Geospatial Inequities and Community-Based Behavioral Interventions for Type 2 Diabetes Control in Health Region 10, Thailand

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Abstract

Geographic inequity remains a critical barrier to equitable diabetes control under universal health coverage systems. This study applied geoinformatics-based spatial epidemiology to examine the spatial distribution of type 2 diabetes burden, healthcare accessibility, and geographic variation in community-based behavioral intervention outcomes in Health Region 10, northeastern Thailand. A cross-sectional analytical design was conducted across five provinces, 70 districts, and 611 sub-districts, with an intervention component implemented in 24 purposively selected communities. Spatial clustering was assessed using Global Moran's I, Local Indicators of Spatial Association, and Getis-Ord Gi. Accessibility to diabetes services was quantified using the Enhanced Two-Step Floating Catchment Area method with Gaussian distance-decay weighting. Associations between accessibility and glycemic control were examined using multilevel regression, spatial econometric modeling, and geographically weighted regression. Diabetes burden showed significant spatial clustering (Global Moran's I = 0.342, p < 0.001). E2SFCA accessibility scores varied substantially across sub-districts, with urban areas showing higher accessibility than rural and remote rural areas. Lower accessibility was significantly associated with poorer glycemic control and a higher likelihood of unchanged or increased fasting blood sugar. Participants residing more than 20 km from comprehensive diabetes services had worse glycemic outcomes than those within 5 km. Intervention effectiveness also varied geographically, with urban communities showing greater glycemic improvement than peri-urban and remote rural communities. Spatial error modeling confirmed significant spatial dependence (ρ = 0.28, p < 0.001), while geographically weighted regression revealed local heterogeneity in the accessibility–glycemic control relationship. These findings demonstrate that spatial accessibility is both a determinant of diabetes outcomes and a moderator of intervention effectiveness. Integrating GIS-based accessibility modeling into chronic disease planning can support spatially targeted, equity-oriented diabetes control in underserved areas.

Keywords: Diabetes Control, Enhanced Two-Step Floating Catchment Area, Geographic Inequity, Geographically Weighted Regression, Spatial Epidemiology

1. Introduction

Type 2 diabetes mellitus (T2DM) represents one of the most pressing global health challenges of the 21st century, affecting more than 537 million adults worldwide and projected to reach 783 million by 2045 [1]. The disease imposes substantial clinical, economic, and health-system burdens, particularly in low- and middle-income countries where healthcare resources are constrained and access to chronic disease services remains uneven [2]. In Thailand, diabetes prevalence has increased markedly over recent decades, with persistent challenges in screening, treatment continuity, and glycemic control [3]. This escalating burden is not only a biomedical problem but also a spatial equity challenge, as diabetes outcomes often vary across geographic and socioeconomic gradients [4].

Despite Thailand's achievement of Universal Health Coverage (UHC) in 2002, formal health insurance entitlement does not necessarily guarantee equal spatial access to care. Diabetes management requires regular clinical monitoring, medication continuity, lifestyle counseling, and long-term follow-up. These requirements make geographic accessibility particularly important for patients living in rural and peripheral areas. Health Region 10, located in northeastern Thailand and comprising

Ubon Ratchathani, Yasothon, Amnat Charoen, Sisaket, and Mukdahan provinces, exemplifies this policy-relevant paradox. The region contains extensive rural settlements, border-adjacent communities, agricultural livelihoods, and areas affected by seasonal road accessibility constraints. Patients in remote rural areas may face long travel distances to healthcare facilities, limited public transportation, fragmented service delivery, and reduced availability of comprehensive diabetes care. These structural barriers can contribute to delayed diagnosis, inconsistent medication adherence, irregular follow-up visits, and poorer glycemic outcomes compared with urban populations [5] and [6].

The persistence of geographic inequities in diabetes care highlights limitations in conventional health-service planning. Traditional approaches often rely on administrative boundaries, facility counts, or population-to-provider ratios, which may fail to capture real travel impedance, road-network structure, service-capacity variation, and distance-decay effects [7]. In this context, geoinformatics provides a stronger analytical foundation for identifying where disease burden is concentrated, where service accessibility is insufficient, and where interventions may require spatially differentiated implementation strategies. Spatial epidemiological methods can determine whether diabetes burden is randomly distributed or geographically clustered. Global Moran’s I can quantify overall spatial autocorrelation, while Local Indicators of Spatial Association (LISA) and Getis-Ord Gi* statistics can identify local hotspots, coldspots, and spatial outliers [8] and [9].

Healthcare accessibility can be further evaluated using GIS-based spatial accessibility models. The Two-Step Floating Catchment Area method and its enhanced form, the Enhanced Two-Step Floating Catchment Area (E2SFCA), are widely used to estimate spatial access by integrating healthcare supply, population demand, catchment thresholds, and distance-decay weighting [10] and [11]. Compared with simple distance or administrative coverage measures, E2SFCA is more appropriate for chronic disease service planning because it represents both the capacity of healthcare facilities and the competing demand from populations within service catchments. In addition, spatial econometric modeling and geographically weighted regression (GWR) can address two core methodological challenges in spatial health research: spatial dependence and local heterogeneity. Spatial econometric models reduce bias arising from spatially correlated residuals, while GWR allows relationships between accessibility and health outcomes to vary across geographic space [12] and [13].

Although community-based behavioral interventions have shown potential for improving diabetes self-management, their real-world effectiveness may differ across geographic contexts. Diabetes schools, peer support networks, and community health volunteer engagement may produce stronger effects in areas where patients can regularly attend activities, access follow-up care, and maintain contact with health personnel. In contrast, remote rural communities with low service accessibility may experience lower participation, weaker implementation fidelity, and reduced intervention benefit. Thus, geographic accessibility may operate through two interrelated pathways: first, as a direct structural determinant of service utilization, medication continuity, and clinical monitoring; and second, as a contextual moderator that shapes the effectiveness of community-based behavioral interventions [14] and [15].

To address these gaps, this study applies an integrated spatial-behavioral geoinformatics framework to examine diabetes control in Health Region 10, Thailand. The framework positions geographic context as a structural determinant of diabetes outcomes and as a moderator of intervention effectiveness. It combines spatial clustering analysis, E2SFCA accessibility modeling, spatial econometric regression, and GWR to generate decision-grade evidence for precision public health targeting. This integrated approach is intended to move beyond routine mapping by linking disease burden, service accessibility, spatial dependence, and intervention heterogeneity into a single analytical model for equity-oriented chronic disease planning.

This study was guided by three primary objectives: (1) to characterize the spatial distribution of diabetes prevalence and glycemic control across Health Region 10 and identify geographic clusters of high disease burden; (2) to quantify healthcare accessibility to diabetes services using E2SFCA methodology and examine its association with patient-level glycemic control, measured using fasting blood sugar (FBS); and (3) to evaluate the effectiveness of a multi-component community-based behavioral modification intervention and assess whether intervention effects are moderated by baseline geographic accessibility. The study hypothesized that diabetes burden would exhibit significant positive spatial autocorrelation, lower spatial accessibility would be associated with poorer glycemic control after accounting for individual and community-level covariates, and intervention effectiveness would be attenuated in low-accessibility settings where geographic barriers constrain program fidelity and participant engagement.

