EXPLORING DEMOGRAPHIC, SOCIO-ECONOMIC, AND ENVIRONMENTAL CORRELATES OF DIABETES DEATH RATES: A CASE STUDY OF CONNECTICUT, U.S.

Yunliang MENG[A*]

Received: December 9, 2024 | Revised: January 12, 2025 | Accepted: February 5, 2025
Paper No. 25-67/1-735

A* Central Connecticut State University, 06053, New Britain, Connecticut, USA
https://orcid.org/0000-0003-3756-6334, mengy@ccsu.edu (corresponding author)

Citation: MENG, Y. 2025. Exploring Demographic, Socio-Economic, and Environmental Correlates of Diabetes Death Rates: A Case Study of Connecticut, U.S. *Folia Geographica*, 67(1), 5-21.

Abstract
Deaths caused by diabetes have increased significantly over the past 2 decades, becoming a public health concern in the U.S. Guided by social determinants of health theory, this research uses Ordinary Least Squares regression to examine the relationship between diabetes death rates and contextual demographic, socio-economic and environmental characteristics at the county subdivision level in the State of Connecticut, U.S. The results show that explanatory variables, such as percent of Hispanic population, population density, unemployment rate, the percent of population beyond 1 mile from supermarket, the percent of population beyond 1 mile for urban areas or 10 miles for rural areas from supermarket, the percent of households reported not having sufficient funds in the last 12 months to purchase food are statistically significantly associated with diabetes death rates. This research enables health practitioners and policy makers to gain a better understanding of the demographic, socio-economic and environmental determinants of diabetes death rates at the county subdivision level. Accordingly, provided are policies to reduce the death rates. This study presents an initial and exploratory step towards better understanding of diabetes death rates in Connecticut, U.S., but much more in-depth work is needed before health researchers and practitioners understand why explanatory factors only explained up to 57.8 % of the diabetes death rates in the state.

Key words
Diabetes Death Risk, Regression, Connecticut.

INTRODUCTION

Diabetes is a chronic, metabolic disease characterized by elevated levels of blood glucose (or blood sugar), which leads over time to serious damage to the heart, blood vessels, eyes, kidneys and nerves. Diabetes constitutes a worldwide public health problem that affected 422 million people in 2014 (WHO, 2024a). In 2021, diabetes was the direct cause of 1.6 million deaths and 47% of all deaths due to diabetes occurred before the age of 70 years (WHO, 2024b). Recent projections suggest that this prevalence is likely to increase in the next 20 years, affecting 592 million people (10.1%) in 2035 (Baena-Díez et al. 2016). In the U.S., 38 million people or about 1 in 10 Americans have diabetes (CDC, 2024a). Approximately, 96 million American adults or more than 1 in 3 aged 18 and above have prediabetes and more than 8 in 10 of prediabetes patients don't know they have it (CDC, 2024b). Diabetes and diabetes-related health complications can be serious and costly. As the eighth leading cause of death in the United States in 2021, diabetes costs a total estimated $413 billion in medical costs and lost work and wages (CDC, 2024c). In fact, people with diagnosed diabetes have more than twice the average medical costs that people without diabetes have. Additionally, diabetes is a major cause of blindness, kidney failure, heart attacks, coma, stroke and lower limb amputation and can consequently lead to deaths.

Diabetes prevalence is associated with demographic and socio-demographic variables, physical inactivity and built environment factors such as access to healthy foods and the rural–urban matrix (Hipp and Chalise, 2015). One of the great challenges in understanding the associations between built environment attributes and diabetes deaths is that both factors vary across Connecticut. Although studies of diabetes have found spatial variations in diabetes incidence and prevalence, there is a paucity of research on how the spatial prevalence of diabetes deaths may or may not be associated with the spatial prevalence of built environment attributes. Given this paucity, more empirical research is needed to investigate the spatial difference in diabetes deaths and identify contextual characteristics that underlie existing differences in diabetes deaths. In addition, the geographic studies of diabetes deaths were almost all carried out at the county level in the U.S., largely because this is the level that CDC compiles and disseminates diabetes death data. However, research conducted at the county level provides very limited implications for a state like Connecticut which has no county level government to implement policing, public health, and/or social policies.

OBJECTIVES

This research article fills these gaps by examining the relationship between the diabetes death rates and demographic, socio-economic, environmental predictors at the county subdivision level across Connecticut. It should be noted that county subdivisions are better known as cities, towns or municipalities in the U.S. This research benefits not only the academic community, but also the governmental agencies (i.e. public health or social services) that need to understand the geographical variations in demand for their services and the effective interventions that will have the best impact in reducing the deaths caused by diabetes. This is especially important in a post COVID-19 pandemic world where resources may be limited or depleted due to the high inflation.

