Geographic Epidemiology of Diabetes-Related Complications and Hospitalizations in Florida

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

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December 2023

Acknowledgements

First and foremost, I would like to express my deepest gratitude to my faculty mentor, Dr. Agricola Odoi, who encouraged me to pursue a doctoral degree and has been an exceptionally caring, supportive, and dedicated advisor. I feel incredibly fortunate to have had the opportunity to learn from him, and this dissertation could not have been completed without his supervision and expertise. I would also like to express my sincere thanks to each of the members of my advisory committee, Drs. Kristina Kintziger, Louis Rocconi, and Russell Zaretzki, whose support and expertise have been invaluable. I would also like to thank the Florida Department of Health and Agency for Health Care Administration for providing the hospital discharge data that made this research possible. In particular, I am grateful to Dr. Keshia Reid, Chris Duclos, and Alan Mai for their help in this process and for their insightful feedback. To my colleagues in the CEM program, I am so appreciative of your friendship and advice. In addition, I would like to thank Morgan Tolbert for always going the extra mile with her administrative support. I am also deeply grateful to the CEM program for the financial support that has enabled me to pursue this degree. Lastly, I would like to thank my friends and family for their understanding and encouragement throughout my graduate school career. My sweet dog, Piper, has been an unwavering companion over the course of multiple graduate programs. And to my husband Steve, I cannot begin to express my appreciation for your love, patience, and support - I am deeply grateful.

Abstract

Background: Understanding disparities in and drivers of adverse diabetes outcomes is important for guiding strategies to improve diabetes management, reducing risks of complications, and eliminating disparities. Thus, studies investigating disparities and predictors of these complications as well as diabetes-related hospitalization (DRH) rates are useful for guiding efforts to reduce these disparities and improve diabetes related health outcomes. Therefore, the objectives of this research were to: (i) identify predictors of severity of diabetes complications; (ii) investigate local geographic disparities of DRH rates; and (iii) identify determinants of geographic disparities of DRH rates and determine if the strengths of associations between the identified determinants and the outcome vary spatially.

Methods: Retrospective analyses were conducted using hospital discharge data from Florida from 2016 to 2019. Population average models, estimated using generalized estimating equations, were used to identify individual- and ZIP code tabulation area (ZCTA)-level predictors of severe diabetes complications. Raw and spatial empirical Bayes smoothed DRH rates were computed at the ZCTA-level. High-rate DRH clusters were identified using Tango's flexible spatial scan statistic. Ordinary least squares and multiscale geographically weighted regression models were fit to identify predictors of DRH rates and describe spatial heterogeneity of regression coefficients.

Results: Significant predictors of severity of diabetes complications included age, race/ethnicity, gender, comorbidities (hypertension, hyperlipidemia, obesity, depression, and arthritis), type of health insurance coverage, and neighborhood socioeconomic status. The statewide DRH rate was 8.5 per 1,000 person-years. Significant spatial clusters of DRH rates tended to be in rural rather than urban areas. Areas with high DRH rates tended to have higher: (i) proportions of older adults, (ii) non-Hispanic Black residents, and (iii) unemployment rates; and lower: (i) levels of income, (ii) health insurance coverage, and (iii) vehicle access. There was evidence of heterogeneity of regression coefficients at local, regional, and statewide scales.

Conclusions: The identification of high-rate DRH clusters and determinants of severe complications and hospitalization rates provides useful information to guide resource allocation and locally-focused health planning such that communities with the highest burdens are prioritized to reduce the observed disparities and improve diabetes outcomes.

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List of Abbreviations

ACS: American Community Survey

ACSC: Ambulatory Care Sensitive Condition

aDCSI: Adapted Diabetes Complications Severity Index

AHRQ: Agency for Healthcare Research and Quality

AICc: Bias-Corrected Akaike's Information Criterion

BW: Bandwidth

CDC: Centers for Disease Control and Prevention

CFR: Code of Federal Regulations

CI: Confidence Interval

DCSI: Diabetes Complications Severity Index

DRH: Diabetes-Related Hospitalization

DSME: Diabetes Self-Management Education

EDGE: Education Demographic and Geographic Estimates

ENP: Effective Number of Parameters

FSSS: Flexible Spatial Scan Statistic

GEE: Generalized Estimating Equations

GIS: Geographic Information System

GWR: Geographically Weighted Regression

HbA1c: Hemoglobin A1c

HIPAA: Health Insurance Portability and Accountability Act

ICD-10-CM: International Classification of Diseases, Tenth Revision, Clinical Modification