The expected contribution of this study is twofold. First, it advances geoinformatics-based health equity research by demonstrating how spatial accessibility, spatial dependence, and intervention heterogeneity can be analyzed jointly in a chronic disease context. Second, it provides a practical spatial decision-support framework for regional health authorities seeking to prioritize high-burden, low-access areas, allocate resources more equitably, and strengthen diabetes control under Thailand's UHC system.

2. Methods

2.1 Study Design and Setting

A cross-sectional analytical study was conducted by integrating three complementary research components: (1) spatial epidemiological analysis of diabetes burden and healthcare accessibility patterns; (2) evaluation of a community-based behavioral modification intervention; and (3) spatial econometric modeling to account for spatial dependence and local heterogeneity. This design was selected to link disease distribution, spatial access to diabetes services, and geographically varied intervention outcomes within a single geoinformatics-based analytical framework.

The study was conducted in Health Region 10, northeastern Thailand, covering five provinces: Ubon Ratchathani, Yasothon, Amnat Charoen, Sisaket, and Mukdahan (Figure 1). The region covers approximately 48,138 km² and consists of 70 districts and 611 sub-districts. It is characterized by predominantly rural settlement patterns, agricultural livelihoods, relatively low household income, mixed terrain, border-adjacent communities, and flood-prone areas. These geographic characteristics make the region suitable for evaluating spatial inequities in chronic disease control.

Data collection was conducted between January 2023 and December 2024. All spatial datasets, including sub-district boundaries, healthcare facility locations, road-network data, and patient residence-linked spatial units, were georeferenced to the World Geodetic System 1984 (WGS84). For spatial measurement and network-based distance calculation, the datasets were projected to Universal Transverse Mercator (UTM) Zone 48N. This projection was used to ensure metric accuracy in distance, accessibility, and spatial modeling procedures.

The study unit for spatial epidemiological analysis was the sub-district. The intervention component was implemented in 24 purposively selected communities representing different levels of diabetes burden, healthcare accessibility, and urban-rural context. This multilevel spatial design allowed the study to examine both regional patterns of diabetes burden and local variation in intervention effectiveness.

2.2 Subjects and Ethical Considerations

For the intervention component, 24 communities were purposively selected to represent variation in urban-rural context, baseline diabetes burden, spatial accessibility to diabetes services, and socioeconomic conditions. This sampling strategy was used to ensure that the intervention sites reflected the geographic heterogeneity of Health Region 10 and allowed comparison of intervention outcomes across different accessibility contexts.

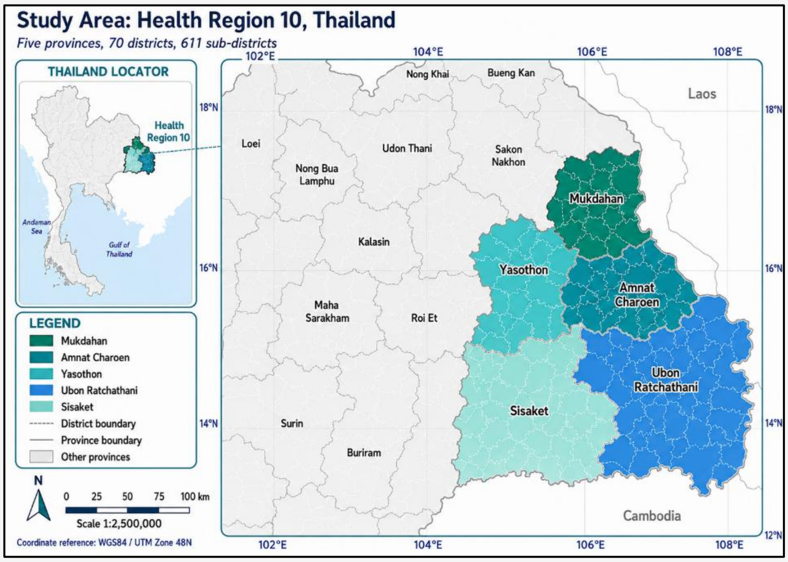

Figure 1: Health Region 10, Thailand

Eligible participants were adults with diagnosed type 2 diabetes mellitus who met the following inclusion criteria: (1) diagnosis of T2DM for at least six months; (2) age between 30 and 70 years; (3) residence in one of the selected study communities; (4) at least one recorded fasting blood sugar (FBS) measurement within three months before baseline assessment; and (5) provision of written informed consent. Participants were excluded if they had severe acute diabetic complications requiring hospitalization, cognitive impairment that limited their ability to provide informed consent, pregnancy, concurrent participation in another structured diabetes intervention program, or planned relocation during the study period. The primary clinical outcome was change in fasting blood sugar between baseline and follow-up. FBS was measured in mg/dL using standard enzymatic laboratory methods at accredited health facilities. Changes in glycemic status were categorized into three groups: (1) decreased FBS, indicating improvement; (2) unchanged FBS, defined as a change within ±5 mg/dL from baseline; and (3) increased FBS, indicating worsening glycemic status. This categorical classification was adopted because HbA1c data were not consistently available in routine surveillance records and because short-term FBS change was considered suitable for evaluating community-level behavioral intervention outcomes.

The study was approved by the Ubon Ratchathani University Human Research Ethics Committee (protocol HE64-156). All participants provided written informed consent before participation. Patient-level data were de-identified before analysis, securely stored, and used only for research purposes. Spatial linkage was performed at aggregated geographic levels to protect participant confidentiality. Data management followed the conditions approved by the institutional ethics committee and complied with Thailand's Personal Data Protection Act B.E. 2562 (2019), which regulates the collection, use, disclosure, and protection of personal data [16].

2.3 Spatial Autocorrelation and Cluster Detection

Diabetes prevalence rates were visualized at the sub-district level using choropleth mapping with quantile classification. This mapping approach was used to examine the geographic distribution of diabetes burden and to provide an initial visual assessment of spatial heterogeneity across Health Region 10. Global Moran's I statistic was calculated to test whether diabetes prevalence showed significant spatial autocorrelation or followed a pattern of complete spatial randomness. Moran's I is a global spatial autocorrelation statistic widely used to assess whether similar values are spatially clustered, dispersed, or randomly distributed across geographic units [17]. The statistic was estimated using a queen-contiguity spatial weights matrix, in which sub-districts sharing either a common boundary or vertex were treated as spatial neighbors. Statistical significance was assessed using 999 random permutation tests at a significance level of $\alpha = 0.05$.

Local Indicators of Spatial Association (LISA) were then computed to identify local clustering patterns. LISA enables the decomposition of global spatial autocorrelation into local spatial association patterns and is commonly used to identify significant local clusters and spatial outliers [18]. Sub-districts were classified into four spatial association categories: high-high clusters, representing high-prevalence areas surrounded by high-prevalence neighbors; low-low clusters, representing low-prevalence areas surrounded by low-prevalence neighbors; high-low outliers, representing high-prevalence areas surrounded by low-prevalence neighbors; and low-high outliers, representing low-prevalence areas surrounded by high-prevalence neighbors. This local cluster analysis was used to identify priority areas for spatially targeted diabetes control. Getis-Ord Gi* hotspot analysis was also applied as a complementary cluster-detection method using distance-based spatial weights. The Getis-Ord family of statistics is designed to detect statistically significant spatial concentrations of high or low values within a defined neighborhood structure [19]. Areas with significant positive Gi* z-scores were interpreted as hotspots, while areas with significant negative Gi* z-scores were interpreted as coldspots.