LITERATURE REVIEW

Social determinants of health (SDOH) demonstrate non-medical factors can influence people's health outcomes and have emerged as a strategy for addressing health disparities (Hill-Briggs et al., 2020; Cooper et al., 2024). They are often quantified by the conditions in which people are born, grow, work, live, and age, and the wider set of forces shaping the conditions of people's daily life. Guided by SDOH as a framework and a salutogenic approach to health promotion, previous studies show diabetes death rates can be explained by a wide range of demographic, socio-economic and environmental variables. For example, age is a major risk factor for diabetes and prediabetes, since elderly people have a higher prevalence of diabetes and prediabetes than the younger people and are more likely to develop complications in the cardiovascular, retinal, and renal systems (Amir et al., 2020; Fong et al., 2021). Racial and ethnic minority populations have a higher prevalence of diabetes than non-minority individuals. Diabetes prevalence was higher among Black and Hispanic people compared to White people. The age- and sex-adjusted diabetes prevalence was 12.1% for non-Hispanic White, 20.4% for non-Hispanic Black, 22.1% for Hispanic (Cheng et al., 2019). Sex differences in body composition and fat deposition clearly contribute to the gap of diabetes risk between males and females (Mauvais- Jarvis et al., 2017; Ciarambino, 2022). Diabetes is more common in males rather than females. Worldwide, an estimated 17.7 million more men than women have diabetes (Kautzky-Willer et al., 2023). An empirical analysis of data taken from a Behavioral Risk Factor Surveillance System (BRFSS) conducted on rural and urban residents from 47 states in the US showed that a higher proportion of rural residents reported diabetes than urban residents among all racial/ethnic classifications (Hale et al., 2010).

Empirical research demonstrates that obesity is highly associated with perturbation of glucose metabolism, resulting in the development of type 2 diabetes (Chandrasekaran and Weiskirchen, 2024). Being overweight (Body Mass Index or BMI of 25-29.9), affected by obesity (BMI of 30-39.9) or morbid obesity (BMI of 40 or greater), greatly increases people's risk of developing type 2 diabetes, since the more excess weight a person has, the more resistant the person's muscle and tissue cells become to the person's own insulin hormone (Kahn and Flier, 2000). Mahoney et al. (2020) found that having health insurance was associated with decreased odds for undiagnosed prediabetes and type 2 diabetes in American adults. The findings highlight a large proportion of individuals without health insurance have undiagnosed prediabetes or type 2 diabetes and are therefore probably not managing their blood glucose levels properly (Mahoney et al., 2020).

Previous research discloses that mortality risk is higher among people with low socioeconomic status and diabetes as compared to those with higher SES and diabetes (Brown et al., 2004; Saydah et al., 2013). Varanka-Ruuska et al. (2018) found unemployment was associated with 1.6-fold odds for prediabetes, and 1.7-fold odds for type 2 diabetes. Prevalence of diabetes disproportionately impacted lower-income populations. Compared with those with a middle income, the risk of development of type 2 diabetes for people with low income is 50% higher (Hsu et al., 2012). People with lower educational attainment tend to have poorer glycemic control and higher mortality risk (Doshi et al., 2016; Saydah et al., 2013).

Empirical studies shows that food insecurity is associated with increased all-cause mortality and compromised diet quality, especially in individuals experiencing very low food security (Fu et al., 2023). Food insecurity, for example, disrupted dietary patterns and food intake potentially leading to inadequate consumption of healthful food, is associated with adverse health outcomes including diabetes and cardiovascular disease (Ma et al., 2024). Poor access to healthy food has been linked to an increase in diabetes prevalence rate (Berkowitz et al., 2018). Food deserts exacerbate the limited access of healthy foods because of their lack of fresh produce and other healthy food options (Berkowitz et al., 2018). The death rate from diabetes in a food desert is twice that of areas with access to grocery stores (Curry, 2009).

The term polycrisis captures the complex nature of deaths caused by diabetes and their demographic, socio-economic, and environmental correlates (e.g. socio-economic inequalities, food insecurity, and healthcare disparities). Morin and Kern (1999, p. 74) proposed the term polycrisis over two decades ago. They emphasized that the most vital issue of nowadays was not any single threat but the 'complex inter-solidarity of problems, antagonisms, crises, uncontrollable processes, and the general crisis of the planet'. Lawrence et al. (2024) define a polycrisis as 'the causal entanglement of crises in multiple systems in ways that significantly degrade humanity's prospects. Matlovic and Matlovicová (2024) define polycrisis as 'the inter-connected crises in environmental, economic, political, social, health, and technological domains, whose combined effects are greater than the sum of individual crises'. Matlovic and Matlovicova (2024) also argue for adopting a post-disciplinary approach to study polycrisis.

STUDY AREA

Connecticut was one of the original 13 states and is one of the six New England states located in the northeastern corner of the USA. It ranks 48th among the 50 U.S. states in terms of total physical area but its population density ranks 4th. Connecticut has a mix of coastal cities and rural areas dotted with small towns. Totally, it has a mix of 169 county subdivisions, including 19 cities, one borough, and 149 incorporated towns. See Figure 1 below.

Lying in the midst of the great urban-industrial complex along the Atlantic coast, it borders Massachusetts to the north, Rhode Island to the east, Long Island

Sound (an arm of the Atlantic Ocean) to the south, and New York to the west. Hartford, in the north-central part of the state, is the capital. The state's greatest east-west length is about 180 km, and its maximum north-south extent is about 110 km. Connecticut is an important study area for contextual analysis of diabetes death rates due to the following reasons: 1) In 2017, diabetes was the seventh leading cause of death in Connecticut. Diabetes may lead to premature deaths. 2) There has been no scholarly research conducted in Connecticut on diabetes death patterns and their relationship to contextual characteristics of county subdivisions.

DATA AND METHODS

This study is based on drug overdose death data collected and managed by the Connecticut Department of Public Health (CDPH). The data consisted of 3,767 reported diabetes deaths that occurred in 169 county subdivisions in Connecticut from January 1st, 2018 to December 31st, 2022. Then, diabetes death rates were calculated for each county subdivision in Connecticut as the number of reported drug overdose deaths per 10,000 total population. See Figure 2 below.