ICD-10-PCS: International Classification of Diseases, Tenth Revision, Procedure Coding System

IQR: Interquartile Range

IRB: Institutional Review Board

KM: Kilometer

LLR: Log-Likelihood Ratio

MGWR: Multiscale Geographically Weighted Regression

mRFEI: Modified Retail Food Environment Index

NAICS: North American Industry Classification System

NDI: Neighborhood Deprivation Index

OLS: Ordinary Least Squares

OR: Odds Ratio

PCA: Principal Components Analysis

PLACES: Population-Level Analysis and Community Estimates

PQI: Prevention Quality indicator

QIC_u: Modified Quasi-Likelihood Information Criterion

RR: Rate Ratio

SAS: Statistical Analysis System

SEB: Spatial Empirical Bayes

SNAP: Supplemental Nutrition Assistance Program

SSN: Social Security Number

TIGER: Topologically Integrated Geographic Encoding and Referencing

UDS: Uniform Data System

US: United States

USA: United States of America

UTK: University of Tennessee, Knoxville

VA: Veterans Affairs

VIF: Variance Inflation Factor

ZCTA: ZIP Code Tabulation Area

ZIP: Zone Improvement Plan

CHAPTER 1

Introduction

Diabetes mellitus affects over 37 million adults in the United States, and it is estimated that 23% of adults with diabetes have yet to be diagnosed [1]. The condition is characterized by hyperglycemia, which either results from insulin resistance or impaired insulin production [2]. Inadequate control of diabetes can cause acute metabolic complications, and can also lead to long-term complications such as heart disease, stroke, renal disease, and neuropathy [3,4]. These complications can ultimately lead to functional limitations, physical disability, impacts on quality of life, and premature mortality [3,5–9]. In 2019, diabetes was the seventh leading cause of death in the United States [10]. Since many of the sequelae of diabetes may be prevented/delayed with appropriate management, early diagnosis, glycemic control, and management of cardiovascular risk factors are considered key components of diabetes care [11–13]. Indeed, diabetes is referred to as an ambulatory care sensitive condition (ACSC) because hospitalizations due to diabetes and its complications are generally preventable if the condition is managed effectively in the outpatient setting [14].

Reducing the burden of preventable diabetes-related complications and hospitalizations represents an important opportunity to improve population health in the United States. This is particularly true in southeastern states, which have the highest burden of diabetes in the nation [15,16]. Florida is the most populous state in this region, and it is estimated that at least 2.5 million of the state’s adult residents have diabetes [17,18]. In order to mitigate the burden of diabetes complications in Florida, it will be essential to focus intervention strategies on populations at high risk of adverse diabetes outcomes. Understanding the drivers of these outcomes is useful for guiding strategies to improve diabetes management and reduce risks of complications.

Unfortunately, there is a lack of information regarding the distribution and determinants of diabetes complications and hospitalizations at the local level in Florida. Therefore, the overall goal of this research was to investigate disparities and determinants of diabetes complications and hospitalizations, and provide information to guide evidence-based health planning to reduce inequities in adverse diabetes outcomes. The specific objectives of this project were to: (i) identify individual- and area-level predictors of severe diabetes complications among hospitalized adult patients (Chapter 2); (ii) investigate the geographic distribution of diabetes-related hospitalization rates at the ZIP code tabulation area (ZCTA) level, identify significant local clusters of high hospitalization rates, and describe characteristics of ZCTAs within the observed spatial clusters (Chapter 3); and (iii) identify determinants of diabetes-related hospitalization rates at the ZCTA level and assess if the strengths of these relationships vary by geographic location and at different spatial scales (Chapter 4). All studies were retrospectively conducted in Florida, using hospital discharge data provided by the Agency for Health Care Administration, through a Data Use Agreement with the Florida Department of Health.

This dissertation contains five separate chapters. The introductory chapter includes a brief background and the objectives of this work. Chapters 2, 3, and 4 describe the methods and results of studies addressing the objectives listed above. The findings of Chapters 2, 3, and 4 have been submitted for publication and are currently under peer review. Lastly, Chapter 5 summarizes and discusses the findings of this work, and outlines directions for future research.