All spatial autocorrelation and cluster-detection analyses were conducted using GeoDa 1.20 and ArcGIS Pro 3.1. GeoDa was used for exploratory spatial data analysis, global and local spatial autocorrelation, and spatial weights construction [20]. ArcGIS Pro was used for cartographic visualization, spatial data management, and supplementary hotspot mapping [21]. The combined use of Global Moran's I, LISA, and Getis-Ord Gi* strengthened the spatial validity of the analysis by capturing both overall spatial dependence and localized clustering of diabetes burden. The illustration of the spatial autocorrelation and cluster analysis are presented in Figure 2.

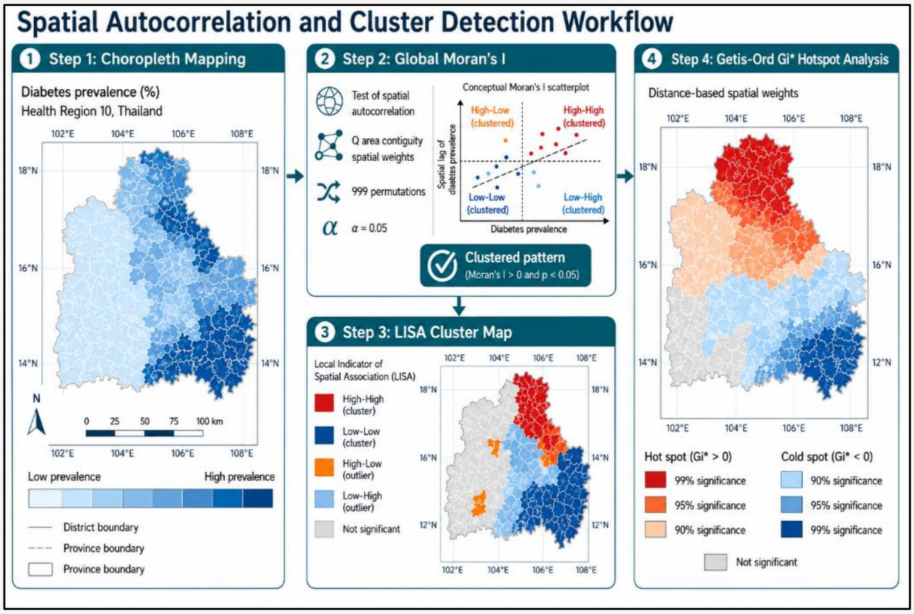

Figure 2: Spatial autocorrelation and cluster detection workflow used to identify global clustering, local clusters, hotspots, and cold spots of diabetes prevalence in Health Region 10, Thailand

2.4 Healthcare Accessibility Modeling

Spatial accessibility to diabetes services was quantified using the Enhanced Two-Step Floating Catchment Area (E2SFCA) method. This method was selected because it improves conventional provider-to-population ratio and straight-line distance measures by incorporating healthcare supply, population demand, catchment thresholds, and distance-decay effects within a GIS-based analytical framework [10] and [11]. In this study, E2SFCA was used to estimate sub-district-level accessibility to diabetes services across Health Region 10. The E2SFCA procedure consisted of two analytical steps. In the first step, a supply-to-demand ratio was calculated for each healthcare facility by dividing weighted service capacity by the diabetes-related population demand within its catchment area. In the second step, the accessibility score for each population location was computed by summing the distance-weighted supply-to-demand ratios of all accessible facilities within the defined catchment. The general distance-decay function was specified in Equation 1:

$$f(d_{ij}) = Exp\left(-\frac{d_{ij}^2}{d_0^2}\right)$$

Equation 1

Where d_{ij} represents travel time or travel distance between population location ***i*** and healthcare facility ***j***, and d_0 represents the catchment threshold. A Gaussian distance-decay function was applied to assign higher weights to nearby facilities and progressively lower weights to distant facilities within the catchment.

The primary catchment threshold was set at 30 km, corresponding approximately to 45 minutes of local travel. This threshold was determined based on consultation with local health officials and community representatives. Travel time was calculated using network analysis on the validated road network. Road speeds were adjusted by road classification: 80 km/h for highways, 60 km/h for provincial roads, and 40 km/h for local roads. To reflect seasonal travel constraints in the study area, travel speeds were reduced by 30% during the rainy season from May to October. Healthcare supply was weighted by facility service capacity, including the number of consultation rooms, operating hours, and availability of diabetes-related clinical personnel. Population demand was estimated using age-adjusted diabetes prevalence at the sub-district level. Sensitivity analyses were conducted using alternative catchment thresholds of 20 km and 40 km and alternative distance-decay parameters. E2SFCA analysis was implemented in Python 3.9 using NetworkX for network-based travel-time estimation and GeoPandas for spatial data processing and geospatial integration [22] and [23].

2.5 Community-Based Behavioral Intervention

The community-based behavioral intervention was designed to improve diabetes self-management through health education, peer support, and strengthened community health volunteer engagement. The intervention was developed to address knowledge, skills, motivation, medication adherence, social support, and continuity of care, which are recognized as essential components of diabetes self-management support [24] and [25]. The intervention consisted of three integrated components.

Component 1: Community Diabetes Schools: Community Diabetes Schools were conducted monthly, with each session lasting approximately two hours. The sessions used interactive and participatory learning methods. The curriculum covered diabetes pathophysiology and complications during months 1–2, dietary modification and meal planning during months 3–4, physical activity and exercise during months 5–6, medication management and adherence during months 7–8, self-monitoring and foot care during months 9–10, and stress management during months 11–12. Sessions were facilitated by trained nurses and dietitians using culturally adapted learning materials, demonstrations, practical activities, and take-home resources. Attendance was recorded, and make-up sessions were offered when participants missed scheduled activities.

Component 2: Peer Support Networks: Peer Support Networks were organized as biweekly 90-minute meetings led by trained peer leaders. Peer leaders were selected from diabetes patients with good glycemic control, communication skills, and leadership potential. Activities included experience sharing, mutual encouragement, problem-solving discussions, group physical activity, and cooking demonstrations. Peer leaders received 16 hours of training in group facilitation, active listening, goal setting, and recognition of warning signs requiring referral. Support groups consisted of 8–12 participants and were formed based on geographic proximity and participant preference.

Component 3: Enhanced Community Health Volunteer Support: Community health volunteers received 24 hours of intensive training in behavioral counseling, medication review, hypoglycemia recognition, referral protocols, lifestyle counseling, and complication screening. Trained volunteers conducted monthly home visits to provide individualized support, assess medication adherence, reinforce lifestyle goals, identify barriers to self-management, and support timely referral when needed. Volunteers received performance-based incentives of 300 Baht per completed visit, monthly supervision, and quarterly refresher training. Implementation fidelity was monitored using attendance logs, session observation records, and community health volunteer visit documentation. A random 20% sample of intervention sessions was observed to assess adherence to intervention protocols. Baseline assessments included FBS measurement, dietary behavior, physical activity, medication adherence, diabetes self-efficacy, diabetes distress, and perceived social support. These measures were used to evaluate participant characteristics and to support interpretation of geographic variation in intervention outcomes.