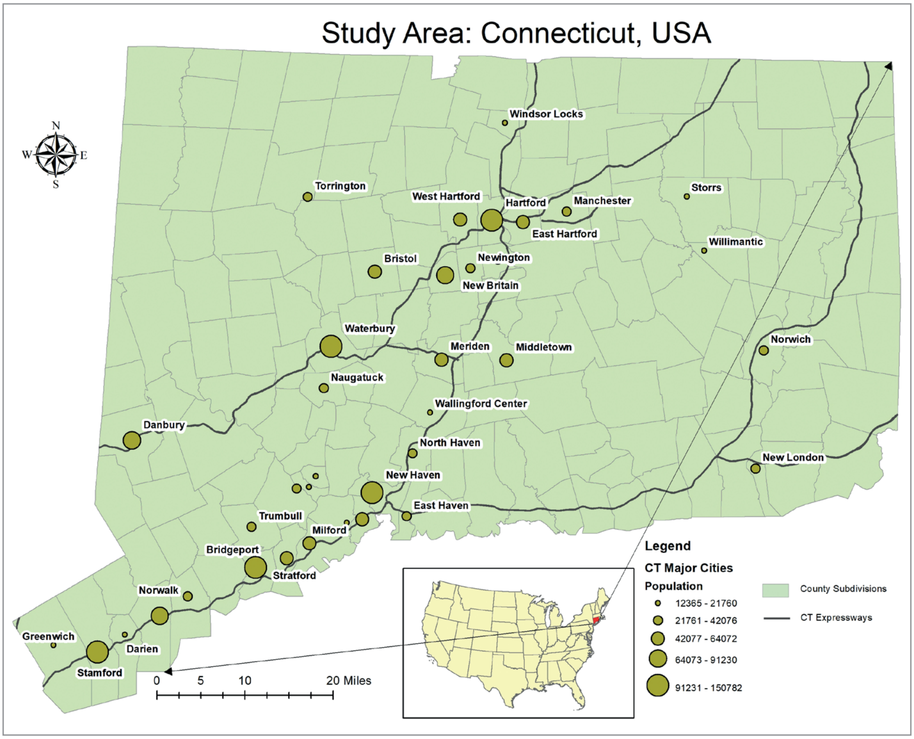

Fig. 1 Study Area: Connecticut, USA
Source: Census Bureau (2024; 2025)

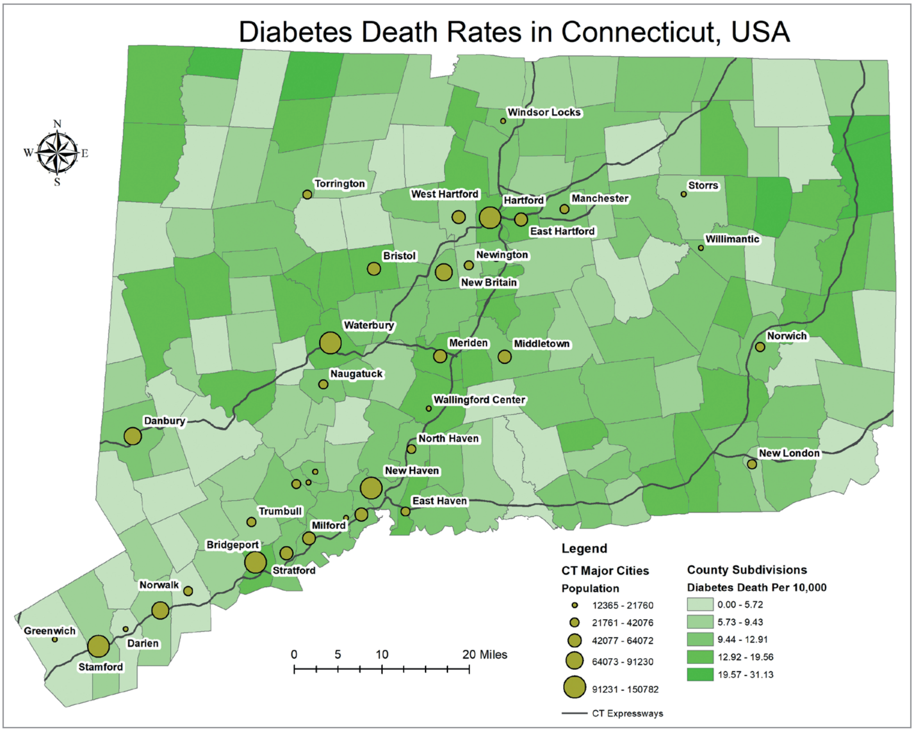

Fig. 2 Diabetes Death Rates in Connecticut, USA

Source: CENSUS BUREAU (2024; 2025); Connecticut Department of Public Health (2025)

The descriptive statistics for the dependent variable – diabetes death rates are shown in Table 1. Thereafter, the diabetes death rates table was joined with a shapefile consisting of 169 county subdivisions based on the unique 10-digit county subdivision Federal Information Processing System code assigned by the U.S. Census Bureau using ArcMap 10.8.2 (ESRI, 2021). This enabled the diabetes death rates to be later aligned with contextual variables for further analysis.

Tab. 1 Descriptive Statistics for the Dependent Variable – Drug Overdose Death Rates

	Min	Max	Median	Standard Deviation
Diabetes death rates: Diabetes deaths per 10,000 people	0.0	31.1	74.8	4.8

Source: Census Bureau (2024; 2025)

This study considers 16 contextual variables as potential explanatory variables and the descriptive statistics for each explanatory variable are shown in Table 2.