CHAPTER 2

Investigation of predictors of severity of diabetes complications among hospitalized patients with diabetes in Florida, 2016-2019

A version of this chapter has been submitted for peer review at *BMC Public Health*. My contributions to this manuscript included study design, data preparation and analysis, and drafting and editing the manuscript. Dr. Agricola Odoi was also involved in the design of the study and revision of the manuscript. Co-authors from the Florida Department of Health, Dr. Keshia Reid, Chris Duclos, and Alan Mai, were involved in data curation and revision of the manuscript. All authors read and approved the final manuscript.

2.1 Abstract

Background: Severe diabetes complications impact the quality of life of patients and may lead to premature deaths. However, these complications are preventable through proper glycemic control and management of risk factors. Understanding the risk factors of complications is important in guiding efforts to manage diabetes and reduce risks of its complications. Therefore, the objective of this study was to identify risk factors of severe diabetes complications among adult hospitalized patients with diabetes in Florida.

Methods: Hospital discharge data from 2016 to 2019 were obtained from the Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. Adjusted Diabetes Complications Severity Index (aDCSI) scores were computed for 1,061,140 unique adult patients with a diagnosis of diabetes. Severe complications were defined as those with an aDCSI≥4. Population average models, estimated using generalized estimating equations, were used to identify individual- and area-level predictors of severe diabetes complications.

Results: Non-Hispanic Black patients had the highest odds of severe diabetes complications compared to non-Hispanic White patients among both males (Odds Ratio [OR] = 1.20, 95% Confidence Interval [CI]: 1.17, 1.23) and females (OR=1.27, 95% CI: 1.23, 1.31). Comorbidities associated with higher odds of severe complications included hypertension (OR=2.30, 95% CI: 2.23, 2.37), hyperlipidemia (OR=1.29, 95% CI: 1.27, 1.31), obesity (OR=1.24, 95% CI: 1.21, 1.26) and depression (OR=1.09, 95% CI: 1.07, 1.11), while the odds were lower for patients with a diagnosis of arthritis (OR=0.81, 95% CI: 0.79, 0.82). Type of health insurance coverage was associated with the severity of diabetes complications, with significantly higher odds of severe complications among Medicare (OR=1.85, 95% CI: 1.80, 1.90) and Medicaid (OR=1.83, 95% CI: 1.77, 1.90) patients compared to those with private insurance. Residing within the least socioeconomically deprived ZIP code tabulation areas (ZCTAs) in the state had a protective effect compared to residing outside of these areas.

Conclusions: Racial, ethnic, and socioeconomic disparities in the severity of diabetes complications exist among hospitalized patients in Florida. The observed disparities likely reflect challenges to maintaining glycemic control and managing cardiovascular risk factors, particularly for patients with multiple chronic conditions. Interventions to improve diabetes management should focus on populations with disproportionately high burdens of severe complications to improve quality of life and decrease premature mortality among adult patients with diabetes in Florida.

2.2 Background

Diabetes mellitus is one of the most common chronic diseases in the United States (U.S.), with an estimated 28.5 million diagnosed cases among adults in 2019 [1]. Complications of diabetes are a significant public health burden [19], and result in substantial economic costs to patients and healthcare systems [20,21]. Short-term effects of uncontrolled diabetes include acute metabolic complications such as diabetic ketoacidosis or hypoglycemic coma [4]. Long-term effects of diabetes, on the other hand, are associated with both macrovascular and microvascular complications. The macrovascular complications include cardiovascular disease, peripheral vascular disease, and stroke [3,4], while microvascular complications include retinopathy, neuropathy and nephropathy [4]. Retinal lesions may lead to progressive visual impairment resulting in blindness, while neuropathy increases the risk of lower-extremity ulcerations that may necessitate amputation [3,4]. Nephropathy can ultimately progress to end-stage renal disease, requiring chronic dialysis treatment or kidney transplantation [3,4]. Such complications can permanently impact quality of life [7–9], and are associated with depression [22], functional limitations, and premature mortality [3,5,6]. Therefore, the primary goal of diabetes care is to prevent complications through glycemic control and management of cardiovascular risk factors [11–13]. Hospitalizations due to complications of diabetes, which is considered an ambulatory care sensitive condition, often reflect problems with access to or utilization of quality outpatient care [14,23–25].