2.6 Statistical Analysis

Descriptive statistics were calculated to summarize participant characteristics, clinical outcomes, accessibility measures, and community-level variables. Continuous variables with approximately normal distributions were reported as means and standard deviations, while skewed continuous variables were reported as medians and interquartile ranges. Categorical variables were summarized using frequencies and percentages. Baseline characteristics were compared across geographic contexts and accessibility levels to describe the spatial and demographic structure of the study population.

Multilevel linear regression models were specified to evaluate intervention effects while accounting for clustering of participants within communities. Random intercepts were included at the community level to account for intra-community correlation. Fixed effects included time, intervention exposure, time-by-intervention interaction, E2SFCA accessibility score, urban-rural classification, and patient-level covariates including age, sex, diabetes duration, baseline FBS, and comorbidities. Effect modification by geographic accessibility was assessed using interaction terms between intervention exposure and E2SFCA accessibility. Multilevel modeling is appropriate for hierarchically structured health data because it accounts for dependence among observations within higher-level units [26]. To address residual spatial dependence that may violate the independence assumption of conventional regression, spatial econometric models were estimated at the sub-district level. Spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) specifications were considered. Lagrange Multiplier diagnostics were used to guide model selection. A queen-contiguity spatial weights matrix was constructed and row-standardized before model estimation. Direct and indirect effects were calculated where spatial spillover effects were relevant, particularly for spatial Durbin specifications. Spatial econometric modeling was used because spatially correlated outcomes can bias conventional regression estimates and inference [27] and [28].

Geographically weighted regression (GWR) was employed to examine local spatial heterogeneity in the relationship between healthcare accessibility and FBS outcomes. Unlike global regression models, GWR allows parameter estimates to vary across geographic locations, making it suitable for identifying areas where accessibility has stronger or weaker associations with glycemic control. The optimal bandwidth was selected using corrected Akaike Information Criterion (AICc), and adaptive bisquare kernels were applied to accommodate variation in spatial density across the study area. Local coefficient estimates were mapped to visualize geographic variation in the accessibility–FBS relationship. GWR and related geographically weighted models are widely used to explore spatial non-stationarity in relationships between explanatory variables and outcomes [29] and [30].

All statistical tests were two-tailed, with statistical significance set at $\alpha = 0.05$. Missing data, which accounted for less than 5% of most variables, were handled using multiple imputation with 20 imputed datasets under the missing-at-random assumption. Multiple imputation by chained equations was applied to reduce bias associated with incomplete covariate data [31]. Statistical power calculations indicated 80% power to detect an intervention effect size of Cohen's d = 0.35 and an accessibility association equivalent to $R^2 = 0.15$, given the study sample size and design. Statistical and spatial analyses were conducted using Stata 17, R 4.2, Python 3.9, and relevant spatial analysis packages, including spatialreg and GWmodel.

3. Results

3.1 Baseline Characteristics and Sample Description

A total of 1,847 patients with type 2 diabetes from 24 communities participated in the intervention evaluation. Complete baseline and follow-up data were available for 1,692 participants, corresponding to a retention rate of 91.6%. The study sample was predominantly female, with women accounting for 63.2% of participants. The mean age was 58.4 years (SD = 8.9; range: 30–70 years), and the mean duration of diabetes was 7.3 years (SD = 4.8).

At baseline, the mean FBS level was 8.6% (SD = 1.4%), and 78.3% of participants were classified as having poor glycemic control using the study-defined threshold of FBS ≥ 7%. Most participants were enrolled in the Universal Coverage Scheme (82.1%), followed by the Civil Servant Medical Benefit Scheme (13.4%) and the Social Security Scheme (4.5%). Educational attainment was generally low: 45.8% of participants had completed only primary education, while 31.2% had no formal education. Most participants were engaged in agricultural occupations (71.4%). The median monthly household income was 8,500 Baht (IQR: 5,000–15,000 Baht). Common comorbidities included hypertension (68.9%), dyslipidemia (52.3%), and obesity, defined as BMI ≥ 25 kg/m² (41.7%). These baseline characteristics indicate that the intervention population represented a predominantly rural, socioeconomically vulnerable diabetes population with a high burden of uncontrolled glycemia and cardiometabolic comorbidity. Detailed baseline characteristics by intervention group and geographic context are presented in Table 1.

Table 1: Mean HbA1c levels by healthcare accessibility quintile

Accessibility quintile	Mean HbA1c (%) ± SD
Q1 (Lowest)	8.4 ± 1.2
Q2	7.9 ± 1.1
Q3	7.5 ± 1.0
Q4	7.2 ± 0.9
Q5 (Highest)	6.9 ± 0.8

3.3 Healthcare Accessibility and Glycemic Control

E2SFCA accessibility scores showed substantial spatial variation across sub-districts, indicating marked geographic inequity in access to diabetes services. Lower healthcare accessibility was consistently associated with poorer glycemic control. Mean HbA1c levels decreased progressively from the lowest to the highest accessibility quintile, suggesting a clear accessibility–glycemic control gradient. Multilevel regression analysis further confirmed the independent association between spatial accessibility and glycemic control. After adjustment for age, sex, diabetes duration, comorbidities, socioeconomic status, and community-level clustering, higher E2SFCA accessibility was significantly associated with lower HbA1c levels ($\beta = -0.23$, 95% CI: -0.35 to -0.11, $p < 0.001$). This result indicates that each one-unit increase in the E2SFCA accessibility score was associated with a 0.23 percentage-point lower HbA1c value.

Distance-band analysis showed a similar pattern. Participants residing more than 20 km from comprehensive diabetes services had significantly poorer glycemic control than those living within 5 km of such services, with an adjusted mean HbA1c difference of +1.1 percentage points (95% CI: 0.8 to 1.4, $p < 0.001$). These findings indicate that spatial accessibility to diabetes services is strongly associated with glycemic outcomes, even after controlling for individual-level and community-level factors.

3.2 Spatial Distribution and Clustering of Diabetes Burden

Sub-district-level diabetes prevalence in Health Region 10 ranged from 3.2% to 14.8%, with a regional mean of 8.9% (SD = 2.3%). The choropleth visualization revealed a non-uniform spatial pattern of diabetes burden across the 611 sub-districts, with higher-prevalence areas concentrated in specific geographic zones rather than evenly distributed across the region (Figure 3). Global spatial autocorrelation analysis confirmed that diabetes prevalence was significantly clustered. Global Moran's I was 0.342 ($p < 0.001$), indicating positive spatial autocorrelation and rejecting the null hypothesis of complete spatial randomness. This result demonstrates that sub-districts with similar diabetes prevalence values were more likely to be located near one another.

Local cluster analysis further identified distinct spatial patterns of diabetes burden. LISA results classified 187 sub-districts (14.9%) as high-high clusters, indicating high-prevalence sub-districts surrounded by neighboring sub-districts with similarly high prevalence. These clusters were predominantly located in border-adjacent districts of Ubon Ratchathani and Sisaket provinces. In contrast, 142 sub-districts (11.3%) were classified as low-low clusters, indicating low-prevalence sub-districts surrounded by neighboring sub-districts with similarly low prevalence, mainly in central urban areas.

