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Diabetes prevalence in the state of Alabama: identifying the risk factors

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Abstract

Diabetes mellitus, a chronic metabolic disorder characterized by elevated blood glucose, remains a pressing public health challenge in the United States. This study aims to identify spatial clusters of diabetes and examine associated factors at a granular scale using the state of Alabama. Data on diabetes prevalence, socioeconomic, environmental and behavioural risk factors were extracted at the census tract level from the CDC PLACES Project. Moran's I and Getis-Ord Gi* were first used to assess the spatial autocorrelation and spatial clusters of diabetes, respectively. Due to the existence of spatial autocorrelation (Moran's $I = 0.275$, $p<0.001$) of diabetes prevalence, three additional spatial statistical techniques, including the Spatial Lag Model (SLM), the Spatial Error Model (SEM) and Geographically Weighted Regression (GWR), were used to examine its associated factors while detecting the local spatial variations. Several significant clusters of high diabetes prevalence were found in most counties in the middle, known as the Black Belt. The GWR model ($R^2 = 0.921$ & AICc = 2414.0) outperformed SLM and SEM and was therefore used to explore the strong spatial heterogeneity in the associated risk factors. Statistically significant predictors identified were smoking, drinking, obesity, poverty, and age 65+. These localized findings enable governments to develop interventions targeting risk factors to address diabetes prevalence in the state of Alabama.

Key words: diabetes prevalence, risk factors, spatial statistics, Geographically Weighted Regression (GWR), Alabama, USA.

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Introduction

Diabetes mellitus is a multifaceted chronic disease influenced by an array of interactions mainly behavioural, socioeconomic, demographic and environmental factors. Epidemiological research has consistently focused on behavioural risk factors such as smoking, alcohol consumption, physical inactivity, obesity and inadequate sleep as primary drivers of diabetes risk (Lu *et al*., 2025). Socioeconomic factors such as poverty, unemployment, low educational attainment, and food insecurity exacerbate the exposure to these behaviours by constraining access to healthy food, healthcare services, and opportunities for physical activity (Bazzano *et al*., 2024). Demographic characteristics, such as age, also influence diabetes prevalence as diabetes, which is significantly common among older adults due to cumulative exposure to risk factors and age-related physiological vulnerability (McDaniel & Chou, 2022). Altogether, these determinants do not operate in the same way across space rather, there exist geographical clusters and these interacts with localized social and economic contexts producing an uneven pattern of diabetes prevalence (Manu *et al*., 2025). This spatial epidemiological perspective emphasizes that neighbourhood-level conditions act as contextual risk environments, reinforcing the need for geographically explicit analytical approaches.

The disease can lead to severe conditions such as blindness, renal disease, amputation, cardiovascular disease. It thus poses a substantial impact on the health and economy of nations around the world (Jiang *et al*., 2023). Currently, over 537 million adults are affected, and diabetes is one of the most pressing global health challenges of the 21st century (Matthews *et al*., 2024; Zhu *et al*., 2024). Across the globe, the United States (U.S.) has consistently ranked among nations with the highest prevalence of diabetes (Manu, 2025; Morrato *et al*., 2007). Approximately, one in three persons in the U.S. has prediabetes, which is defined as higher than normal blood sugar level but not yet high enough for a Type 2 diabetes diagnosis. In total, nearly 136 million adults are either living with diabetes or prediabetes nationwide (Manu & Gamage, 2025; Parab *et al*., 2025). Out of this figure, 38.4 million are assumed to have diabetes, but with just 29.7 million persons diagnosed, 8.7 million remains undiagnosed and therefore not receiving treatment (Johnson *et al*., 2020). Diabetes has significant economic implications for the U.S., with an estimated cost as of 2022 of 412.9 billion USD, which includes 306.6 billion in direct medical costs and 106.3 billion in indirect costs attributed to diabetes (Parker *et al*., 2024).

In the U.S., the region with the highest rate of diabetes is the south-eastern region, with a prevalence in the diabetes belt of 11.7% (95% CI=11.4%, 12.0%) (Barker *et al*., 2011; Abdurashidova *et al*., 2024). Alabama is one of the states with the highest prevalence of diabetes, with a rate of 14.9 % (Lee *et al*., 2022). Despite this striking prevalence, little is known about hotspots and the associated social, economic, and environmental factors that drive this exceptionally high diabetes rate. Although national and state-level estimates provide valuable overviews, they obscure important spatial differences that might occur at finer geographic scales. Aggregated statistics can therefore mask vulnerable localities where socioeconomic deprivation, environmental conditions and healthcare shortages converge to heighten disease risk (Correya *et al.*, 2020). Understanding these within-state disparities is crucial for tailoring interventions that reach populations most affected by chronic disease. To address this limitation, recent studies have turned to small-area geographic analysis to examine spatial variability in diabetes prevalence and its determinants. Barker *et al.* (2011) first used the Behavioural Risk Factor Surveillance System (BRFSS) 2007–2008 data to delineate the diabetes belt, a cluster of 644 contiguous counties with prevalence rates of 11% or higher. Subsequent research refined these approaches with more advanced spatial models. Hipp & Chalise (2015) applied Geographically Weighted Regression (GWR) to the 2013 BRFSS data and showed that education, poverty and physical inactivity were unevenly associated with diabetes across U.S. counties. Feldman *et al.*, (2020) employed a random-effects within-between model using 2003-2012 BRFSS data to evaluate contextual influences, while Shrestha *et al.*, (2016) mapped persistent county-level clusters using Getis-Ord Gi* statistics finding consistent high-risk zones in the rural South. Despite the valuable insights provided, these county-level analyses overlook intra-county variation that may be critical for identifying specific neighbourhoods in need of targeted health interventions.

More recent investigations have integrated environmental and behavioural dimensions into diabetes research. Schmittdiel *et al.*, (2018) demonstrated that neighbourhoods with limited walkability and fewer nearby parks exhibited significantly higher diabetes rates, even after accounting for socioeconomic differences. This aligns with findings by Drewnowski *et al.,* (2014), who used empirical Bayesian smoothing and spatial regression to examine tract-level diabetes prevalence in King County, Washington. They observed that local socioeconomic conditions, particularly education levels and housing values, were strongly associated with diabetes, with obesity mediating much of this relationship (Drewnowski *et al.*, 2014). These studies reinforce the importance of neighbourhood environments and community resources as structural determinants of this chronic disease.

Several other analyses have employed similar methodological frameworks and variables to uncover local health disparities. For instance, Sharma (2023) utilized GWR and spatial error models to investigate obesity and diabetes co-morbidities across census tracts in Mississippi, finding that physical inactivity and poverty were spatially clustered drivers of both conditions. In another example, Khan *et al.* (2021) integrated spatial lag and GWR models to analyze diabetes prevalence in Florida, showing that healthcare access and racial composition explained considerable variation in disease burden. Likewise, Lord *et al.* (2023) applied Multiscale GWR (MGWR) to explore diabetes prevalence in Florida and revealed that income and education operated at broader spatial scales, whereas built-environment features influenced local variation. Collectively, these studies demonstrate the utility of spatially explicit modelling particularly GWR and spatial autoregressive techniques for detecting place-specific relationships between health outcomes and their determinants.

The objectives of this study are to; first, conduct a spatial analysis to identify and map census-tract–level spatial clusters of diabetes prevalence across the state of Alabama. The next is to assess the local risk factors that has led to the diabetes prevalence and pattern in the state using global spatial statistical models and to examine spatial heterogeneity in the relationships between diabetes prevalence and key behavioural, socioeconomic, and demographic risk factors using geographically weighted regression and lastly to propose policy recommendations geared toward curbing diabetes prevalence in the state of Alabama. This study's results will generate detailed, location-specific evidence to support policymakers and public health professionals in designing targeted interventions to reduce disparities and improve diabetes outcomes in this disproportionately affected region.