Tab. 2 Descriptive Statistics for the Explanatory Variables

Variables	Min	Max	Median	Standard Deviation
Demographic				
Age: % aged 65 and above	10.47	33.74	18.97	4.38
Race 1: % of Hispanic	0.38	46.11	7.12	8.68
Race 2: % of Blacks	0.00	54.75	1.98	7.21
Gender: % of males	39.91	62.17	49.64	2.79
Population density: the number of people per square kilometer	10.96	2950.96	169.74	472.24
Health				
Healthcare coverage: % without health insurance	0.60	14.30	3.10	2.50
Overweight and obesity rate: % of population whose BMI is equal or larger than 25	44.00	73.05	60.00	6.82
Disadvantage Status				
Joblessness: Unemployment rate	0.40	13.20	4.7	2.15
Poverty: % living under the poverty line	0.20	26.90	5.6	5.13
Education: % of people who don't have a college degree	12.62	79.03	48.37	14.18
Food Access				
% of population beyond 1 mile from supermarket	0.00	14.31	3.3	2.15
% of population beyond 1 mile for urban areas or 10 miles for rural areas from supermarket	0.00	91.07	25.79	27.28
% of households reported not having sufficient funds in the last 12 months to purchase food	2.00	33.30	8.00	5.06

Source: Census Bureau (2024; 2025); Connecticut Department of Public Health (2025)

The 11 contextual variables, covering demographic, health, disadvantage status, and food access were chosen to reflect the key dimensions underlying the variation in the risk of diabetes deaths as suggested by existing empirical research described in literature review. The demographic and socio-economic variables – residential population, age, race, gender, healthcare coverage, disability, joblessness, household type, education, and poverty were taken from the 2018-2022 American Community Survey (ACS) five-year estimates (Census Bureau, 2024).

The most recent overweight and obesity rate and the percentage of households reported not having sufficient funds in the last 12 months to purchase food were collected by DataHaven in 2015. The rest of the food access variables comes from Food Access Research Atlas which was prepared by the United States Department of Agriculture (2024).

The age variable was calculated by the percentage of people aged 65 and above. The race 1 and 2 variables were measured by the percentage of Hispanic and Black people in the residential population respectively. The gender variable was quantified by the percentage of males in the population. The population density was calculated by the number of people per square kilometer. The healthcare coverage variable was measured by the percentage of people without health insurance coverage. The overweight and obesity rate was quantified by the percentage of population whose BMI is equal or larger than 25. The jobless variable was determined by the unemployment rate. The poverty variable was measured as the percentage of people living under the poverty line. The education variable was calculated by the percentage of people without a college degree. The food access variable was quantified by the percentage of people living beyond 1 mile from the nearest supermarket, the percentage of people living beyond 1 mile for urban areas or 10 miles for rural areas from the nearest supermarket, and the percentage of households reported not having sufficient funds in the last 12 months to purchase food.

RESULTS AND DISCUSSION

The first step is to examine the dependent variable, diabetes death rates, and explore its spatial heterogeneity. If the dependent variable is not spatially clustered, there is no need to build a spatially explicit model. The Moran's I Index (Anselin, 1995) provided by ArcMap 10.8.2 (ESRI, 2021) was used to identify the clustering of diabetes death rates across county subdivisions in the State of Connecticut. Moran's I ranges from −1.0, perfectly dispersed (e.g., a checkerboard pattern), to a +1.0, perfectly clustered. In this research, Moran's I score (0.052) and p value (0.273) were generated, indicating that diabetes death rates in Connecticut are spatially random, and the results are statistically insignificant.

The OLS multivariate model (Aiken and West, 1991) in the Statistical Package for the Social Sciences (SPSS) 29 was then used to conduct linear regressions, since the dependent variable is not spatially clustered. If the standard regression equation in the investigation of the dependent variable is given by:

$$Y_i = \beta_0 + \sum_k \beta_k x_{ki} + \varepsilon_i$$

where Yi is the diabetes death rate at county subdivision i, β_0 is a constant term (i.e., the intercept), β_k measures the relationship between the independent variable x_k and Y for the set of i county subdivisions, and εi is the error associated with county subdivision i. It should be noted that i ∈ C = {1,2,…,n} which is the index set of locations of n observations (i.e. all county subdivisions in Connecticut). The summary of the OLS analysis results is presented in Table 3.

In the OLS regression, included were variables that are statistically significantly correlated with the diabetes death rates ($p < 0.05$). The OLS model is statistically significant ($F = 6.7$, $p < 0.01$). The R2 and adjusted R2 values are 0.623 and 0.578 which means that the OLS model explained 57.8% of the variance in county subdivision-level diabetes death rates in Connecticut. The VIF values for all variables was less than 5.0, a commonly used cutoff point (Becker et al., 2014; Ringle et al., 2015), suggesting no severe multicollinearity issue was detected among the explanatory variables (see Table 3). In other words, the correlations among the 5 included explanatory variables are low.

