in today's Africa similar to African migrants in Europe? The RODAM study. *BMC Medicine, 14*(1), 166. https://doi.org/10.1186/s12916-016-0709-0

Anselin, L., & Rey, S. J. (2014). *Modern spatial econometrics in practice: A guide to GeoDa, GeoDaSpace and PySAL.* Chicago, IL: GeoDa Press.

Bahendeka, S., Kaushik, R., Swai, A. B., Otieno, F., Bajaj, S., Kalra, S., ... & Karigire, C. (2019). EADSG guidelines: Insulin storage and optimisation of injection technique in diabetes management. *Diabetes Therapy, 10*(2), 341-366. https://doi.org/10.1007/s13300-019-0574-x

Barker D. J. (1981). Geographical variations in disease in Britain. *British medical journal (Clinical research ed.)*, *283*(6288), 398–400. https://doi.org/10.1136/bmj.283.6288.398

Beaglehole, R., Bonita, R., Horton, R., Adams, C., Alleyne, G., Asaria, P., ... & Watt, J. (2011). Priority actions for the non-communicable disease crisis. *The Lancet, 377*(9775), 1438-1447. https://doi.org/10.1016/S0140-6736(11)60393-0

CCTH. (2022). *Annual report. Cape Coast Teaching Hospital*. Cape Coast

Chen, X., Orom, H., Hay, J. L., Waters, E. A., Schofield, E., Li, Y., & Kiviniemi, M. T. (2019). Differences in rural and urban health information access and use. *Journal of Rural Health*, *35*(3), 405–417. https://doi.org/10.1111/jrh.12335

Danne, T., Nimri, R., Battelino, T., Bergenstal, R. M., Close, K. L., DeVries, J. H., ... & Phillip, M. (2017). International consensus on use of continuous glucose monitoring. *Diabetes Care, 40*(12), 1631-1640. https://doi.org/10.2337/dc17-1600

Danquah, I., Bedu-Addo, G., Terpe, K. J., Micah, F., Amoako, Y. A., Awuku, Y. A., ... & Mockenhaupt, F. P. (2012). Diabetes mellitus type 2 in urban Ghana: characteristics and associated factors. *BMC Public Health*, *12*, 1-8. https://doi.org/10.1186/1471-2458-12-210

Ghana Statistical Service (GSS) (2021). *Ghana 2021 Population and Housing Census (PHC). General report. Volume 3C. Ghana Statistical Service.* Accra. https://statsghana.gov.gh/searchread.php?searchfound=NzgwOTIyMTI4OTQuMDYz/search/soq24q5779

Harjutsalo, V., Sjöberg, L., & Tuomilehto, J. (2008). Time trends in the incidence of type 1 diabetes in Finnish children: a cohort study. *The Lancet, 371*(9626), 1777-1782. https://doi.org/10.1016/S0140-6736(08)60765-5

Heppenstall, A., Crooks, A., Malleson, N., Manley, E., Ge, J., & Batty, M. (2021). Future developments in geographical agent-based models: Challenges and opportunities. *Geographical Analysis, 53*(1), 76-91. https://doi.org/10.1111/gean.12267

Kengne, A. P., Masconi, K., Mbanya, V. N., Lekoubou, A., Echouffo-Tcheugui, J. B., & Matsha, T. E. (2013). Risk predictive modelling for diabetes and cardiovascular disease. *Critical*

Reviews in Clinical Laboratory Sciences, 51(1), 1–12. https://doi.org/10.3109/10408363.2013.853025

Mayer-Davis, E. J., Kahkoska, A. R., Jefferies, C., Dabelea, D., Balde, N., Gong, C. X., ... & Craig, M. E. (2018). ISPAD clinical practice consensus guidelines 2018: Definition, epidemiology, and classification of diabetes in children and adolescents. *Pediatric Diabetes*, *19*(Suppl 27), 7. https://doi.org/10.1111/pedi.12773

Ministry of Health (15 November 2022). *Twenty-four million adults in Africa are currently living with diabetes.* Ministry of Health, Accra. https://www.moh.gov.gh/24-million-adults-in-africa-are-currently-living-with-diabetes/