Materials and Methods

Study area

The study area is the state of Alabama in southeast U.S. The state has a population of 5,157,699, with a composition of 64.1% whites, 26.1% blacks and others 9.8% (U.S. Census Bureau, 2025). As seen in Figure 1, there are a total of 67 counties and for this study a total of 1,434 census tracts were used for the analysis.

Data sources and processing

The Centers for Disease Control and Prevention (CDC) issues

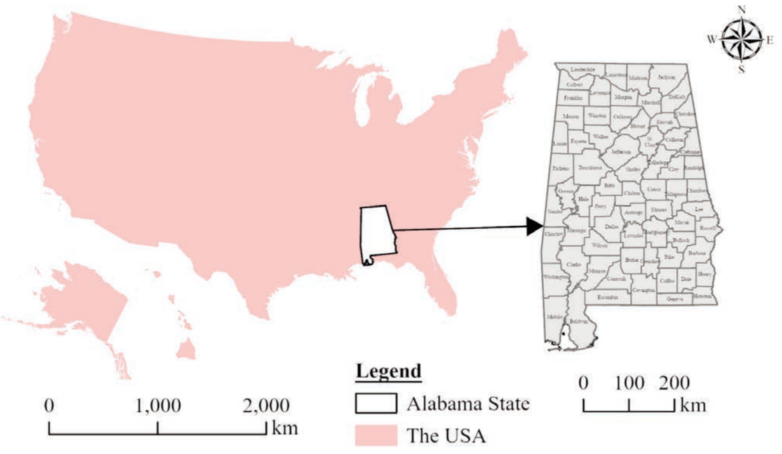


Figure 1. State of Alabama, USA.

a free, Population and Community Estimates (PLACES) that provides localized health data for the entire U.S., covering counties, cities, census tracts, and ZIP codes. We used the most recent CDC PLACES data to examine spatial clustering and diabetes correlates across Alabama at the Census Tract level.

The geographic boundaries of Alabama and its census tracts were obtained from the US Census Bureau TIGER/Line database and served as the spatial unit of analysis. Census tracts were selected as the spatial unit for analysis because they provide a finer resolution and allows for the identification of more localized spatial diabetes prevalence (Dailey *et al.,* 2024). The Alabama census tracts level diabetes prevalence and all the socioeconomic and behavioural variables were obtained from the CDC PLACES Project 2024 release. This project is based on model-based estimates of diagnosed diabetes and other health, socioeconomic and environmental variables using surveyed data by the BRFSS and American Community Survey (CDC, 2024). For this study and for the purpose of data, analysis diabetes prevalence was used as the dependent variable. The health, socioeconomic and environmental variables are shown in Table 1. All datasets were spatially joined using census tract GEOID identifiers to ensure alignment. Variables were inspected for missing values and consistency prior to spatial statistical analysis. Because PLACES estimates are model-based and aggregated at the tract level, results were interpreted within an ecological framework.

Spatial statistics

The analysis employed the Spatial Lag Model (SLM), which includes a spatially lagged dependent variable (Anselin *et al.*, 1996) to test whether diabetes prevalence in one census tract is influenced by prevalence in neighbouring tracts, capturing potential spatial spill-over effects, and the Spatial Error Model (SEM), which accounts for spatial autocorrelation in the error term, indicating the presence of unobserved, spatially structured influences that may bias conventional regression estimates (Anselin *et al.*, 1996; Anselin & Rey, 1991; Ma *et al.*, 2025). We used GWR to relax the assumption of spatial stationarity by allowing coefficients to vary locally, thereby identifying place-specific variations in the

Table 1. Variables and their definitions used in this study.

Domain	Variable	Designation	Definition
Age	Above 65 years	Age 65+	Model-based estimate for persons aged 65 years and older
Education	Without high school diploma	no_hs_dipl	Percentage of adults aged 25+ without a high school diploma or GED
Health	Diabetes prevalence	diabetes	Crude prevalence of diagnosed diabetes among adults more than 18 years of age
	Routine medical check-ups	check-up	Model-based estimate for crude prevalence of routine check-up within the past year among adults >18 years
	Poor or fair health	poor_fair	Model-based estimate for crude prevalence of fair or poor health among adults more than 18 years of age
	Smoking	smoking	Model-based estimate for crude prevalence of current cigarette smoking among adults more than 18 years of age
	Drinking	drinking	Model-based estimate for crude prevalence of binge drinking among adults more than 18 years of age
	High cholesterol	High chol	Model-based estimate for adults aged >18 years, who have ever been told by a do tor that they have high cholesterol
	Physical inactivity	phys_inactive	Model-based estimate for crude prevalence in the population>18 years without leisure-time physical activity
	Obesity	obesity	Model-based estimate for crude prevalence of obesity among adults more than 18 years of age
	Sleep deprivation	short_sleep	Percentage of adults more than 18 years of age. who sleep less than 7 hours on average in a 24-hour period
	Depression	depression	Model-based estimate for crude prevalence of depression among adults more than 18 years of age
	Low emotional/social support	low_support	Model-based estimate for crude prevalence of lack of social and emotional support among adults >18 years
Economy	No health insurance	no_insurance	Model-based estimate for crude prevalence of lack of health insurance among adults aged 18-64 years
	Food stamp dependence	foodstamps	Model-based estimate for crude prevalence of received food stamps in the past 12 months among adults >18 years
	No transportation	no_transport	Model-based estimate for crude prevalence in population >18 years without reliable transportation in the past 12 months
	Housing insecurity	housing_insec	Model-based estimate for crude prevalence in population >18 years with housing insecurity in the past 12 months
	Food insecurity	food_insec	Model-based estimate for crude prevalence in population >18 years with food insecurity in the past 12
	Poverty	poverty	Model-based estimate for persons below poverty level 150%
	Unemployment rate	unemp	Model-based estimate for unemployed civilians >16 years
Population	Minority	minority	Percentage of population identified as racial/ethnic minority
	African American	black	Percentage of residents identified as African Americans
	Latino or Hispanic	latino	Percentage of residents identified as Hispanics or Latinos
	Asian	asian	Percentage of residents identified as Asians
	Native American	native_american	Percentage of residents identified as American Indians or Alaska Natives
	Native Hawaiian	native_hawaiian	Percentage of residents identified as Native Hawaiians or other Pacific Islanders

relationships between diabetes prevalence and its predictors (Fotheringham *et al.*, 1996; Gao *et al.*, 2020). To evaluate the model performance, we compared the adjusted R² and the corrected Akaike Information Criterion (AICc) of the three spatial statistic methods. The model with the highest adjusted R^2 and lowest AICc was used to further analyze the associated factors. Global Moran's *I* in ArcGIS Pro was used to assess whether there exists spatial autocorrelation of census tract-level diabetes prevalence (Zhou *et al.*, 2025). To further understand the spatial pattern of diabetes prevalence in the study area, Getis-Ord Gi* in ArcGIS Pro was applied to identify potential clusters (Mazza *et al.*, 2025). For spatial relationship we used a contiguity approach (edges-only) after trying alternatives, such as k-nearest neighbours, fixed distance and inverse distance. It was selected because it provided a more precise and localized representation of spatial relationships by considering only census tracts that share common boundaries. This better reflects the spatial interaction patterns relevant to diabetes prevalence in the region. Positive z-scores represented hotspots (areas where high values are surrounded by high values), while negative z-scores indicated cold spots (areas where low values clustered together (Grigorev *et al.*, 2025). Statistical significance was assessed at the 90%, 95%, and 99% confidence levels to highlight the most robust clusters. This resulted in a hotspot map displaying locations of diabetes hotspots and coldspots.

Variables were identified through literature review and identified gaps to ensure relevance. They were assessed for multicollinearity using the Variance Inflation Factor (VIF) and variables with VIF values greater than 10 were excluded to reduce redundancy and improve model stability and a correlation matrix was generated to justify using the remaining variables.