While hospitalizations due to diabetes complications may be prevented with timely access to care and effective management [14], there have been substantial increases in diabetes-related hospitalizations, amputations, and hospital costs in Florida in recent years [26]. Complications of diabetes will likely present an ongoing challenge due to Florida's growing population of adults aged 65 and over [27]. Age is a known risk factor for Type 2 diabetes, which represents 90-95% of the diabetes burden in the U.S. [3]. Older adults account for the majority of healthcare resource utilization attributable to diabetes [21], and are also projected to account for most of the future increase in diabetes prevalence in the U.S. [28]. Reducing the burden of preventable diabetes-related complications represents an important opportunity to meaningfully improve the health of Floridians.

There is evidence of disparities in diabetes prevalence and participation in diabetes preventive programs in Florida (diabetes self-management education) [29,30]. This suggests that there might also be disparities in complications of diabetes in the state. However, there is a lack of information on distribution or determinants/predictors of diabetes complications in Florida. Since severe complications of diabetes pose the greatest burden to patients and health systems [31], identifying determinants/predictors of these complications is important for guiding strategies aimed at reducing the burden. Therefore, the objective of this study was to identify individual- and area-level predictors of severe diabetes complications among hospitalized adult patients in Florida.

2.3 Methods

2.3.1 Ethics approval

This study was approved by the University of Tennessee, Knoxville Institutional Review Board (Number: UTK IRB-22-07182-XP).

2.3.2 Study area

This study was conducted in the state of Florida, which is located in the Southeastern United States and comprises 67 counties and 983 ZIP code tabulation areas (ZCTAs) [32]. In 2019, Florida had an estimated population of 20.9 million people, with 20.1% of the population aged 65 and older [33]. ZCTA-level population ranged from 0 to 76,508 residents [33]. An estimated 14.0% of Floridians had income below the poverty level in 2019, and 19.5% of adults under the age of 65 did not have health insurance coverage [34,35]. In 2019, the estimated statewide prevalence of diabetes among adults in Florida was 11.7% [36].

2.3.3 Data sources and preparation

2.3.3.1 Patient-level variables

Hospital discharge data from 2016 to 2019 were obtained from the Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. Data management was performed using SAS 9.4 [37]. Variables extracted included masked Social Security Number (SSN), patient age, sex, race and ethnicity, admission and discharge dates, principal payer, patient ZIP code and county of residence, principal International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) diagnosis code, and all other ICD-10-CM diagnosis codes. Records of hospitalized patients between the ages of 18 and 100 with a diagnosis of Type 1 or Type 2 diabetes mellitus (ICD-10-CM codes E10.x or E11.x) in any diagnosis field were selected for inclusion in the study, yielding 2,581,031 hospitalizations. Dichotomous variables were generated for each entry to indicate the presence/absence of a diagnosis for each of the following co-morbidities: hypertension, hyperlipidemia, obesity, depression, and arthritis. Diagnosis codes used to construct each of the comorbidity variables are displayed in Table 2.1.

Principal payer was classified into the following groups: Medicare (patients with Medicare or Medicare managed care plans); Medicaid (Medicaid, Medicaid managed care, or Kidcare); private insurance (commercial health insurance, worker's compensation, or commercial liability coverage); Veterans Affairs (VA), TriCare, federal, state and local government; self-pay (patients with no health insurance coverage); non-payment, and other. The non-payment designation applies to several categories, including clinical trials or other research, charity, and refusal to pay or debt.

Adapted Diabetes Complications Severity Index (aDCSI) scores were calculated for each hospitalization using the ICD-10-CM diagnosis codes [31,38,39]. The DCSI is a validated 14-level (scores of 0 to 13) measure that is a better predictor of mortality than a simple count of number of diabetic complications a patient has [31,38]. Seven categories of diabetes complications are included in the computation of DCSI score: cardiovascular, cerebrovascular, metabolic, renal, neurologic, ophthalmic, and peripheral vascular [38]. Complications for each of the seven categories are assigned

Table 2.1. Diagnosis codes used to identify selected comorbidities among hospitalized patients with diabetes in Florida, USA, 2016-2019.