Tab. 3 Results from Ordinary Least Square Model of Drug Overdose Death Rates at County Subdivision-Level in Connecticut

Dependent Variable	Independent Variables	Standardized β	p value	VIF
Diabetes Death Rates	**Intercept**	-----	< 0.01	-----
	% of Hispanic	0.203	< 0.05	1.355
	The number of people per square kilometer	-0.221	< 0.05	1.732
	Unemployment rate	-0.161	< 0.05	1.342
	% of population beyond 1 mile from supermarket	0.273	< 0.01	1.554
	% of population beyond 1 mile for urban areas or 10 miles for rural areas from supermarket	0.151	< 0.01	1.153
	% of households reported not having sufficient funds in the last 12 months to purchase food	0.309	< 0.05	1.522

As shown in Table 3, there is a positive and significant relationship between diabetes death rates and the percentage of Hispanic people. In other words, the higher the percentage of Hispanic people in the population, the higher the diabetes death rates. The research result is consistent with previous research showing that Hispanics were 1.5 times more likely than non-Hispanic Whites to die from diabetes (Office of Minority Health, 2020). This conveys a huge cost or burden to Hispanic community in Connecticut. On one side, Hispanic population make up the state's largest minority group, but they also have the highest poverty rate among the major race and ethnicity groups. According to 1-year estimates from the 2021 American Community Survey (ACS), there are roughly 637,113 people of Hispanic or Latino ethnicity residing in Connecticut, accounting for 17.7% of Connecticut's total population. Hispanic residents of Connecticut have a poverty rate of 21.4% in 2021 which is higher than the poverty rates of Asian (8.7%), White (17.3%), Black (17.3) and American Indians/Natives (20.7%). On the other side, the total estimated cost of diagnosed diabetes in Connecticut in 2017 is $3.7 billion. People with diabetes have medical expenses approximately 2.3 times higher than those who do not have diabetes. In addition, another $960 million was spent on indirect costs from lost productivity or lives due to diabetes. Since most of Hispanic population in Connecticut live in towns and cities located in Hartford, Fairfield, and New Haven counties, needed is a tailored diabetes intervention program for Hispanic population in those areas that promotes a healthy diet, regular physical exercises, maintaining a normal body weight, and avoiding tobacco uses. Diabetes can be treated, and its serious consequences can be avoided or at least delayed with a heathy diet, regular physical activity, affordable medication, and regular screening and treatment for complications.

There is a negative and significant relationship between diabetes death rates and the population density. In other words, the higher the number of people per square kilometer, the higher the diabetes death rates. The study result supports the previous research done by Dugani et al. (2022), showing U.S. rural areas have higher death rates caused by diabetes than more urbanized environments. Diabetes requires lifelong care. Accessing that care may be more difficult in rural areas than in more urbanized areas. In addition, people who live in rural areas may be at higher risk for developing diabetes at the first place. The Connecticut Office of Rural Health (CT-ORH) defines a Connecticut town as rural if it satisfies two conditions: the total population of the town is 10,000 residents or fewer and has a population density less than 500 people per square mile. There are 68 towns that meet the state's criteria for a rural designation. In addition, the CT-ORH definition includes towns that contain a census tract designated as rural by Health Resources and Services Administration as of 2020, adding 9 additional towns. This combined definition consists of 77 towns statewide which make up 45.5% of total number of county-subdivisions in Connecticut. In 2021, Connecticut has a population of 3,583,561 residents of whom 326,132 (9.1%) live in rural towns. Needed is improved access to diabetes preventive health services for the residents living in the 77 rural towns. The CT-ORH also needs to prioritize initiatives and dedicate resources to enhance access to quality and affordable health care for the rural Connecticut residents to avoid or delay diabetes related deaths.

There is a negative and significant relationship between diabetes death rates and the joblessness. In other words, the lower the unemployment rate, the higher the diabetes death rate which is inconsistent with the literature (Varanka-Ruuska, et al. 2018; Wadhera et al., 2020). This may be caused by an increasingly serviced or sedentary lifestyle (i.e. watching TV; sitting at work and other sitting; increased mechanization and driving) in the employed population (Hu 2011; Richards et al., 2022). Additionally, a reduction in unemployment which often leads to an increase in average income would result in higher levels of spending on discretionary foods (i.e. high caloric with poor nutritional value), which may result in an increase in the prevalence of diabetes and consequently higher diabetes death rates (Penrose and Cava, 2021; Richards et al., 2022). Conversely an increase in unemployment may reduce the proportion of income spent on these discretionary foods (Penrose and Cava; Richards et al., 2022). According to Rodriguez-Sanchez and Cantarero-Prieto's (2017) research, diabetes prevalence is significant and negatively related to short-term unemployment (or unemployed for less than one year), but significant and positively associated with long-term (or unemployed for one year or more). People with diabetes are more likely to experience problems in obtaining employment after being unemployed than people without diabetes (Robinson et al., 1990). The ACS data do not differentiate the length of unemployment, so it is challenging to confirm whether the counter-intuitive relationship between the joblessness and diabetes death rates more likely applies to towns or cities that have higher short-term unemployment rates or not. More in-depth studies are needed to further investigate the relationship between joblessness and diabetes death rates in Connecticut.