Results

Spatial distribution of tract-level diabetes prevalence

As shown in Figure 2 and Table 2, diabetes prevalence at the census tract level ranges from 1.8% to 32.9%. The census tracts with the highest prevalence 26.3% to 32.9% were found to be concentrated in the middle, known as the Black Belt region that includes Greene, Perry, Dallas, Wilcox and Lowndes counties. Census tracts with low diabetes prevalence (ranging from 1.8% to 8.8%) were seen across various counties but heightened in Shelby and Tuscaloosa counties.

Global Moran's *I* for the census tract level diabetes prevalence was found to be 0.275 ($p<0.001$), demonstrating a strong statistically positive pattern in Alabama. Using contiguity edges only, the results indicated that neighbouring census tracts tended to have similar rates, forming clear clusters of high and low values. The results warranted the use of the Getis-Ord Gi* for local cluster detection across the census tracts as shown in Figure 3. The areas with the high prevalence zones are essentially the Black Belt counties, Greene, Sumter, Choctaw, Hale, Marengo, Hale, Perry, Dallas, Lowndes, Butler, Bullock, Macon, Barbour. Other counties that also showed high hotspots were Monroe, Conecuh and Clark.

The cold spots areas identified were seen in Shelby, Madison, Lee and some parts of Tuscaloosa.

Multicollinearity results showed a number of variables with high VIF; those exceeding 10 were removed to avoid redundancy. Correlation matrix was run on the remaining variables to ensure stable correlation as shown in Figure 4. Table 3 lists the remaining variables.

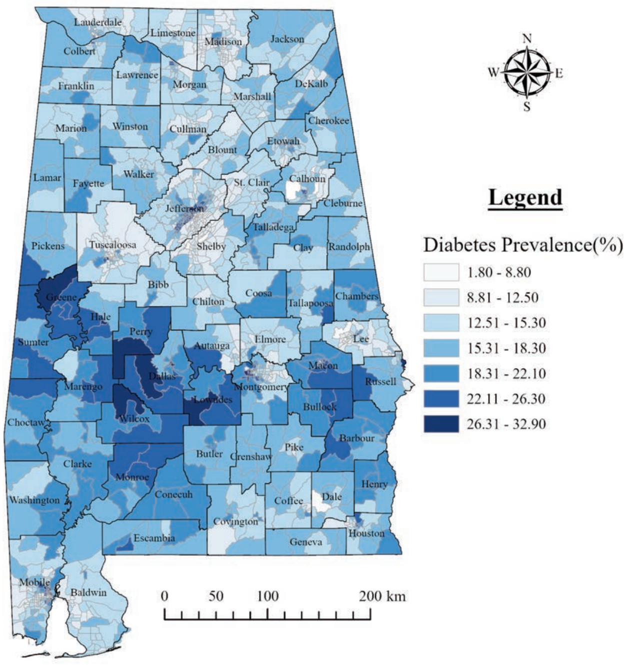


Figure 2. Spatial distribution of diabetes prevalence at the census tract level in Alabama, USA.

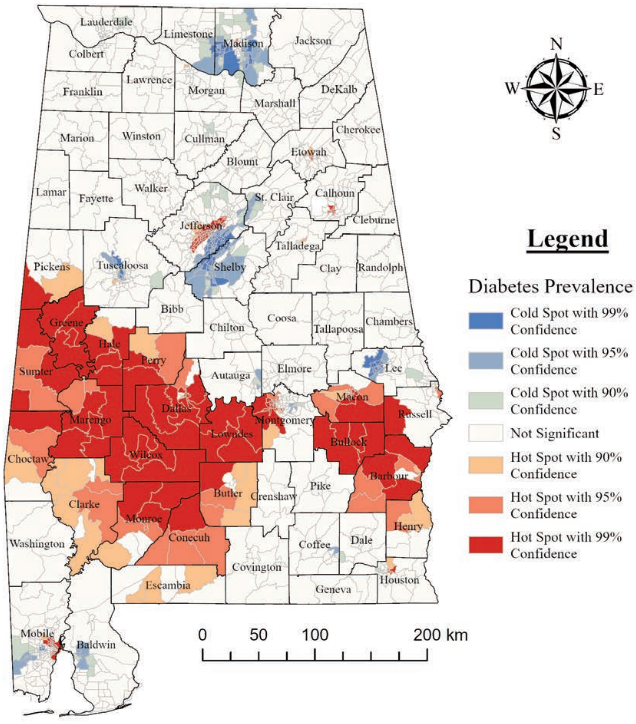
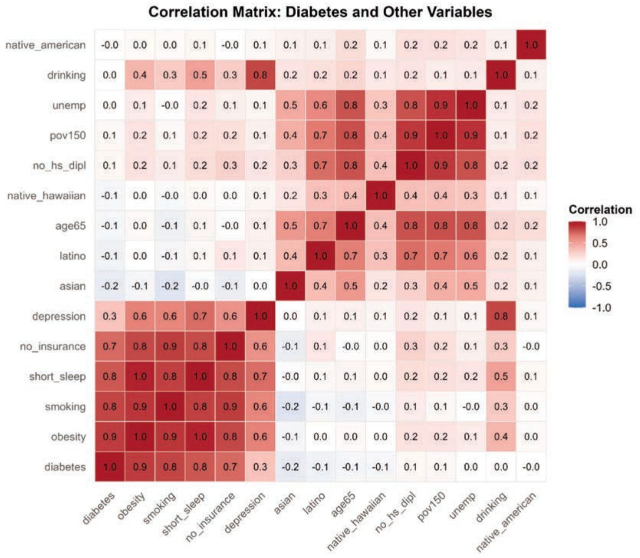


Figure 3. Hot spot and cold spot of diabetes prevalence at the census tract level in Alabama, USA. Clustered high-prevalence diabetes counties in shades of (prevalence ranging from 90% to 99% confidence intervals); Clustered low-prevalence diabetes counties in shades of (prevalence ranging from 90% to 99% confidence intervals).

Spatial statistics

After it was established that spatial autocorrelation, the remaining risk factors were adopted for the spatial regression in SLM and SEM. Amongst the remaining variables ‘smoking’ (0.2661, <0.001), ‘drinking’ (-0.6420, <0.001), ‘Obesity’ (0.4670, <0.001) and ‘Age+’ (0.0005, <0.001) exhibited a significant impact on spatial heterogeneity of diabetes for the SLM (R^2 - 0.6820, AIC 2457.7723). Other variables that also performed better were ‘No Insurance’, ‘Poverty and unemployment’. The rest of the variables were not statistically significant (p>0.5). SEM performed better than SLM with an R^2 of -0.6820 and AIC of 2457.7723. The variables that were statistically significant were ‘smoking’ (0.1984, < 0.001), ‘drinking’ (−0.6613, < 0.001), ‘obesity’ (0.5721, < 0.001), and ‘Age 65+’ (0.0003, < 0.001), similar to the SLM results. In this model ‘no high school diploma’ also performed slightly better along with ‘no insurance’, ‘unemployment’ and ‘Latino’. The other variables were not statistically significant (Table 4).