Condition	ICD-10-CM Diagnosis Codes
Hypertension	I10.x, I11.x, I12.x, I13.x, I15.x
Hyperlipidemia	E78.00, E78.01, E78.1, E78.2, E78.3, E78.41, E78.49, E78.5
Obesity	Z68.54, Z68.3, Z68.4, Z68.35, Z68.36, Z68.37, Z68.38, Z68.39, E66.01, E66.2, E66.09, E66.1, E66.8, E66.9
Depression	F31.3-6, F32.x, F33.0-3, F33.40-42, F33.8, F33.9, F34.1
Arthritis	M05.x, M06.x, M12.0x, M15.x, M16.x, M17.x, M18.x, M19.x

scores from 0 to 2 based on presence and severity (with the exception of neuropathy, which has a maximum of 1). These are generated from ICD-10-CM codes and renal laboratory parameters, and are summed to yield the patient's total DCSI score [31,38]. The adapted DCSI (aDCSI) does not include laboratory parameters, but is otherwise identical to the original DCSI and exhibits similar performance [39]. In order to identify patients with severe complications, aDCSI score was categorized into a dichotomous variable (aDCSI < 4 and aDCSI ≥ 4). An aDCSI score ≥ 4 indicates that a patient: (a) has at least one complication related to the majority of the body systems assessed in the index, and/or (b) has one or more complications classified as severe. Compared with lower aDCSI scores, having an aDCSI score ≥ 4 is associated with higher odds of hospitalization and mortality, and higher costs of inpatient care and prescription medications [40].

A single admission was randomly selected for each patient with a unique identifier (masked SSN) to limit potential bias from patients with repeated hospitalizations during the study period. A total of 83,843 entries did not include a unique patient identifier, indicating that the patient did not provide an SSN upon admission to the hospital. Findings of initial descriptive analyses suggested these patients differed from those who did report SSNs with respect to several characteristics, and therefore these entries were retained as their exclusion could bias the findings of the analysis. Furthermore, recent research suggests that hospital patients who do not report an SSN tend to be from vulnerable sub-populations that may be at higher risk of adverse health outcomes compared to the general population [41].

Since individual identifiers were not present to enable selection of unique patients from this group of entries, a matching scheme was employed to link records that were most likely to have originated from a single patient. Three potential matching schemes were investigated: (1) age, gender, diabetes type, and ZIP code, (2) age, gender, diabetes type, ZIP code, race, and ethnicity (where neither race nor ethnicity were unknown), and (3) age, gender, diabetes type, ZIP code, race, and ethnicity (where race and ethnicity matched between records but could be unknown). Time between hospitalizations was taken into consideration when identifying an age match. To validate the matching schemes, each was applied to a test set of 2,370 entries from 1,000 randomly selected patients with known unique identifiers. Matching scheme (3) had the best performance for identifying true pairs of records from the same individual, with 69.8% sensitivity, 100% specificity, and strong agreement with true matches based on a kappa test of agreement (kappa = 0.8113). Additional matching schemes that considered diagnosis codes were investigated, but provided no improvements in performance. Linked pairs of matching entries were transformed to clusters of entries with common identifiers using the Transitive Record Linkage macro in SAS [42,43]. In total, 43,807 unique patients were identified from this group, and a single entry was randomly selected from each for further analysis.

2.3.3.2 ZCTA-level variables

Patient ZIP codes were joined to ZIP code tabulation areas (ZCTAs) using the Uniform Data System (UDS) Mapper ZIP code to ZCTA crosswalk [44]. Fifteen ZCTAs with total populations of fewer than 100 people were excluded to minimize bias from areas with very low population counts [45], resulting in the exclusion of 1.5% of ZCTAs and 0.045% of patients (n = 464) from the study. Theoretical domains and data sources for ZCTA-level variables investigated are listed in Table 2.2. Each ZCTA was classified as either rural or non-rural based on locale assignments published by the National Center for Education Statistics [46].

Physician information extracted from the Florida Department of Health, Division of Medical Quality Assurance's Florida Healthcare Practitioner Data Portal [47] included physician ID, specialty, practice ZIP code, county and state, license status, activity description, and dates of issuance and expiration. This Data Portal can be accessed at https://mqa-internet.doh.state.fl.us/downloadnet/GeneralInformation.aspx. Physicians with internal medicine or family practice specialties were considered primary care physicians. Since license status prior to expiration is not listed for physicians with expired licenses, only physicians with a clear and active license at the time of data accession (01/2021) were included for further analysis. Therefore, 3.21% of practice addresses for physicians with unknown license status during the study period were excluded. Physician practice address ZIP codes were joined to ZCTAs and the number of physicians was aggregated to the ZCTA level.