Spatial outlier patterns were also detected. A total of 23 sub-districts were classified as high-low outliers, representing high-prevalence sub-districts surrounded by lower-prevalence neighboring areas. Another 31 sub-districts were classified as low-high outliers, representing low-prevalence sub-districts surrounded by higher-prevalence neighboring areas. These outlier locations indicate local discontinuities in the spatial distribution of diabetes burden. Getis-Ord Gi* hotspot analysis supported the LISA findings. Statistically significant hotspots (Gi* > 1.96, $p < 0.05$) were concentrated in peripheral rural zones, while coldspot patterns were observed in areas with relatively lower diabetes prevalence. Taken together, the choropleth mapping, Global Moran's I, LISA, and Getis-Ord Gi* analyses demonstrate clear spatial dependence and localized clustering of diabetes burden in Health Region 10.

3.3 Healthcare Accessibility and Glycemic Control

E2SFCA accessibility scores varied widely across sub-districts, ranging from 0.08 to 4.73, with a mean score of 1.42 (SD = 0.89). This variation indicates substantial geographic inequity in access to diabetes services across Health Region 10. Urban sub-districts demonstrated markedly higher accessibility scores (mean = 3.21) than rural sub-districts (mean = 1.08) and remote rural sub-districts (mean = 0.45). Glycemic control also showed notable geographic variation.

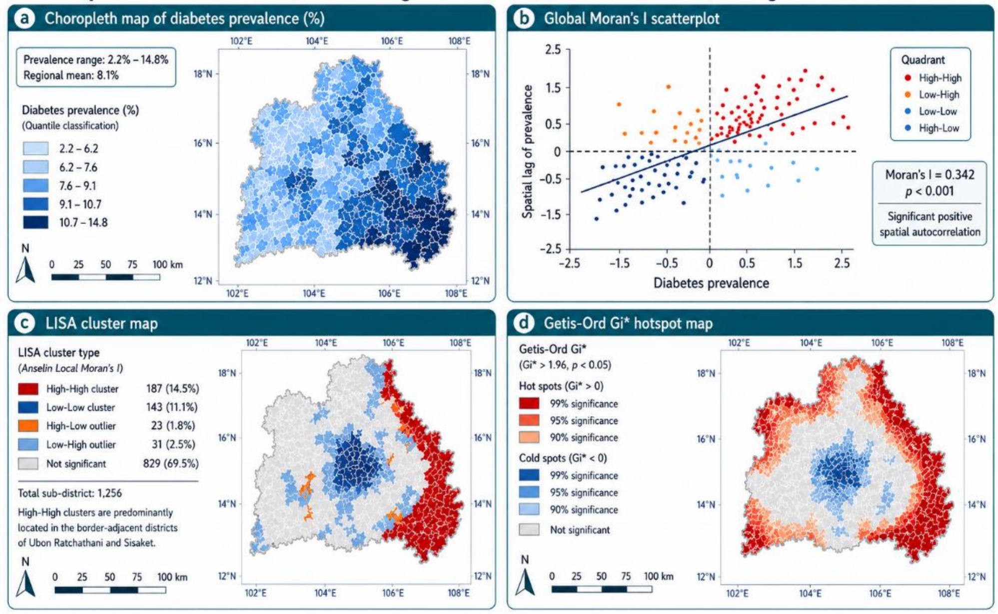

Figure 3: Spatial distribution and clustering of diabetes prevalence in Health Region 10, Thailand: (a) diabetes prevalence by sub-district, (b) Global Moran's I scatterplot, (c) LISA cluster map, and (d) Getis-Ord Gi hotspot

Mean HbA1c levels across sub-districts ranged from 6.8% to 9.2%, with a regional mean of 7.8% (SD = 0.6%). Lower healthcare accessibility was consistently associated with poorer glycemic control. When stratified by E2SFCA accessibility quintiles, mean HbA1c declined progressively from the lowest to the highest accessibility quintile. The lowest accessibility quintile (Q1) had the highest mean HbA1c level at 8.4% (SD = 1.2), whereas the highest accessibility quintile (Q5) had the lowest mean HbA1c level at 6.9% (SD = 0.8), demonstrating a clear accessibility–glycemic control gradient (Table 1).

Multilevel regression analysis confirmed the independent association between spatial accessibility and glycemic control. After adjustment for age, sex, diabetes duration, comorbidities, socioeconomic status, and community-level clustering, higher E2SFCA accessibility was significantly associated with lower HbA1c levels (β = -0.23, 95% CI: -0.35 to -0.11, $p < 0.001$). This finding indicates that each one-unit increase in the E2SFCA accessibility score was associated with a 0.23 percentage-point reduction in HbA1c. Distance-band analysis showed a consistent pattern. Participants residing more than 20 km from comprehensive diabetes services had significantly poorer glycemic control than those living within 5 km, with an adjusted mean HbA1c difference of +1.1 percentage points (95% CI: 0.8 to 1.4, $p < 0.001$). These findings demonstrate that spatial accessibility to diabetes services was strongly associated with glycemic outcomes, even after adjustment for individual-level and community-level covariates.

3.4 Intervention Outcomes and Geographic Moderation

Implementation fidelity varied substantially across geographic contexts. Urban and peri-urban communities achieved higher mean session attendance rates (78.4%, SD = 12.3%) than remote rural communities (51.7%, SD = 18.9%; $p < 0.001$), indicating unequal program participation across accessibility settings. Overall, the community-based behavioral intervention produced a significant reduction in fasting blood sugar (FBS) from baseline, with a mean change of -0.9 mg/dL (95% CI: -1.1 to -0.7; $p < 0.001$). However, intervention effectiveness showed clear geographic heterogeneity. Urban settings demonstrated the largest FBS reduction (mean = -1.2 mg/dL, 95% CI: -1.5 to -0.9), followed by peri-urban areas (mean = -0.8 mg/dL, 95% CI: -1.1 to -0.5) and remote rural sites (mean = -0.4 mg/dL, 95% CI: -0.7 to -0.1).

Multilevel models testing effect modification showed a statistically significant interaction between baseline E2SFCA accessibility and intervention effectiveness ($\beta_{\text{interaction}}$ = 0.18, p = 0.003). This result indicates that intervention benefits were attenuated in low-accessibility settings. In other words, communities with lower spatial accessibility to diabetes services experienced smaller improvements in FBS after the intervention than communities with higher accessibility. These findings demonstrate that geographic accessibility moderated intervention effectiveness. Although the behavioral intervention improved glycemic outcomes overall, its impact was weaker in remote rural communities where lower accessibility may have constrained participation, continuity of support, and implementation fidelity.

4. Discussion

This geospatial analysis demonstrates that diabetes burden, healthcare accessibility, and intervention effectiveness in Health Region 10 are strongly structured by geographic context. The findings show three major patterns: first, diabetes prevalence was spatially clustered rather than randomly distributed; second, lower E2SFCA accessibility was associated with poorer glycemic control, measured by HbA1c; and third, the effectiveness of the community-based behavioral intervention varied by geographic accessibility. Together, these results indicate that geographic inequity is not only a background characteristic of diabetes care but also a measurable determinant of clinical outcomes and a moderator of intervention impact.