Using the same set of variables, a GWR was performed and it demonstrated a significantly better performance compared to both SLM and SEM, results are shown in Table 5. It achieved a higher R^2 = 0.921 and a lower AICc = 2414.0, it also had statistically sig-



	diabetes	obesity	smoking	short_sleep	no_insurance	depression	asian	latino	age65	native_hawaiian	no_hs_dipl	pov150	unemp	drinking	native_american
native_american	-0.0	0.0	0.0	0.1	-0.0	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.2	0.1	1.0
drinking	0.0	0.4	0.3	0.5	0.3	0.8	0.2	0.2	0.2	0.1	0.2	0.1	0.1	1.0	0.1
unemp	0.0	0.1	-0.0	0.2	0.1	0.1	0.5	0.6	0.8	0.3	0.8	0.9	1.0	0.1	0.2
pov150	0.1	0.2	0.1	0.2	0.2	0.1	0.4	0.7	0.8	0.4	0.9	1.0	0.9	0.1	0.2
no_hs_dipl	0.1	0.2	0.1	0.2	0.3	0.2	0.3	0.7	0.8	0.4	1.0	0.9	0.8	0.2	0.2
native_hawaiian	-0.1	0.0	-0.0	0.0	0.0	0.1	0.2	0.3	0.4	1.0	0.4	0.4	0.3	0.1	0.1
age65	-0.1	0.0	-0.1	0.1	-0.0	0.1	0.5	0.7	1.0	0.4	0.8	0.8	0.8	0.2	0.2
latino	-0.1	0.0	-0.1	0.1	0.1	0.1	0.4	1.0	0.7	0.3	0.7	0.7	0.6	0.2	0.1
asian	-0.2	-0.1	-0.2	-0.0	-0.1	0.0	1.0	0.4	0.5	0.2	0.3	0.4	0.5	0.2	0.1
depression	0.3	0.6	0.6	0.7	0.6	1.0	0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.8	0.1
no_insurance	0.7	0.8	0.9	0.8	1.0	0.6	-0.1	0.1	-0.0	0.0	0.3	0.2	0.1	0.3	-0.0
short_sleep	0.8	1.0	0.8	1.0	0.8	0.7	-0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.5	0.1
smoking	0.8	0.9	1.0	0.8	0.9	0.6	-0.2	-0.1	-0.1	-0.0	0.1	0.1	-0.0	0.3	0.0
obesity	0.9	1.0	0.9	1.0	0.8	0.6	-0.1	0.0	0.0	0.0	0.2	0.2	0.1	0.4	0.0
diabetes	1.0	0.9	0.8	0.8	0.7	0.3	-0.2	-0.1	-0.1	-0.1	0.1	0.1	0.0	0.0	-0.0

Figure 4. Spatial distribution of diabetes prevalence at the census tract level in Alabama, USA.

Table 2. Descriptive statistics of independent variables.

Domain	Designation	Mean	Minimum	Maximum	SD
Health access	no_insurance	11.82	3.9	11.82	3.82
Health status	diabetes	15.58	1.8	32.9	4.65
	check-up	79.90	67.70	86.70	2.51
	poor_fair	24.72	8.4	52.4	7.73
	depression	24.5	17.20	39.60	2.57
Behavioural risk factors	smoking	17.59	5.5	35.70	5.02
	drinking	14.03	7.6	24.50	2.50
	High chol	36.54	3.5	56.0	9.9
	phys_inactive	33.33	13.2	54.4	7.6
	obesity	40.51	23.80	60.6	6.40
	short_sleep	40.20	26.10	56.60	5.32
Socio-economic status	low_support	26.5	15.8	39.8	4.44
	no_hs_dipl	7.65	2.5	26.73	6.30
	foodstamps	18.15	2.0	78.2	12.47
	no_transport	11.41	3.2	38.1	5.2
	housing_insec	16.53	4.0	49.30	7.55
	food_insec	20.1	3.6	65.50	10.53
	poverty	11.01	3.20	78.95	6.47
	unemp	6.52	13.00	31.41	2.33
Demographic structure	age 65+	14.00	2.10	69.59	8.59
	minority	37.44	6.55	88.00	14.96
	black	38.3	8.6	93.0	8.4
	latino	24	1.8	58.0	4.9
	asian	12.3	4.0	56.0	5.1
	native_american	22.8	3.0	78.0	5.2
	native_hawaiian	17.16	2.0	89.0	11.04

SD, standard deviation.

Table 3. Refined list of variables.

Domain	Variable	Conceptual contribution
Behavioural risk factors	smoking, drinking, obesity, short_sleep	Captures lifestyle-related health risks
Mental health	depression	Represents the psycho-social dimension
Health access	no_insurance	Represents structural healthcare access
Socioeconomic status	poverty, unemployed, nohighschool	Economic & educational deprivation
Demographic structure	age 65+, latino, asian, native_american, native_hawaiian	Population composition and age patterns

nificant variables: ‘Smoking’, ‘Drinking’, ‘Age 65+’,’Obesity’ and ‘Poverty’. ‘Depression’, ‘sleep’, ‘no insurance’ and ‘unemployment’ were marginally significant. The remaining variables were not significant.

The GWR also showed the spatial variability of these variables in space, and it helps capture the local differences of the various statistically significant variables as shown in the maps below (Figures 5 to 9). This shows how the GWR model yields both statistical performance and also aids in the planning of targeted, tailor-made policies that can help address risk factors for various locations in Alabama. The GWR analysis revealed that the effects of the five significant predictors: ‘drinking’, ‘smoking’, ‘obesity’, ‘poverty’ and ‘65+’ differed markedly across Alabama, reflecting spatial variation in diabetes determinants. The relationship between diabetes prevalence and these predictors shifted in both strength and direction from one area to another. As shown in the

Table 4. Model results.

Variable	SLM		SEM	
	Coefficient	p	Coefficient	p
Smoking	0.2661	< 0.001 ***	0.1984	< 0.001 ***
Drinking	−0.6420	< 0.001 ***	−0.6613	< 0.001 ***
Obesity	0.4670	< 0.001 ***	0.5721	< 0.001 ***
Depression	−0.0273	0.3467	−0.0097	0.7375
Short Sleep	0.0465	0.0704	−0.0248	0.4339
No Insurance	−0.1026	0.0132 *	−0.1221	0.0032 **
Poverty	−0.0002	0.0013 **	0.0000	0.7383
Unemployment	−0.0014	0.0121 *	−0.0014	0.0072 **
No school diploma	−0.0003	0.2720	−0.0006	0.0042 **
Age 65 +	0.0005	< 0.001 ***	0.0003	< 0.001 ***
Latino	0.0002	0.1173	0.0003	0.0331 *
Asian	0.0000	0.9607	0.0002	0.3261
Native American	0.0001	0.9062	0.0012	0.0979
Native Hawaiian	0.0006	0.9164	−0.0067	0.2140
Model	R^2	Adjusted R^2	AIC	
SLM	-0.6820	-0.7216	2457.7723	
SEM	-0.7016	-0.7418	2457.7723	

*** $p<0.001$ (Highly significant); ** $p<0.01$ (Moderately significant); *$p<0.05$ (Marginally significant); No stars = Not statistically significant. SLM, Spatial Lag Model; SEM, Spatial Error Model; AIC, Akaike Information Criterion.

Table 5. Geographically weighted regression results.

Variable	Mean coefficient	SD	Min	Max	% p<0.05
Smoking	0.271	0.0354	0.202	0.325	100***
Drinking	−0.611	0.0913	−0.755	−0.454	100***
Obesity	0.467	0.0288	0.415	0.507	100***
Depression	−0.0315	0.0492	−0.122	0.0466	25.2*
Short sleep	0.026	0.0595	−0.0567	0.131	41.1*
No insurance	−0.0731	0.0584	−0.188	0.0091	44.2*
Poverty	−0.0002	0.0000	−0.0003	−0.0002	100***
Unemployment	−0.0012	0.0003	−0.0017	−0.0008	42.3*
No school diploma	−0.0003	0.0001	−0.0005	−0.0001	0
Age 65+	0.0006	0.0000	0.0005	0.0007	100***
Latino	0.0002	0.0001	0.0001	0.0003	0
Asian	−0.0001	0.0001	−0.0002	0	0
Native American	0.0001	0.0002	−0.0003	0.0004	0
Native Hawaiian	0.0020	0.0024	−0.0036	0.0051	0
R^2	0.921				
Adjusted R^2	0.919				
AICc	2414.0				

*Note: *** Highly significant (≥75% tracts); **Moderately significant (50-74.9 %); *Marginally significant (25-49.9 %); No stars = Not significant (<25%). SD, Standard Deviation; AICc, Corrected Akaike Information Criterion.*

maps, darker shades of blue suggest stronger positive coefficients, meaning that the variables had a greater local influence on diabetes rates.

'Smoking' showed strong positive effects in parts of Dallas, Greene and Hale counties along with other areas in the Black Belt and across the state. Drinking also showed strong effects in some parts of Tuscaloosa, St. Clair, Mobile, and Baldwin counties. This suggests that lifestyle choices contribute heavily to diabetes prevalence in most areas of the state of Alabama, as shown in Figures 5 and 6. On the other hand, there were areas that displayed weak and negative associations for drinking (Figure 6), and significant portions of the Black Belt showed weak and negative relationships.