Pharmacy data were extracted from the same Florida Healthcare Practitioner Data Portal [47] and included practice address ZIP code and state, dates of license issuance and expiration, and pharmacy status. Pharmacies with a non-expired license during the study period that were listed as closed at the time of data accession (03/2021) were included during the last full year prior to license expiration. Pharmacy ZIP codes were joined to ZCTAs and aggregated to the ZCTA level. Total population, obtained from the U.S. Census Bureau American Community Survey 5-year estimates

Table 2.2. Theoretical domains and data sources of ZIP code tabulation area (ZCTA) variables investigated as predictors of severe complications among hospitalized patients with diabetes in Florida, USA, 2016-2019.

Variable names and domains	Data sources
Rurality	
ZCTA locale designations	U.S. Department of Education National Center for Education Statistics – Education Demographic and Geographic Estimates (EDGE) Program
Healthcare access	
Number of primary care physicians per 10,000 population Number of pharmacies per 10,000 population	Florida Healthcare Practitioner Data Portal, American Community Survey (ACS) 2015-2019 5-year estimates (Table DP05)
Food environment	
Number of grocery stores or supermarkets per km^2 Number of convenience stores per km^2 Number of limited service (fast food) restaurants per km^2	U.S. Census Bureau 2016 Annual Economic Survey (Table CB1600ZBP), U.S. Census Bureau TIGER/Line Shapefiles
Education	
Percentage of population 25 years or older with less than a high school education	ACS 2015-2019 5-year estimates (Table S1501)
Employment	
Unemployment rate in population 16 years and older Percentage of males aged 20-64 not participating in the labor force	ACS 2015-2019 5-year estimates (Table S2301)
Housing	
Percentage renter-occupied housing units	ACS 2015-2019 5-year estimates (Table DP04)
Percentage vacant housing units	ACS 2015-2019 5-year estimates (Table DP04)
Percentage occupied housing units with >1 occupant per room	ACS 2015-2019 5-year estimates (Table S2501)
Percentage renter- and owner-occupied households where gross rent or selected monthly owner costs are at least 50% of household income	ACS 2015-2019 5-year estimates (Table B25070 and B25095)
Median value of owner-occupied housing units	ACS 2015-2019 5-year estimates (Table DP04)
Occupation	
Percentage of employed males 16 and older with management occupations Percentage of employed males 16 and over with professional occupations Percentage of employed females 16 and over with management occupations Percentage of employed females 16 and over with professional occupations	ACS 2015-2019 5-year estimates (Table S2401)
Poverty	
Percent of families with income below poverty level	ACS 2015-2019 5-year estimates (Table S1702)
Percentage of female-headed households with own children under 18 years of age	ACS 2015-2019 5-year estimates (Table S1101)
Percentage of households with annual income of less than $30,000	ACS 2015-2019 5-year estimates (Table B19001)
Percentage of families with public assistance income or in households receiving Supplemental Nutrition Assistance Program (SNAP) benefits	ACS 2015-2019 5-year estimates (Table B19123)
Percentage of occupied households with no vehicles available	ACS 2015-2019 5-year estimates (Table DP04)
Racial composition	
Percentage non-Hispanic Black residents	ACS 2015-2019 5-year estimates (Table DP05)
Residential stability	
Percentage of current residents living in the same house as 1 year ago	ACS 2015-2019 5-year estimates (Table B07001)
Percentage of residents 65 years and older	ACS 2015-2019 5-year estimates (Table DP05)

for 2015-2019 [48], was used to compute the number of practicing primary care physicians and pharmacies per 10,000 population in each ZCTA.

The number of grocery stores or supermarkets, convenience stores, and limited service (fast food) restaurants at the ZIP code level were obtained from the U.S. Census Bureau 2016 Annual Economic Survey [49,50]. Food establishment data were joined to ZCTAs [44]. Land area of each ZCTA was extracted from U.S. Census Bureau TIGER/Line shapefiles, and used to calculate pharmacy, supermarket, convenience store, and fast food restaurant density [51].