There is a positive and significant relationship between diabetes death rates and the three food access variables. In other words, the higher the percentage of population beyond 1 mile from supermarket, the percentage of population beyond 1 mile for urban areas or 10 miles for rural areas from supermarket, the percentage of households reported not having sufficient funds in the last 12 months to purchase food, the higher the diabetes death rates. Research shows that adults who experience food insecurity are 2 to 3 times more likely to have type 2 diabetes (Fitzgerald et al, 2011; Seligman et al, 2007). Additionally, nutritious foods may be too expensive for some people, which limits healthy food choices. Foods that are cheaper and easier to find tend to be lower-quality processed foods. They're usually high in added sugars, saturated fat, and sodium (salt). While these foods can provide plenty of calories, they can increase the risk of developing type 2 diabetes. For people who already have diabetes, food insecurity can affect how well they manage their diabetes. Food insecurity can lead to diabetes-related complications, poorer mental health, hospitalizations and death. According to recent data from Feeding America, food insecurity is rising in Connecticut, disproportionately affecting Black and Hispanic households. Alarmingly, about 468,150 (approximately 1 in 8) Connecticut residents struggle with hunger and more than 112,000 (1 in 6) children are food insecure (Dewey et al., 2024). Additionally, food deserts refer to areas where at least a third of the population (or 500 people) live at least one mile (if in a city) or 10 miles (if in a rural area) from the nearest grocery store. In 2019, the most recent data available, about 8 percent of Connecticut's census tracts were considered a food desert. Census tracts which are classified as food deserts are mapped on food access research atlas (U.S. Department of Agriculture, 2024). Living in a food desert exacerbates Connecticut residents' ability to access the healthy and fresh foods they want. As a result, it can lead to an increased risk of diabetes prevalence and increased mortality rates for the residents. Lifting communities out of poverty is a long-term solution to food insecurity, removing or alleviating barriers for food access could be a short-term solution. Needed are solutions such as providing tax incentives to encourage grocery stores opening in census tracts that are classified as food deserts by the U.S. Department of Agriculture (2024), regulating grocery stores to sell more unprocessed, fresh, and healthful foods; or expanding food assistance programs to low-income households in Connecticut.

The rest of the explanatory variables are insignificantly related to the dependent variable in this study. The residuals of the OLS model were not spatially auto-correlated (Moran's I = 0.044, p = 0.473), indicating that the OLS model neither overestimates diabetes death rates for some county subdivisions, nor underestimates the results for some others. Kolmogorov-Smirnov and Shapiro-Wilk tests were used to test the normality of OLS model residuals. Both p values are greater than 0.05 which confirms that the underlying residuals are normally distributed, meaning the OLS model's inferences (like confidence intervals and p-values) are reliable and less affected by outliers.

Tab. 4 Tests of Normality for OLS Model Residuals

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	**df**	**Significance**	**Statistic**	**df**	**Significance**
Standardized Residual	0.286	169	0.220	0.865	169	0.541

This study is not without limitations. First, county subdivision boundaries in Connecticut were used, so the relationships between diabetes death rates and contextual characteristics at the county subdivision level cannot be interpreted as and/or applied to individual level relationships. Second, it should be noted that the dataset prepared by the Connecticut Department of Public Health may underestimate the diabetes death rates to some extent, because the diabetes death data were compiled based on death certificates in Connecticut. However, the proportion of deaths attributable to diabetes in the US is as high as 12 percent—three times higher than estimates based on death certificates suggest (Stokes and Preston, 2017). Third, diabetes death data were collected between 2018 and 2023, but the most recent food access variables were collected in 2019. The most recent and complete overweight and obesity rates in Connecticut were gathered in 2015. The temporal mismatch between the independent variables and diabetes death could affect the validity of the findings. In addition, the R2 values accounted for 57.8% of the diabetes death rates, which means that other risk factors (e.g. access to healthcare infrastructures, early diagnosis of diabetes, and a change of personal lifestyle) associated with the diabetes death rates need to be added into the OLS models. For example, dietary adjustments and exercise remain important components to reduce diabetes risks alongside the wide array of novel glucose-lowering medications (Yeh et al. 2023). Additionally, having regular check-ups and undergoing the required tests are important in the early diagnosis and treatment of diabetes. As a result of early diagnosis of diabetes, treatment can be started early and deaths caused by diabetes could be prevented or delayed.

CONCLUSIONS

The relationships between the diabetes death rates and contextual variables are still under investigation and little research has been done in Connecticut. This study discloses the complex nature of the relationship between deaths caused by diabetes and their demographic (i.e. percent of Hispanic and the number of people per square kilometer), socio-economic inequalities (i.e. unemployment rate), and environmental correlates (e.g. food insecurity and the percent of people living in the food desert) and calls for understanding it in the context of polycrisis framework (Lawrence et al., 2024; Matlovič and Matlovičov, 2024). By using OLS, health researchers and practitioners can gain an understanding of health-related issues and respond to the notion that "all health is local" (Gebreab and Diez-Roux, 2012). For example, the risk of diabetes mortality correlated strongly with unemployment rate, a measure of social stratification, increasing 2.5% for each 1% increase in unemployment rate (Wadhera et al., 2020). However, the death rate is largely negatively correlated with unemployment rate across the cities and towns in Connecticut. In other words, the diabetes death rates are more likely to be higher in cities and towns where unemployment rates are lower. In addition, the results of this study can also be used by the CDPH to tailor unique diabetes prevention and intervention strategies to different targeted cities and towns in Connecticut. This study presents an initial and exploratory step towards better understanding of diabetes death rates in Connecticut, U.S., but much more in-depth work is needed before health researchers and practitioners understand why explanatory factors only explained up to 57.8% of the diabetes death rates in the state.

REFERENCES

AMIR, R., SUHL, S., ALEXANDER, C.M. (2020) Renal Evaluation and Protection. *Clinics in Geriatric Medicine*, 36(3): 431-445.

ANSELIN, L. (1995) Local Indicators of Spatial Association – LISA, *Geographical Analysis*, 27(2) 93-115.