'Obesity' (Figure 7) also showed positive relationships with diabetes prevalence in Greene, Hale, Dallas, Lowndes, and Bullock counties, as well as in some other counties like Monroe. Poverty (Figure 8) also showed strong effects in areas like Tuscaloosa, Houston, Lee, Mobile, Baldwin, and Escambia an area populated by tribal nations.

'Age 65+' (Figure 9) also showed moderate positive associations, mainly in southern and eastern parts of the state such as Baldwin, Dale, and Houston counties, pointing to the growing influence of aging on diabetes outcomes in some parts of Alabama. Overall, the GWR findings confirm that the risk factors operate unevenly across space, reinforcing the need for locally tailored strategies. Targeted public health interventions that reflect community-specific demographic and socioeconomic contexts would therefore be more effective than broad, state-wide measures.

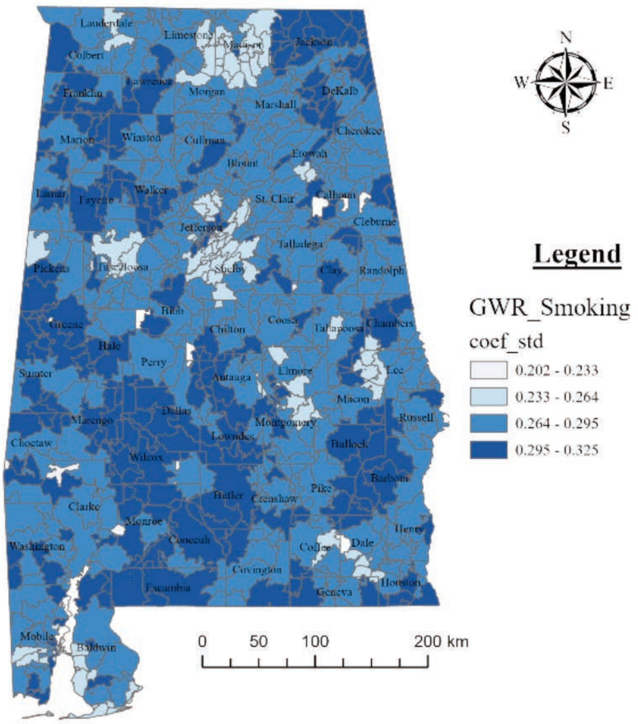


Figure 5. Smoking GWR Local Coefficient Map.

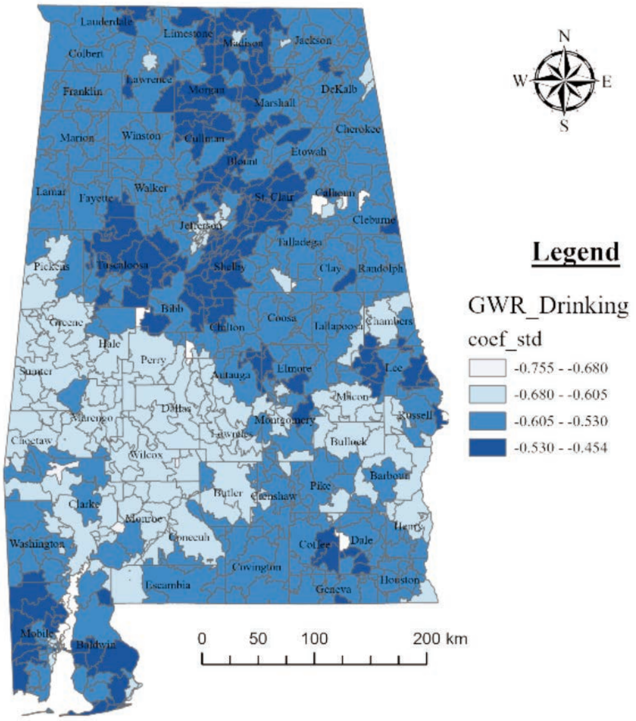


Figure 6. Drinking GWR Local Coefficient Map.

Discussion

Diabetes is a major public health challenge in the state of Alabama. Insights into diabetes prevalence, cluster and risk factors is essential to reducing diabetes prevalence across the state. Using spatial statistics, the study highlights the spatial pattern of diabetes, quantified and showed the relationships between diabetes and behavioural, environmental and socioeconomic risk factors. Through these findings on diabetes and risk factors that had been overlooked have been made available to enable policy formation.

Diabetes prevalence in the state of Alabama is significantly higher than the national average of 11.5%. The census tract prevalence shows that the diabetes prevalence is very high across the entire state and ranges from 22.11 to 32.90. The culturally entrenched soul food culture and dishes with added sugar, refined grains and sweetened beverages coupled with other socioeconomic disparities such as poverty is linked to diabetes prevalence in Alabama (Bovell-Benjamin *et al*., 2009; Lytle & Sokol, 2017). The Moran's *I* and Getis-Ord Gi* analyses also confirmed that diabetes in the state presents a statistical significant clustering, previous studies also established this fact and classify the state of Alabama as part of the diabetes belt of the USA (McMurry *et al.*, 2022).

This aligns with previous studies that labelled that area as a place entrenched in socioeconomic and healthcare disparities (Kuhajda *et al.*, 2006; Safford *et al.*, 2023). Other studies also revealed that the Black Belt region of Alabama, has significant food insecurity amongst many of its counties, with many areas there classified as food deserts (Sprehe *et al.*, 2024). Others also revealed that a substantial number of individuals living in that area survive on the SNAP program as such lack access to healthy food leading to obesity and ultimately diabetes (Kellegrew *et al.*, 2017; Walker *et al.*, 2018). Cheap food such as processed food and simple carbohydrates are items that individuals use their food stamps to acquire and has led to excessive sugar consumption (Kellegrew *et al.*, 2017). By contrast, areas observed as cold spots are Shelby, St. Clair, and Lee suggesting the presence of healthcare infrastructure and public health programs, for instance Shelby is part of the Birmingham Metropolitan area and an area that used to be the capital of the state of Alabama (Korf *et al.*, 2022). Previous studies confirmed that areas that have a significantly better socioeconomic conditions have lower rates of diabetes (Choi *et al.*, 2025).

The spatial regression models showed the intricate impart of predictors on diabetes prevalence. The Spatial lag and Spatial error model both revealed factors such as Smoking, Drinking, Obesity and Age 65+ that were statistically significant. This finding is consistent with previous studies that suggest diabetes prevalence is linked to lifestyle habits such as smoking and drinking along with dietary habits that lead to obesity (Pan *et al.*, 2025). Other studies globally have also confirmed diabetes typically kicks in mostly amongst the elderly (Cox *et al.*, 2022; Pan *et al.*, 2025; Wright *et al.*, 2020). The spatial lag also revealed that poverty was moderately significant in the state contrary to other studies (Packer *et al.*, 2025). While Spatial error revealed that no insurance, unemployment and no high school diploma also being moderately significant. Higher education levels have been shown to lead to a general understanding of healthcare instructions such as glycaemic control (Alnahdi *et al.*, 2025). The two models also revealed risk factors such as depression, short sleep, Native Americans, and Native Hawaiian were not statistically significant, which differs from existing studies as depression has been shown as a risk factor

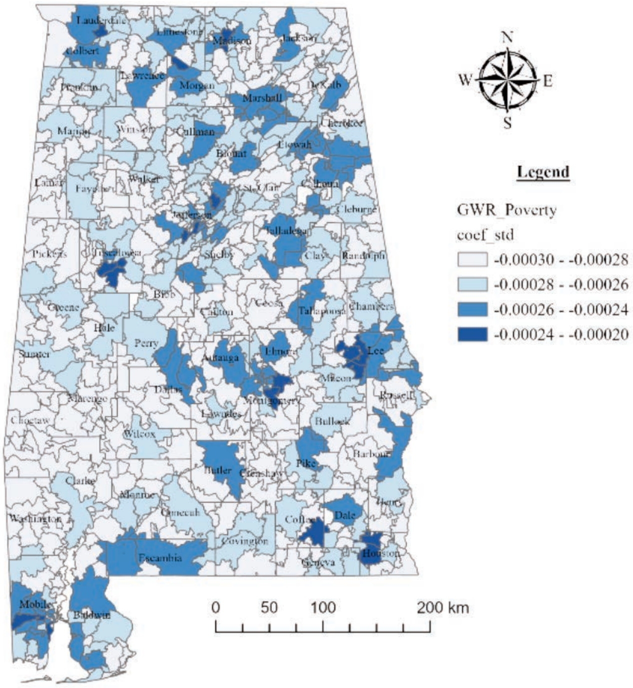


Figure 8. Poverty GWR Local Coefficient Map.