Recent studies published in the *International Journal of Geoinformatics* have emphasized the growing role of GIS in health disparity analysis, disease surveillance, healthcare service coverage, spatial disease modeling, and health preparedness [32][33][34][35] and [36]. These studies support the use of geospatial methods to identify where health risks are concentrated, where service coverage is inadequate, and where policy responses should be spatially prioritized. The present study extends this line of geoinformatics research by applying spatial clustering analysis, E2SFCA accessibility modeling, spatial econometric modeling, and geographically differentiated intervention assessment to diabetes control in northeastern Thailand. The significant positive spatial autocorrelation of diabetes prevalence, indicated by Global Moran's I, confirms that high-burden and low-burden sub-districts were geographically patterned. LISA and Getis-Ord Gi* analyses further identified local clusters, spatial outliers, hotspots, and coldspots. These findings are consistent with recent IJG health-geoinformatics studies showing that GIS-based disease surveillance can reveal spatial concentrations and temporal-spatial disease patterns that are not visible through conventional aggregate reporting [35] and [36]. For diabetes control, this means that regional averages may conceal localized high-burden areas that require intensified screening, follow-up, health education, and resource allocation.

The E2SFCA results provide additional evidence that diabetes service accessibility is unevenly distributed across Health Region 10. Urban sub-districts had substantially higher accessibility scores than rural and remote rural sub-districts, reflecting differences in facility availability, service capacity, travel distance, and road-network connectivity. The observed accessibility HbA1c gradient indicates that patients in lower-accessibility areas experienced poorer glycemic control. This finding is aligned with IJG evidence showing the utility of GIS for analyzing health center service coverage, spatial health disparities, hospital coverage areas, and response-time constraints [32] and [33]. In the context of Thailand's Universal Health Coverage system, the present findings suggest that legal or financial entitlement to care must be complemented by spatially realistic access to services.

The intervention results demonstrate that community-based behavioral programs may not produce uniform effects across space. Although the intervention significantly reduced HbA1c overall, urban communities experienced larger improvements than peri-urban and remote rural communities. The significant interaction between baseline E2SFCA accessibility and intervention effectiveness suggests that geographic accessibility moderated intervention outcomes. Low-accessibility settings may reduce attendance, weaken implementation fidelity, limit continuity of follow-up, and constrain the ability of community health volunteers to provide consistent support. This finding strengthens the argument that behavioral interventions should be geographically adapted rather than implemented as a uniform package across heterogeneous rural-urban contexts.

From a geoinformatics perspective, the main contribution of this study is the integration of spatial clustering analysis, E2SFCA accessibility modeling, spatial econometric regression, and geographically weighted regression into a single decision-support framework. This approach moves beyond descriptive mapping by linking disease burden, service accessibility, spatial dependence, and intervention heterogeneity. Recent IJG studies have similarly demonstrated that GIS can support public health decision-making by integrating spatial data, health indicators, service infrastructure, and disease-risk information into operational planning frameworks [32][34] and [36]. The present study advances this direction by showing how spatial methods can be applied not only to disease surveillance but also to chronic disease intervention evaluation.

The use of spatial econometric modeling and geographically weighted regression further strengthens the methodological contribution of the study. Spatial econometric analysis accounts for spatial dependence that may bias conventional regression estimates, while GWR enables the identification of local variation in the relationship between healthcare accessibility and glycemic control. This is particularly important for chronic disease management because accessibility effects may not be spatially uniform. Areas with low baseline accessibility may experience greater marginal benefit from service expansion, mobile clinics, or strengthened community health volunteer support. This local heterogeneity is central to precision public health and spatially targeted resource allocation.

These findings have direct policy implications for diabetes control in Health Region 10. First, high-burden and low-accessibility sub-districts should be prioritized for targeted resource allocation. Second, remote rural communities may require additional implementation support, including mobile diabetes clinics, transport-sensitive appointment systems, strengthened community health volunteer coverage, and digitally supported follow-up. Third, regional health authorities should consider establishing a GIS-based diabetes monitoring dashboard that integrates diabetes prevalence, HbA1c outcomes, facility capacity, road-network accessibility, E2SFCA scores, and intervention performance indicators. Such a system would support continuous monitoring of spatial inequities and provide evidence for adaptive resource allocation.

This study has several limitations. First, the cross-sectional analytical component limits causal interpretation of the association between spatial accessibility and glycemic control. Second, although E2SFCA improves accessibility measurement, travel-time estimates may still be affected by unmeasured local conditions such as seasonal flooding, informal transport routes, and household-level mobility constraints. Third, the intervention communities were purposively selected rather than randomly sampled, which may limit generalizability. Fourth, routine health data may contain measurement variation across facilities. Nevertheless, the integration of multiple geospatial analytical methods provides robust evidence that geographic context matters for diabetes control and intervention implementation.

Consistent with this interpretation, related geospatial and community health studies in Thailand have demonstrated that spatial information, surveillance-system design, service delivery assessment, and community-based implementation capacity are important for localized public health action. A dengue hemorrhagic fever surveillance model in Si Sa Ket Province showed that GIS can support the identification of disease-risk populations and provincial surveillance-system development [37]. Evidence from COVID-19 crisis-management systems, vaccination-service assessment, and risk perception with preventive behaviors further indicates that public health responses require integration of disease burden, service capacity, community behavior, and operational preparedness [38][39] and [40]. In addition, evidence on public health professional competencies and community-based self-care intervention highlights the importance of local implementation capacity when health outcomes depend on service access, patient behavior, and continuity of support [41] and [42]. These studies reinforce the present study's argument that spatially explicit analysis can be extended from infectious disease surveillance to chronic disease equity, healthcare accessibility assessment, and geographically differentiated intervention planning.

Overall, the results support a shift from uniform chronic disease programming toward spatially targeted diabetes control. Geographic accessibility should be treated as a structural determinant of diabetes outcomes and as a key consideration in intervention design. For Health Region 10, improving diabetes equity will require not only community-level behavioral interventions but also spatially explicit service planning that prioritizes high-burden, low-access areas. This geoinformatics-based approach can strengthen evidence-based resource allocation and support more equitable chronic disease management under Thailand's Universal Health Coverage system.

5. Conclusions

Health Region 10 exhibits pronounced spatial inequities in diabetes burden, healthcare accessibility, and glycemic control. Diabetes prevalence was spatially clustered across sub-districts, and lower E2SFCA accessibility was associated with poorer HbA1c outcomes. The findings also showed that community-based behavioral intervention effects were geographically heterogeneous, with weaker improvements observed in low-accessibility and remote rural settings. Geographic accessibility therefore functions as both a structural determinant of diabetes outcomes and a moderator of intervention effectiveness. These results indicate that uniform diabetes intervention models are insufficient for achieving equitable glycemic control across spatially diverse settings. Under Thailand's Universal Health Coverage system, equity in health entitlement should be complemented by equity in practical geographic access to diabetes services.