BAENA-DÍEZ, J.M., PEÑAFIEL, J., SUBIRANA, I., RAMOS, R., ELOSUA, R., MARÍN-IBAÑEZ, A., GUEMBE, M.J., RIGO, F., TORMO-DÍAZ, M.J., MORENO-IRIBAS, C., CABRÉ, J.J., SEGURA, A., GARCÍA-LAREO, M., GÓMEZ, D.L., CÁMARA, A., LAPETRA, J., QUESADA, M., MARRUGAT, J., MEDRANO, M.J., BERJÓN, J., FRONTERA, G., GAVRILA, D., BARRICARTE, A., BASORA, J., GARCÍA, J.M., PAVONE, N.C., LORA-PABLOS, D., MAYORAL, E., FRANCH, J., MATA, M., CASTELL, C., FRANCES, A., GRAU M. (2016) Risk of Cause-specific Death in Individuals with Diabetes: A Competing Risks Analysis. *Diabetes Care*, 39(11): 1987-1995.

BERKOWITZ, S.A., KARTER, A.J., CORBIE-SMITH, G., SELIGMAN, H.K., ACKROYD, S.A., BARNARD, L.S., ATLAS, S.J., WEXLER, D.J. (2018) Food Insecurity, Food "Deserts," and Glycemic Control in Patients With Diabetes: A Longitudinal Analysis. *Diabetes Care*, 41(6): 1188-1195.

CENSUS BUREAU (2024). 2018-2022 ACS 5-year Estimates. Retrieved from: https://www.census.gov/programs-surveys/.

CENSUS BUREAU (2025). Mapping Files. Retrieved from: https://www.census.gov/geographies/mapping-files.html.

CENTERS FOR DISEASE CONTROL AND PREVENTION (2024a). Deaths: Final Data for 2020. National Vital Statistics Report. Vol. 72, No. 10 Centers for Disease Control and Prevention (2024a). A Report Card: Diabetes in the United States Infographic. Retrieved from: https://www.cdc.gov/diabetes/communication-resources/diabetes-statistics.html.

CENTERS FOR DISEASE CONTROL AND PREVENTION (2024b). Prediabetes: Could It Be You? Infographic. Retrieved from: https://www.cdc.gov/diabetes/communication-resources/.

CENTERS FOR DISEASE CONTROL AND PREVENTION (2024c). $413 Billion in Diabetes Costs. Retrieved from: https://www.cdc.gov/diabetes/communication-resources/413-billion-diabetes-costs.html.

CHANDRASEKARAN, P., WEISKIRCHEN, R. (2024) The Role of Obesity in Type 2 Diabetes Mellitus-An Overview. *International Journal of Molecular Sciences*, 25(3):1882.

CHENG, Y., KANAYA, A.M, ARANETA, M.R., SAYDAH, S.H., KAHN, H.S., GREGG, E.W., FUJIMOTO, W.Y., IMPERATORE, G. (2019) Prevalence of Diabetes by Race and Ethnicity in the United States, 2011-2016. *The Journal of the American Medical Association*, 322(24): 2389-2398.

CIARAMBINO, T., CRISPINO, P., LETO, G., MASTROLORENZO, E., PARA, O., GIORDANO, M. (2022) Influence of Gender in Diabetes Mellitus and Its Complication. *International Journal of Molecular Sciences* 23(16): 8850.

CONNECTICUT DEPARTMENT OF PUBLIC HEALTH (2025). Research and Data, Retrieved from: https://portal.ct.gov/DPH/Vital-Records/Research-and-Data.

COOPER, Z.W., MOWBRAY, O., JOHNSON, L. (2024) Social determinants of health and diabetes: using a nationally representative sample to determine which social determinant of health model best predicts diabetes risk. *Clinical Diabetes and Endocrinology*, 10 (1):4.

CURRY, A. (2009) Bringing Healthy Fare to Big-City 'Food Deserts'. *Diabetes Forecast*, Retrieved from: https://dosomething.org/article/11-facts-about-food-deserts.

DATAHAVEN (2015) Community Wellbeing Survey Connecticut Statewide Crosstabs.

DEWEY, A., HARRIS, V., HAKE, M., ENGELHARD, E. (2024) Map the Meal Gap 2024: An Analysis of County and Congressional District Food Insecurity and County Food Cost in the United States in 2022. *Feed America*. Retrieved from: https://www.ctfoodshare.org/hunger-in-ct

DUGANI, S.B., WOOD-WENTZ, C.M., MIELKE, M.M., BAILEY, K.R., VELLA, A. (2022) Assessment of Disparities in Diabetes Mortality in Adults in US Rural vs Nonrural Counties, 1999-2018. *JAMA Netw Open,* 5(9): e2232318.

ENVIRONMENTAL SYSTEM RESEARCH INSTITUTE (ESRI), 2021, *ArcGIS Desktop: Release 10.8.2*, Redlands, CA.

FITZGERALD, N., HROMI-FIEDLER, A., SEGURA-PÉREZ, S., PÉREZ-ESCAMILLA, R. (2011) Food Insecurity Is Related to Increased Risk of Type 2 Diabetes among Latinas. *Ethnicity & Disease*, 1(3): 328-34.

FONG, H.K., DESAI, R., FAISALUDDIN, M., PAREKH, T., MAHMOOD, A., SHAH, V., SHAH, P., VARAKANTAM, V.R., HASSAN, F.A., SAVANI, S., DOSHI, R., GANGANI, K. (2021) Sex Disparities in Cardiovascular Disease Outcomes among Geriatric Patients with Prediabetes. *Primary Care Diabetes*,15(1): 95-100.

FU, P., WEN, J., DUAN, X., HU, X., CHEN, F., YUAN, P. (2023) Association between Adult Food Insecurity and Mortality among Adults Aged 20-79 Years with Diabetes: A Population-based Retrospective Cohort Study. *Diabetic Medicine*, 41(4): e15268.