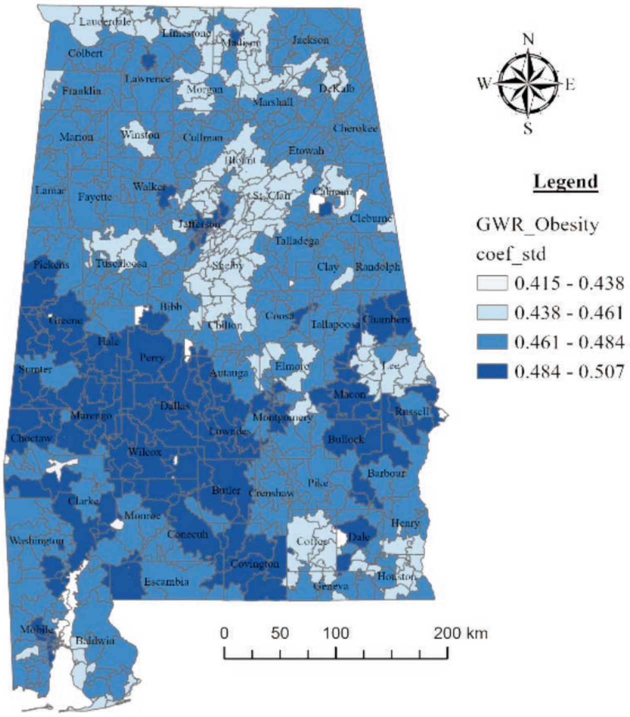


Figure 7. Obesity GWR Local Coefficient Map.

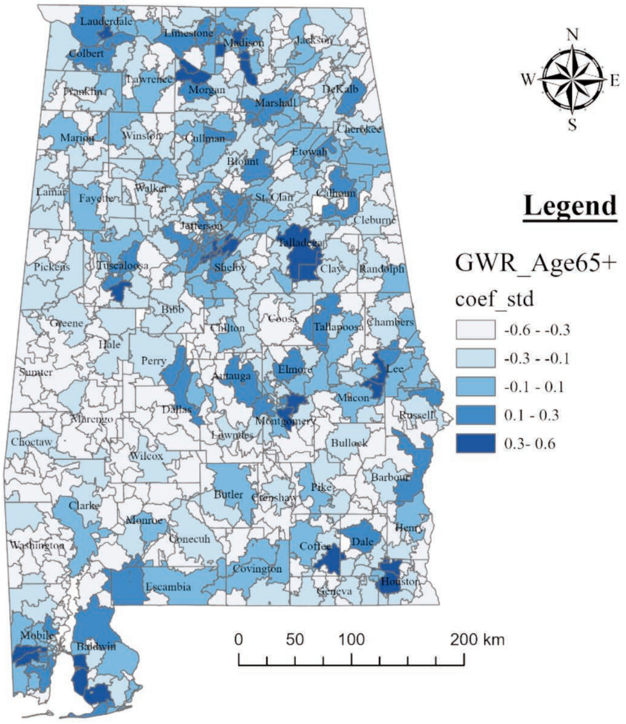


Figure 9. Age 65+ GWR Local Coefficient Map.

(Rayas *et al.*, 2025). Other studies have also established the high prevalence of diabetes among native Americans or tribal nations as such, this results is not consistent with previous studies (Liu *et al.*, 2024). Both models were found to be weak as they had lower R^2 and high AICs as compared to the GWR which recorded a higher R^2 and a lower AICc.

The results of the GWR also revealed smoking, drinking, obesity, poverty and age 65+ as statistically significant variables, it further revealed the spatial heterogeneity in the influence of each of these variables across the state of Alabama as shown in the figures 5 to 9. For instance, smoking which was established in this study as a significant risk factor to diabetes prevalence was found to be a serious contributor to diabetes in areas around the black belt region and other areas across the state. Some studies have suggested a major smoker population in Alabama, with the state ranked as being nation's tenth highest rate of adult smokers (García-Peña *et al.*, 2024; Packer *et al.*, 2025; Siza *et al.*, 2018). Other studies have further established smoking increases diabetes risk by 30 to 40% (Shuaib *et al.*, 2011). Similarly, the results of this study also show drinking as a predictor of diabetes in areas like Tuscaloosa, Lee, Mobile and Baldwin. The result of this research slightly differed from existing studies, as our result found drinking as a contributing factor to diabetes prevalence in the black belt of Alabama to be low. These localized variations align with findings by Barker *et al.*, (2011) and Kolak *et al.*, (2019), who observed that lifestyle behaviours such as alcohol consumption influence diabetes outcomes differently depending on regional culture and healthcare access. Across Alabama, obesity is observed to have significant connection with diabetes prevalence but it is more pronounced in Black Belt counties such as Greene, Hale, Dallas, Marengo and Lowndes, the findings are reinforced through previous studies that identified obesity as a one of the most powerful and spatial persistent contributor to diabetes in most socioeconomically disadvantaged areas (Angelopoulos *et al.*, 2025).

Per the results poverty suggests a complex spatial pattern with strong positives coefficient in areas in Lee, Mobile and Houston while weaker effects emerge in portions of the Black Belt region. This mixed relationship aligns with findings by Birati *et al.* (2022) suggesting that economic hardship alone does not uniformly predict diabetes outcomes but interacts with local mediating factors such as food access, transportation, and preventive health infrastructure. In areas where community networks or public health programs are stronger, the detrimental effects of poverty may be partially mitigated. Meanwhile, the Age 65+ variable exhibits modest to moderate positive coefficients, especially in Montgomery, Baldwin, and Dale counties, confirming demographic research by Banerjee *et al.*, (2025) that associates aging populations with increased chronic disease prevalence due to physiological and behavioural vulnerability. Overall, these spatially varying relationships affirm that the determinants of diabetes are context-dependent and that uniform state-wide strategies may overlook localized needs. The observed patterns underscore the importance of adopting spatially adaptive modelling approaches such as GWR, which as Sangrat *et al.*, (2025) emphasize reveal geographically nuanced risk structures that global models obscure.

The findings of this study call for localized policies to address diabetes prevalence in Alabama. For instance, the promotion of anti-smoking campaigns across the state, particularly in the Black Belt region, would be vital. Targeted obesity and nutrition programs in areas like the Black Belt, where obesity coefficients are high, should also be prioritized. Other community-based initiatives could include the promotion of community fitness programs and the direction of Supplemental Nutrition Assistance Program (SNAP) benefits toward the purchase of organic food items only. In addition, poverty alleviation programs and elderly health service centres should be promoted across the state to ensure equitable access to preventive care and healthier living conditions.

There are a number of limitations in this study. First, the study relied solely on publicly available data, which are self-reported; as such, there could be certain discrepancies. For instance, data on drinking are only available for individuals aged 18 and above, even though there are multiple reports of underage drinking in the Black Belt region. Additionally, other variables such as physical inactivity, routine checkups, and poor health were dropped due to severe multicollinearity, even though they have been found to be linked to diabetes prevalence. Furthermore, although GWR captures spatial heterogeneity, it remains a cross-sectional approach and cannot solely infer causal relationships.