Motala, A. A., Mbanya, J. C., Ramaiya, K., Pirie, F. J., & Ekoru, K. (2022). Type 2 diabetes mellitus in Sub-Saharan Africa: Challenges and opportunities. *Nature Reviews Endocrinology, 18*(4), 219-229. https://doi.org/10.1038/s41574-021-00613-y

Ngesa, O., Mwambi, H., & Achia, T. (2014). A flexible random effects distribution in disease mapping models. *South African Statistical Journal, 48*(1), 83-93. https://hdl.handle.net/10520/EJC154222

Ofori-Asenso, R., Agyeman, A. A., Laar, A., & Boateng, D. (2016). Overweight and obesity epidemic in Ghana-a systematic review and meta-analysis. *BMC Public Health*, *16*(1), 1239. https://doi.org/10.1186/s12889-016-3901-4

Ogle, G. D., James, S., Dabelea, D., Pihoker, C., Svennson, J., Maniam, J., ... & Patterson, C. C. (2022). Global estimates of incidence of type 1 diabetes in children and adolescents: Results from the International Diabetes Federation Atlas. *Diabetes Research and Clinical Practice, 183*, 109083. https://doi.org/10.1016/j.diabres.2021.109083

Ogugua, J. O., Olorunsogo, T. O., Muonde, M., Maduka, C. P., & Omotayo, O. (2024). Developing countries' health policy: A critical review and pathway to effective healthcare systems. *International Journal of Science and Research Archive*, *11*(01), 371-382. https://doi.org/10.30574/ijsra.2024.11.1.0069

Oti-Boateng, E., Ngesa, O., & Osei, F. B. (2016). Spatial modeling of diabetes cases in Ghana. *International Journal of Science and Research, 5*(8), 1404-1409. https://doi.org/10.21275/ART2016964

Patterson, C. C., Harjutsalo, V., Rosenbauer, J., Neu, A., Cinek, O., Skrivarhaug, T., ... & Green, A. (2019). Trends and cyclical variation in the incidence of childhood type 1 diabetes in 26 European centres in the 25-year period 1989–2013: a multicentre prospective registration study. *Diabetologia*, *62*(3), 408-417. https://doi.org/10.1007/s00125-018-4763-3

Sankoh, O., & Byass, P. (2012). The INDEPTH Network: filling vital gaps in global epidemiology. *International Journal of Epidemiology, 41*(3), 579-588. https://doi.org/10.1093/ije/dys081

Stahl-Pehe, A., Baechle, C., Lanzinger, S., Urschitz, M. S., Reinauer, C., Kamrath, C., ... & Rosenbauer, J. (2024). Trends in the incidence of type 1 diabetes and type 2 diabetes in children and adolescents in North Rhine-Westphalia, Germany, from 2002 to 2022. *Diabetes & Metabolism, 50*(5), 101567. https://doi.org/10.1016/j.diabet.2024.101567

Steyn, N. P., & McHiza, Z. J. (2014). Obesity and the nutrition transition in Sub-Saharan Africa. *Annals of the New York Academy of Sciences*, *1311*, 88–101. https://doi.org/10.1111/nyas.12433

Uloko, A. E., Musa, B. M., Ramalan, M. A., Gezawa, I. D., Puepet, F. H., Uloko, A. T., ... & Sada, K. B. (2018). Prevalence and risk factors for diabetes mellitus in Nigeria: a systematic review and meta-analysis. Diabetes *Therapy, 9*(3), 1307-1316. https://doi.org/10.1007/s13300-018-0441-1

UN (2024). *World Diabetes Day: Diabetes and well-being*. United Nations. Geneva. https://www.un.org/en/observances/diabetes-day
WHO (2023). *Diabetes: the silent killer. Analytical factsheet*, March 2023. https://files.aho.afro.who.int/afahobckpcontainer/production/files/iAHO_Diabetes_Regional_Factsheet.pdf
WHO (2024 November 19). *Advancing diabetes care in Ghana: WHO's collaborative efforts on the path to better health*. World Health Organisation. https://www.afro.who.int/countries/ghana/news/advancing-diabetes-care-ghana-whos-collaborative-efforts-path-better-health
Xie, Y., Shekhar, S., & Li, Y. (2022). Statistically-robust clustering techniques for mapping spatial hotspots: A survey. *ACM Computing Surveys, 55*(2), 1-38. https://doi.org/10.1145/348789