Achieving equitable diabetes control in Health Region 10 requires spatially targeted strategies, including prioritizing high-burden and low-accessibility hotspots, strengthening implementation support in remote rural communities, expanding mobile or outreach diabetes services, enhancing community health volunteer capacity, and integrating GIS-based monitoring into routine chronic disease management. A spatial decision-support system combining diabetes prevalence, HbA1c outcomes, healthcare facility capacity, road-network accessibility, E2SFCA scores, and intervention performance indicators would support more precise resource allocation and continuous monitoring of health inequities. Overall, this study demonstrates the value of geoinformatics for chronic disease control. By integrating spatial clustering analysis, accessibility modeling, spatial econometric analysis, and geographically differentiated intervention evaluation, the study provides evidence that place matters in diabetes management. Spatially explicit planning should therefore be embedded into regional diabetes control policy to improve equity, strengthen intervention effectiveness, and support precision public health under universal health coverage.

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References

[1] International Diabetes Federation. (2021), *IDF Diabetes Atlas*. 10th ed. Brussels: International Diabetes Federation. [Online]. Available: https://diabetesatlas.org/. [Accessed: Apr. 15, 2026].

[2] Saeedi, P., Petersohn, I., Salpea, P., Malanda, B., Karuranga, S., Unwin, N., Colagiuri, S., Guariguata, L., Motala, A. A., Ogurtsova, K., Shaw, J. E., Bright, D., Williams, R. and IDF Diabetes Atlas Committee (2019), Global and Regional Diabetes Prevalence Estimates for 2019 And Projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition. *Diabetes Research and Clinical Practice*, Vol. 157; 107843. https://doi.org/10.1016/j.diabres.2019.107843

[3] Aekplakorn, W., Chariyalertsak, S., Kessomboon, P., Sangthong, R., Inthawong, R. and Putwatana, P., (2011). Prevalence and Management of Diabetes and Metabolic Risk Factors in Thai Adults: The Thai National Health Examination Survey IV. *Diabetes Care*. Vol. 34(9); 1980–1985. https://doi.org/10.2337/dc11-0099.

[4] World Health Organization. (2016). Global Report on Diabetes. Geneva: World Health Organization. [Online]. Available: https://www.who.int/publications/i/item/9789241565257. [Accessed: Apr. 15, 2026].

[5] Guagliardo, M., F., (2004). Spatial Accessibility of Primary Care: Concepts, Methods and Challenges. *International Journal of Health Geographics*. Vol. 3(3). https://doi.org/10.1186/1476-072X-3-3.

[6] Apparicio, P., Abdelmajid, M., Riva, M. and Shearmur, R., (2008). Comparing Alternative Approaches to Measuring the Geographical Accessibility of Urban Health Services: Distance Types and Aggregation-Error Issues. *International Journal of Health Geographics*. Vol. 7(7). https://doi.org/10.1186/1476-072X-7-7.

[7] Luo, W. and Wang, F., (2003). Measures of Spatial Accessibility to Health Care in a GIS Environment: Synthesis and a Case Study in the Chicago Region. *Environment and Planning B: Planning and Design*. Vol. 30(6); 865–884. https://doi.org/10.1068/b29120.

[8] Anselin, L., (1995), Local Indicators of Spatial Association-LISA. *Geographical Analysis*. Vol. 27(2); 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

[9] Getis, A. and Ord, J. K., (1992). The Analysis of Spatial Association by use of Distance Statistics. *Geographical Analysis*. Vol. 24(3); 189–206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x.

[10] Luo, W. and Qi, Y., (2009). An Enhanced Two-Step Floating Catchment Area Method for Measuring Spatial Accessibility to Primary Care Physicians. *Health & Place*. Vol. 15(4); 1100–1107. https://doi.org/10.1016/j.healthplace.2009.06.002.

[11] Wan, N., Zou, B. and Sternberg, T., (2012). A Three-Step Floating Catchment Area Method for Analyzing Spatial Access to Health Services. *International Journal of Geographical Information Science*. Vol. 26(6); 1073–1089. https://doi.org/10.1080/13658816.2011.624987.

[12] LeSage, J. P. and Pace, R., K., (2009). *Introduction to Spatial Econometrics*. CRC Press. Florida.

[13] Fotheringham, A., S., Brunsdon, C. and Charlton, M., (2002). Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Wiley, Chichester.

[14] World Health Organization. (2019). *Classification of diabetes mellitus. Geneva: World Health Organization.* [Online]. Available: https://www.who.int/publications/i/item/classification-of-diabetes-mellitus. [Accessed: Apr. 15, 2026].

[15] American Diabetes Association Professional Practice Committee. (2024). Standards of Care in Diabetes—2024. Diabetes Care. Vol.47; S1–S350. https://doi.org/10.2337/dc24-SINT.

[16] Royal Thai Government Gazette. (2019). *Personal Data Protection Act B.E. 2562. Royal Thai Government Gazette*. Vol. 136(69A); 52–95. [Online]. Available: https://ratchakitcha.soc.go.th/documents/17082307.pdf. [Accessed: Apr. 15, 2026].

[17] Moran, P. A. P., (1950). Notes on Continuous Stochastic Phenomena. *Biometrika*. Vol. 37(1–2); 17–23. https://doi.org/10.1093/biomet/37.1-2.17.

[18] Jubit, N., Masron, T., Ridzuan, M., Ahmad, A. and Yoshinari, K., (2024). Revealing Adolescent Drug Trafficking and Addiction: Exploring School Disciplinary and Drug Issues in the Federal Territory of Kuala Lumpur and Selangor, Malaysia. *International Journal of Geoinformatics*, Vol. 20(6); 1–12. https://doi.org/10.52939/ijg.v20i6.3327.

[19]Sae-ngow, P., Kulpanich, N., Worachairungreung, M., Ngansakul, P. and Prasert, T., (2024). Geospatial Analysis for Identifying Blackspots on National and Rural Highways in Thailand. *International Journal of Geoinformatics*, Vol. 20(4); 29–42. https://doi.org/10.52939/ijg.v20i4.3147.

[20] Anselin, L., Syabri, I. and Kho, Y., (2006). GeoDa: An introduction to Spatial Data Analysis. *Geographical Analysis*. Vol. 38(1); 5–22. https://doi.org/10.1111/j.0016-7363.2005.00671.x.

[21] Esri. (2024). ArcGIS Pro: Essential Workflows. Redlands, CA: Environmental Systems Research Institute. [Online]. Available: https://pro.arcgis.com/en/pro-app/latest/get-started/essential-arcgis-pro-vocabulary.htm. [Accessed: Apr. 15, 2026].

[22] Hagberg, A., A., Schult, D., A. and Swart, P., J., (2008). *Exploring Network Structure, Dynamics, and Function using Network*. Proceedings of the 7th Python in Science Conference. 11–15.

[23] Jordahl, K., Van den Bossche, J., Fleischmann, M., Wasserman, J., McBride, J., Gerard, J., Tratner, J., Perry, M., Badaracco, A. G., Farmer, C., Hjelle, G. A., Snow, A. D., Cochran, M., Gillies, S., Culbertson, L., Bartos, M., Eubank, N., Maxalbert, B. A., Rey, S., Ren, C., Arribas-Bel, D., Wasser, L., Wolf, l. J., Journois, M., Wilson, J., Greenhall, A., Holdgraf, C. F. and Leblanc, F., (2020). *GeoPandas: Python Tools for Geographic Data. Zenodo*. [Online]. Available: https://zenodo.org/records/3946761. [Accessed: Apr. 15, 2026].