Conclusions

The present study described spatial dynamics of diabetes prevalence and its relationship with demographic, behavioural, environmental and socioeconomic risk factors. High diabetes rates were found across the state of Alabama with significant clustering in most portions of Black Belt region and other areas in Mobile and Jefferson County. SLM and SEM revealed Smoking, Drinking, Obesity and Age 65+ as primary contributors of diabetes but overall performed poorly compared to the GWR which had a higher R^2 and a lower AICc. The GWR also revealed Smoking, Drinking, Obesity, Age 65+ along with poverty as the primary risk factor for diabetes prevalence in the state of Alabama. The results of the GWR also enabled a comprehensive analysis which revealed the spatial variations of these risk factors across census areas in Alabama. The findings underscore the need to adopt localized policies to address risk factors at local levels rather than general frameworks that have often yielded less reliable results.

References

Abdurashidova M, Khatibi K, Ponce L, Warach SJ, Saber H, 2024. Abstract TP205: Intracranial Stenting With Mechanical Thrombectomy in Acute Ischemic Stroke in the United States. Stroke, 55 (Suppl_1). https://doi.org/10.1161/str.55.suppl_1.tp205

Alnahdi H, Alghamdi R, Alyamani S, Taha S, Rayes R, Almadani A, Yassin H, Alhamed L, Alhozali AM, Alfares K, 2025. Diabetes management: Self-management education and support program evaluations in Jeddah, KSA. J Taibah Univ Med Sci 20:507-16.

Angelopoulos N, Livadas S, Androulakis I, Petkova V, Rizoulis A, Boniakos A, Paparodis R, Tzoulis P, Mentzelopoulou V, Florakis D, Fousteris E, Korakovouni A, Zianni D, Mouslech Z, Rizzo M, Mikhailidis DP, Anagnostis P, 2025. Short-term effects of low-dose tirzepatide on lipid profile, glucose homeostasis and hepatic steatosis index in adults with obesity, but without diabetes mellitus: a prospective observational study. J Diabetes Complications 39:109181.

Anselin L, Bera AK, Florax R, Yoon MJ, 1996. Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ 26:77-104

Anselin L, Rey S, 1991. Properties of tests for spatial dependence in linear regression models. Geogr Anal 23:112-31.

Banerjee S, Khubchandani J, Gonzales-Lagos R, 2025. Diabetes, anxiety, and mortality risk among middle and older-aged Americans. J Diabetes Complications 39:109194.

Barker LEP, Kirtland KAP, Gregg EWP, Geiss LSM, Thompson TJM, 2011. Geographic distribution of diagnosed diabetes in the U.S.: A diabetes belt. Am J Prev Med 40:434-9.

Bazzano AN, Patel T, Nauman E, Cernigliaro D, Shi L, 2024. Optimizing telehealth for diabetes management in the Deep South of the United States: Qualitative study of barriers and facilitators on the patient and clinician journey. J Med Internet Res 26:43583.

Birati Y, Bloch JR, McKeever A, Chiatti BD, 2022. Relationships among neighborhood poverty, access to healthy food, and diabetes self-management in women who received perinatal nurse home visits. J Obstet Gynecol Neonatal Nurs 51:41-52.

Bovell-Benjamin AC, Hathorn CS, Ibrahim S, Gichuhi PN, Bromfield EM, 2009. Healthy food choices and physical activity opportunities in two contrasting Alabama cities. Health Place 15:429-438.

Centers for Disease Control and Prevention (CDC), 2024. National diabetes statistics report: Estimates of diabetes and its burden in the United States. Available from: https://www.cdc.gov/diabetes/data/statistics-report/index.html

Choi B, Choi J, Lee J, Choi E, Jang S, 2025. Socioeconomic disparities in hypertension and diabetes among older adults in South Korea: a trend analysis from a national survey, 2011-2023. Soc Sci Med 382:118350.

Correya TA, Ashraf AP, Griffin R, Aslibekyan S, Kim HD, Middleton S, McCormick K, 2020. Temporal trends in incidence of pediatric type 1 diabetes in Alabama: 2000-2017. Pediatr Diabetes 21:40-47.

Cox ER, Brown WJ, Gajanand T, Bailey TG, Gomersall SR, Chachay VS, Burton NW, Fassett RG, Cox SV, Coombes JS, Keating SE, 2022. Effects of fitness and fatness on age-related arterial stiffening in people with type 2 diabetes. Clin Obes 12:e12519.

Dailey A, Gant Z, Hu X, Lyons SJ, Okello A, Johnson, AS, 2024. A Census Tract-Level Examination of Diagnosed HIV Infection and Social Vulnerability Themes Among Black/African American, Hispanic/Latino, and White Adults, 2019—USA. J. Racial Ethn Health Disparities 11:468-49.

Drewnowski A, Rehm CD, Moudon AV, Arterburn D, 2014. The geography of diabetes by census tract in a large sample of insured adults in King County, Washington, 2005-2006. Prev Chronic Dis 11:140135.

Feldman JM, Lee DC, Lopez P, Rummo PE, Hirsch AG, Carson AP, McClure LA, Elbel B, Thorpe LE, 2020. Assessing county-level determinants of diabetes in the United States (2003-2012). Health Place 63:102324.

Fotheringham AS, Charlton M, Brunsdon C, 1996. The geography of parameter space: An investigation of spatial non-stationarity. Int J Geogr Inf Syst 10:605-21.

Gao C, Feng Y, Tong X, Lei Z, Chen S, Zhai S, 2020. Modeling urban growth using spatially heterogeneous cellular automata models: Comparison of spatial lag, spatial error and GWR. Comput Environ Urban Syst 81:101459.

García-Peña LM, Abel ED, Pereira RO, 2024. Mitochondrial dynamics, diabetes, and cardiovascular disease. Diabetes 73:151-61.

Grigorev A, Lillo-Trynes D, Mihaita AS, 2025. Spatial association between near-misses and accident blackspots in Sydney, Australia: A Getis-Ord Gi* analysis. Available from: http://arxiv.org/abs/2506.03356

Hipp JA, Chalise N, 2015. Spatial analysis and correlates of county-level diabetes prevalence, 2009-2010. Prev Chronic Dis 12:140404.

Jiang W, Chen H, Li H, Zhou Y, Xie M, Zhou C, Yang L, 2023. The short-term effects and burden of ambient air pollution on hospitalization for type 2 diabetes: Time-stratified case-crossover evidence from Sichuan, China. GeoHealth, 7:e2023GH000846.

Johnson EL, Feldman H, Butts A, Chamberlain J, Collins B, Doyle-Delgado K, Dugan J, Leal S, Rhinehart AS, Shubrook JH, Trujillo J, 2020. Standards of medical care in diabetes—2020 abridged for primary care providers. Clin Diabetes 38:10-38.

Kellegrew KP, Powers AR, Struempler B, Parmer S, Funderburk K, 2017. Evaluating barriers to SNAP acceptance in Alabama farmers markets. J Nutr Educ Behav 49:S60-S61.

Khan MM, Roberson S, Reid K, Jordan M, Odoi A, 2021. Geographic disparities and temporal changes of diabetes prevalence and diabetes self-management education program participation in Florida. PLoS One 16:e0254579.

Kolak M, Abraham G, Talen MR, 2019. Mapping census tract clusters of type 2 diabetes in a primary care population. Prev Chronic Dis 16:180502.

Korf B, Absher D, Asif I, Bateman L, Barsh G, Bowling K, Cooper G, Davis B, East K, Finnila C, Goff B, Kelly M, Kelley W, Latner D, Lawlor J, Limdi N, May T, Might M, Moss I, Thompson M, 2022. Integration of genomics into primary care via the Alabama Genomic Health Initiative. Genet Med 24:S314-5.

Kuhajda MC, Cornell CE, Brownstein JN, Littleton MA, Stalker VG, Bittner VA, Lewis CE, Raczynski JM, 2006. Training community health workers to reduce health disparities in Alabama's Black Belt: The Pine Apple heart disease and stroke project. Fam Community Health 29:89-102.