HALE, N.L., BENNETT, K.J., PROBST, J.C. (2010) Diabetes Care and Outcomes: Disparities Across Rural America. *Journal of Community Health*, 35(4): 365-374.

HILL-BRIGGS, F, ADLER, N.E., BERKOWITZ, S.A., CHIN, M.H., GARY-WEBB, T.L., NAVAS-ACIEN, A., THORNTON, P.L., HAIRE-JOSHU, D. (2020) Social Determinants of Health and Diabetes: A Scientific Review. *Diabetes Care*, 44(1): 258-79.

HIPP, J.A., CHALISE, N. (2015) Spatial Analysis and Correlates of County-level Diabetes Prevalence, 2009-2010. *Preventing Chronic Disease*, Vol.12. Retrieved from: https://www.cdc.gov/pcd/issues/2015/14_0404.htm.

HU, F.B. (2011) Globalization of Diabetes. *Diabetes Care*. 34: 1249-1257.

KAHN, B.B., FLIER, J.S. (2000) Obesity and Insulin Resistance. *the Journal of Clinical Investigation*, 106(4): 473-81.

KAUTZKY-WILLER, A., LEUTNER, M., HARREITER, J. (2023) Sex Differences in Type 2 Diabetes, *Diabetologia*. 66(6): 986-1002.

LAWRENCE, M., HOMER-DIXON, T., JANZWOOD, S., ROCKSTÖM, J., RENN, O., DONGES, J.F. (2024) Global Polycrisis: the Causal Mechanisms of Crisis Entanglement. *Global Sustainability*, 7(6): 1-16.

MA, H., WANG, X., LI, X., HEIANZA, Y., KATZMARZYK, P.T., FRANCO, O.H., QI, L. (2024) Food Insecurity and Premature Mortality and Life Expectancy in the US, *JAMA Internal Medicine*. 184(3): 301-310.

MAHONEY, S., BRADLEY, A., PITTS, L., WALETZKO, S., ROBINSON-LANE, S.G., FAIRCHILD, T., TERBIZAN, D.J., MCGRATH, R., (2020) Health Insurance Is Associated with Decreased Odds for Undiagnosed Prediabetes and Type 2 Diabetes in American Adults. *International Journal of Environmental Research and Public Health,* 17(13): 4706.

MATLOVIČ, R., MATLOVIČOVÁ, K. (2024) Polycrisis in the Anthropocene as Key Research Agenda for Geography: Ontological Delineation and the Shift to a Postdisciplinary Approach. *Folia Geographica* 66(1), 5-33.

MAUVAIS-JARVIS, F., MANSON, J.E., STEVENSON, J.C., FONSECA, V.A. (2017) Menopausal Hormone Therapy and Type 2 Diabetes Prevention: Evidence, Mechanisms and Clinical Implications. *Endocrine Reviews*, 38(3):173-188.

MORIN, E., KERN, A.B. (1999) *Homeland Earth: A Manifesto for the New Millenium*. Cresskill, N.J: Hampton Press.

OFFICE OF MINORITY HEALTH (2020) Diabetes and Hispanic Americans, Retrieved from: https://minorityhealth.hhs.gov/diabetes-and-hispanic-americans#.

PENROSE G., CAVA G.L. (2021) Job Loss, Subjective Expectations and Household Spending. RBA Research Discussion Papers rdp2021-08, Reserve Bank of Australia.

RICHARDS, S.E., WIJEWEERA, C., WIJEWEERA, A. (2022) Lifestyle and Socioeconomic Determinants of Diabetes: Evidence from Country-level Data. *PLoS One*, 17(7): e0270476.

SELIGMAN, H.K., BINDMAN, A.B., VITTINGHOFF, E., KANAYA, A.M., KUSHEL, M.B. (2007) Food Insecurity Is associated with Diabetes Mellitus: Results from the National Health Examination and Nutrition Examination Survey (NHANES) 1999-2002. *Journal of General Internal Medicine*, 22(7):1018-1023.

STOKES, A., PRESTON, S.H. (2017) Deaths Attributable to Diabetes in the United States: Comparison of Data Sources and Estimation Approaches. *PLoS One*, 12(1): e0170219.

THE UNITED STATES DEPARTMENT OF AGRICULTURE (2024) Food Access Research Atlas. Retrieved from: https://www.ers.usda.gov/data-products/food-access-research-atlas/.

VARANKA-RUUSKA, T., RAUTIO, N., LEHTINIEMI, H., MIETTUNEN, J., KEINÄNEN-KIUKAANNIEMI, S., SEBERT, S., ALA-MURSULA, L. (2018) The Association of Unemployment with Glucose Metabolism: A Systematic Review and Meta-analysis. *International Journal of Public Health*, 63(4): 435-446.

WADHERA, R.K., KHATANA, S.M., CHOI, E., JIANG, G., SHEN, C., YEH, R.W., KAREN, E., MADDOX, J. (2020) Disparities in Care and Mortality Among Homeless Adults Hospitalized for Cardiovascular Conditions. *JAMA Internal Medicine*, 180(3):357-366.

WORLD HEALTH ORGANIZATION (2024a). Diabetes. Retrieved from: https://www.who.int/health-topics/diabetes#tab=tab_1.

WORLD HEALTH ORGANIZATION (2024b). Diabetes. Retrieved from: https://www.who.int/news-room/fact-sheets/detail/diabetes.

YEH, Y.K., YEN, F.S., HWU, C.M. (2023) Diet and Exercise Are A Fundamental Part of Comprehensive Care for Type 2 Diabetes. *Journal of Diabetes Investigation*, 14(8):936-939.