[24] Powers, M. A., Bardsley, J. K., Cypress, M., Funnell, M. M., Harms, D., Hess-Fischl, A., Hooks, B., Isaacs, D., Ellen, D. M., Maryniuk, M. D., Norton, A., Rinker, J., Siminerio, L. M. and Uelmen, S., (2020). Diabetes Self-Management Education and Support in Adults with Type 2 Diabetes: A Consensus Report. *Diabetes Care*. Vol. 43(7);1636–1649. https://doi.org/10.2337/dci20-0023.

[25] Yimer, Y. S., Addissie, A., Kidane, E. G., Reja, A., Abdela, A. A. and Ahmed, A. A., (2025). Effectiveness of Diabetes Self-Management Education and Support Interventions on Glycemic Levels among People Living with Type 2 Diabetes in the WHO African Region: A Systematic Review and Meta-Analysis. *Frontiers in Clinical Diabetes and Healthcare*. Vol. 3(6). https://doi.org/10.3389/fcdhc.2025.1554524.

[26] Bates, D., Mächler, M., Bolker, B. and Walker, S., (2015). Fitting Linear Mixed-Effects Models using Lme4. *Journal of Statistical Software*. Vol. 67(1); 1–48. https://doi.org/10.18637/jss.v067.i01.

[27] Bivand, R. S., Pebesma, E. and Gómez-Rubio, V., (2013). Applied Spatial Data Analysis with R. 2nd ed. Springer. New York. https://doi.org/10.1007/978-1-4614-7618-4.

[28] Tang, Z., Zhang, Z., Zuo, L., Wang, X., Hu, S. and Zhu, Z., (2020). Spatial Econometric Analysis of the Relationship between Urban Land and Regional Economic Development in the Beijing–Tianjin–Hebei Coordinated Development Region. *Sustainability*. Vol. 12(20). https://doi.org/10.3390/su12208451.

[29] Gollini, I., Lu, B., Charlton, M., Brunsdon, C. and Harris, P., (2015). GWmodel: An R Package for Exploring Spatial Heterogeneity using Geographically Weighted Models. *Journal of Statistical Software*. Vol. 63(17); 1–50. https://doi.org/10.18637/jss.v063.i17.

[30] Fotheringham, A., S., Brunsdon, C. and Charlton, M., (2002). Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Wiley, Chichester.

[31] van Buuren, S. and Groothuis-Oudshoorn, K., (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software.* Vol. 45(3); 1–67. https://doi.org/10.18637/jss.v045.i03.

[32] Piwpong, R., Sujayanont, P., Jundaeng, J., Krates, J., Kijphati, R. and Nithikathkul, C., (2025). Applications of GIS in Analyzing Health Disparities Among the Elderly and Health Center Service Area Coverage: Community Model, Lahansai District, Buriram, Thailand. *International Journal of Geoinformatics*. Vol. 21(4); 131–148. https://doi.org/10.52939/ijg.v21i4.4075.

[33] Thipthimwong, K., Panawathanapisuit, S., Thonthong, T., Yamsri, T. and Plubplatong, T., (2024). A Geographic Information Systems-Based Analysis of Response Time and Hospital Coverage Area in Sukhothai Province, Thailand. *International Journal of Geoinformatics*, Vol. 20(8); 46–55. https://doi.org/10.52939/ijg.v20i8.3449.

[34] Thammaboribal, P., Tripathi, N. K., Junpha, J., Lipiloet, S. and Wongpituk, K., (2024). Examining the Correlation between COVID-19 Prevalence and Patient Behaviors, Healthcare, and Socioeconomic Determinants: A Geospatial Analysis of ASEAN Countries. *International Journal of Geoinformatics*. Vol. 20(3); 95–112. https://doi.org/10.52939/ijg.v20i3.3159.

[35] Samphutthanont, R. and Koyadun, S., (2024). Spatial-Temporal Distribution Pattern of Dengue Fever and Spatial Relationship of the Aedes Mosquito Larvae Index in Phuket Province. *International Journal of Geoinformatics*. Vol. 20(8); 29–45. https://doi.org/10.52939/ijg.v20i8.3447.

[36] Laosupap, K., Wongpituk, K., Butsorn, A., Boonsang, A., Thammaboribal, P., Chankong, W. and Pokomnird, C., (2024). Advancements in Disease Surveillance: The Role of GIS in Global Health Preparedness. *International Journal of Geoinformatics*. Vol. 20(10); 95–108. https://doi.org/10.52939/ijg.v20i10.3663.

[37] Wongpituk, K., Kalayanarooj, S. and Nithikathkul, C., (2020). Geospatial Analysis of DHF Surveillance Model in Si Sa Ket Province, Thailand using Geographic Information System. *International Journal of Geoinformatics*, Vol. 16(3); 97–104. https://ijg.e-geoinfo.com/index.php/journal/article/view/1785.

[38] Laosupap, K., Boonsang, A., Butsorn, A., Tubtimhin, S., Semrum, W., Kamuttachat, K., Chaaumphan, A., and Wongpituk, K., (2024). Development of Systems and Mechanisms for Managing the Coronavirus Disease 2019 Crisis in Det Udom District, Ubon Ratchathani Province, Thailand. *International Journal of Geoinformatics*, Vol. 20(3); 81–94. https://doi.org/10.52939/ijg.v20i3.3139.

[39] Polin, S., Lokavee, S., Sukdee, S., Junpha, J., Harnwunggmoung, A., Samngamdee, M., Ampant, P., Thammaboribal, P. and Wongpituk, K., (2024). Assessment of COVID-19 Vaccination Services During the 5th Wave of the Outbreak in Thailand. *International Journal of Geoinformatics*, Vol. 20(3); 28–36. https://doi.org/10.52939/ijg.v20i3.3125.

[40] Wongpituk, K., Tanthanapanyakorn, P., Sanguanchue, A., Saykaew, T. and Chankong, W., (2021). Perception of Risk, Severity of Disease and Preventive Behaviors of COVID-19 in a New Epidemic Situation among People in Samut Songkhram Province, Thailand. *International Journal of Geoinformatics*, Vol. 17(5); 90–99. https://doi.org/10.52939/ijg.v17i5.2017.

[41] Chankong, W., Noiwat, O., Kaladee, K., Jitaram, P. and Wongpituk, K., (2024). Core Competencies in Administration for Meeting Standard Position Requirements in Public Health Professionals. *International Journal of Geoinformatics*, Vol. 20(10), 58–64. https://doi.org/10.52939/ijg.v20i10.3645.

[42] Tanthanapanyakorn, P., Sanguanchue, A., Khuntikulanon, N., Chanmalee, S., Cetthakrikul, S. and Wongpituk, K., (2021). Effectiveness of the Self-Care Sandbag Exercise Program for the Osteoarthritis of Knee Patients in the Secondary Care in Thailand: Randomized Control Trial. *International Journal of Geoinformatics*, Vol. 17(5), 195–204. https://doi.org/10.52939/ijg.v17i5.2051.