Lee LH, Mancus G, Yuen HK, Wolff PE, Jenkins GR, 2022. What are the factors associated with neighborhood park visits and health in Alabama? A cross-sectional study using a path model. Int J Environ Health Res 32:1542-53.

Liu X, Zhu Y, Seamans M, Nianogo R, Janzen C, Fei Z, Chen L, 2024. Gestational diabetes mellitus and risk of neurodevelopmental disorders in young offspring: Does the risk differ by race and ethnicity? Am J Obstet Gynecol MFM 6:101217.

Lord J, Roberson S, Odoi A, 2023. A retrospective investigation of spatial clusters and determinants of diabetes prevalence: Scan statistics and geographically weighted regression modeling approaches. PeerJ 11:e15107.

Lu B, Li P, Crouse AB, Grimes T, Might M, Ovalle F, Shalev A, 2025. Data-driven cluster analysis reveals increased risk for severe insulin-deficient diabetes in Black/African Americans. J Clin Endocrinol Metab 110:516.

Lytle LA, Sokol RL, 2017. Measures of the food environment: A systematic review of the field, 2007-2015. Health Place 44:18-34

Ma C, Mu R, Li M, He J, Hua C, Wang L, Liu J, Totis G, Yang J, Liu K, Zhou Y, Zhou J, Deng X, Weng S, 2025. A multi-scale spatial-temporal interaction fusion network for digital twin-based thermal error compensation in precision machine tools. Expert Syst Appl 286:127812.

Manu KK, 2025. Spatial analysis of diabetes prevalence of the Black Belt region of Alabama and the role of non-governmental organisations. Master's thesis, The University of Alabama.

Manu KK, Appiah-Opoku S, Weber J, Sultana S, Amanambu AC, 2025. Diabetes prevalence and healthcare accessibility in Alabama's Black Belt region. J Diabetes Endocrinol 15:10-25

Manu KK, Gamage MM, 2025. Understanding diabetes prevalence in the United States of America: A geospatial and socioeconomic perspective. J Diabetes Endocrinol 15:0156.

Matthews J, Soltis I, Villegas-Downs M, Peters TA, Fink AM, Kim J, Zhou L, Romero L, McFarlin BL, Yeo WH, 2024. Cloud-integrated smart nanomembrane wearables for remote wireless continuous health monitoring of postpartum women. Adv Sci 11:e2307609.

Mazza O, Gluck C, Haim A, Bornstein RJ, 2025. Spatial patterns of childhood obesity clusters linked to socioeconomic inequalities. Front Public Health 13:1497090

McDaniel CC, Chou C, 2022. Clinical risk factors and social needs of 30-day readmission among patients with diabetes: A retrospective study of the Deep South. Front Clin Diabetes Healthc 3:1050579.

McMurry TL, Lobo JM, Kang H, Kim S, Balkrishnan R, Anderson R, McCall A, Sohn MW, 2022. Annual wellness visits are associated with increased use of preventive services in patients with diabetes living in the Diabetes Belt. Diabetes Epidemiol Manag 7:100094

Morrato EH, Hill JO, Wyatt HR, Ghushchyan V, Sullivan PW, 2007. Physical activity in U.S. adults with diabetes and at risk for developing diabetes, 2003. Diabetes Care 30:203-9.

Packer M, Lam CSP, Butler J, Zannad F, Vaduganathan M, Borlaug BA, 2025. Is type 2 diabetes a modifiable risk factor for the evolution and progression of heart failure with a preserved ejection fraction? J Am Coll Cardiol 86:1917-31.

Pan Y, Gu R, Wang J, Li Q, Zhang Y, Xu Y, Ji S, Wu J, Wei L, 2025. Gestational diabetes mellitus recurrence rate and risk factors: A systematic review and meta-analysis. Diabetes Res Clin Pract 230:112949.

Parab KV, Gao X, Gothe NP, Wilund KR, Mahajan HP, Singleton CR, 2025. Risk trajectories of type 2 diabetes-related microvascular complications across racial/ethnic groups among older adults. J Racial Ethn Health Disparities https://doi.org/10.1007/s40615-025-02625-0

Parker ED, Lin J, Mahoney T, Ume N, Yang G, Gabbay RA, Elsayed NA, Bannuru RR, 2024. Economic costs of diabetes in the U.S. in 2022. Diabetes Care 47:26-43.

Rayas MS, Mbogo B, Kelly A, Vu P, Magaret A, Daley T, 2025. Association of race and ethnicity with the development of cystic fibrosis-related diabetes. J Cyst Fibros 24:263-70.

Safford MM, Cummings DM, Halladay J, Shikany JM, Richman J, Oparil S, Hollenberg J, Adams A, Anabtawi M, Andreae L, Baquero E, Bryan J, Clark D, Johnson E, Richman E, Soroka O, Tillman J, Cherrington AL, 2023. The design and rationale of a multicenter real-world trial: The Southeastern Collaboration to Improve Blood Pressure Control in the U.S. Black Belt - Addressing the Triple Threat. Contemp Clin Trials 129:107183.

Sangrat W, Sajapitak S, Boonyawiwat V, Thongratsakul S, Poolkhet C, 2025. Integrating systematic review, meta-analysis, and secondary data for spatial and temporal risk analysis of avian influenza in poultry: A comparative evaluation of OLS, GWR, and MGWR models. Prev Vet Med 245:106693.

Schmittdiel JA, Dyer WT, Marshall CJ, Bivins R, 2018. Using neighborhood-level census data to predict diabetes progression in patients with laboratory-defined prediabetes. Perm J 22:18-096.

Sharma A, 2023. Exploratory spatial analysis of food insecurity and diabetes: An application of multiscale geographically weighted regression. Ann GIS 29:485-498.

Shrestha SS, Thompson TJ, Kirtland KA, Gregg EW, Beckles GL, Luman ET, Barker LE, Geiss LS, 2016. Changes in disparity in county-level diagnosed diabetes prevalence and incidence in the United States, between 2004 and 2012. PLoS One 11:e0159876.

Shuaib F, Foushee HR, Ehiri J, Bagchi S, Baumann A, Kohler C, 2011. Smoking, sociodemographic determinants, and stress in the Alabama Black Belt. J Rural Health 27:50-59.

Siza C, Morrison M, Harris S, Hatch T, Tyler M, 2018. Assessment of community awareness and practices concerning indoor air pollutants-Madison County, Alabama, June 2017. MMWR Morb Mortal Wkly Rep 67:447-50.

Sprehe E, Douglas J, Knol L, Heinrich A, Wieringa M, Ford M, 2024. Food insecurity among individuals with traumatic brain injury (TBI) in Alabama. J Acad Nutr Diet, 124

U.S. Census Bureau, 2025. Annual estimates of the resident population. U.S. Department of Commerce.

Walker B, Wolford B, Hofer R, Parmer S, Funderburk K, Struempler B, 2018. Outcome evaluation of Alabama Supplemental Nutrition Assistance Program-Education (SNAP-Ed) social marketing campaign. J Nutr Educ Behav, 50

Wright AK, Welsh P, Gill JMR, Kontopantelis E, Emsley R, Buchan I, Ashcroft DM, Rutter MK, Sattar N, 2020. Age-, sex- and ethnicity-related differences in body weight, blood pressure, HbA1c and lipid levels at the diagnosis of type 2 diabetes relative to people without diabetes. Diabetologia 63:1542-53.

Zhou R, Chen J, Cui S, Li L, Qian J, Zhao H, Huang G, 2025. A data-driven framework to identify influencing factors for soil heavy metal contaminations using random forest and bivariate local Moran's I: A case study. J Environ Manage, 375.

Zhu Y, Zhang H, Xi Y, Zhu H, Lu Y, Luo X, Tang Z, Lei H, 2024. The implication of diabetes-specialized nurses in aiming for the better treatment and management of patients with diabetes mellitus: A brief narrative review. Diabetes Ther 15:917-27.

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