2.3.3.3 Neighborhood deprivation index

Neighborhood Deprivation Index (NDI) values were computed using the method developed by Messer and colleagues [52]. Numerous studies have used the NDI in analyses investigating associations between area-level socioeconomic status and health-related behaviors or outcomes at both the census tract [53–57], and ZCTA levels [58–60].

Twenty census variables representing the following domains were assessed for inclusion in the NDI: education, employment, housing, occupation, poverty, racial composition, and residential stability [52]. Individual variables and their data sources are listed in Table 2.2. Forty-one (4.24%) of the 968 ZCTAs included in the study did not have complete data for all twenty NDI variables. Seventeen continuous variables had one or more missing values, with a maximum of 38 missing observations (for the median household value variable).

Due to the missing data, multiple imputation (*m* = 5) with fully conditional specification was performed using the “mice” package in R [61]. Since many of the variables had significant skewness, imputation with predictive mean matching was used [62,63]. The imputation model for each variable with missing data included the remaining nineteen NDI variables, as well as the rurality variable.

Computation of the NDI involved principal components analysis (PCA) and selection of a subset of candidate census variables that contributed highly to the first component, which was then retained for further analysis [52]. The NDI score for each ZCTA was computed by summing the standardized values of these variables, weighted by their respective loadings on the first principal component. The NDI scores were then standardized to have a mean of 0 and standard deviation of 1, and categorical variables representing NDI tertiles, quartiles, and quintiles were generated.

2.3.4 Statistical analysis

To investigate and identify predictors of severe diabetes complications (aDCSI ≥ 4), population average generalized linear models were fit to the data using generalized estimating equations (GEE), specifying binomial distribution, logit link, and an exchangeable working correlation structure [64,65]. Patients residing within the same ZCTA were treated as clustered observations. Modeling was performed in SAS 9.4 using the GENMOD procedure [37]. First, univariable models were fit to identify potential predictors, and variables associated with the outcome at a liberal p-value of < 0.15 were considered for inclusion in multivariable models. Correlations between potential predictor variables were assessed using Spearman rank-order correlation. If a pair of variables were highly correlated ($|r_s| > 0.7$), then only one was selected for inclusion in the modeling process.

After identification of candidate predictor variables, models with patient-level predictors were fit using backward selection and an inclusion criterion of $p < 0.05$. Changes in the modified quasi-likelihood information criterion (QIC_u), were also used to guide variable selection [64]. Lower values of the QIC_u statistic indicate a model with better fit to the data [64]. If removal of a variable from the model changed the magnitude of another variable's coefficient by more than 20%, it was deemed a potential confounder and considered for retention in the model regardless of its statistical significance. Patient-level variables considered as potential predictors included year of admission, age, gender, race/ethnicity, health insurance coverage, diabetes type, and comorbidities (hypertension, arthritis, hyperlipidemia, depression, and obesity). Since patients who did not report an SSN during hospitalization tend to be from socioeconomically vulnerable groups with low access to healthcare services [41], the presence/absence of an SSN was also assessed as a potential predictor. Age was assessed as both a continuous variable, scaled by subtracting 18 (the minimum age for inclusion), and as a categorical variable. A quadratic term for the continuous age variable was also assessed for significance. An interaction term for gender and race/ethnicity was assessed, based upon findings of previous research [66].

After specification of the patient-level variables in the model, significant ZCTA-level predictors were identified using forward selection with a cutoff of $p < 0.05$, guided by changes in QIC_u. Due to high correlations between food environment and healthcare access variables, physicians per capita and grocery store density were the only predictors from these categories considered for inclusion in the model. Rurality, as well as NDI tertiles, quartiles, and quintiles were also assessed. In addition, since racial composition was not incorporated into the NDI variable, which was only moderately correlated with percentage non-Hispanic Black residents, this was also considered as a potential predictor.

Results for each step in the model-building process for the five imputed datasets were combined using the MIANALYZE procedure in SAS [37]. Results of partial F-tests assessing the overall significance of categorical variables with more than two levels were combined using the “miceadds” package in R [67].

2.4 Results

2.4.1 Descriptive statistics

A total of 1,061,140 hospital records for unique patients between the ages of 18 and 100 with diagnoses of Type 1 or Type 2 diabetes mellitus were included in the study. The median duration of hospitalization was 3 days, with an interquartile range (IQR) of 2 to 6 days and an overall range of 0 to 1,143 days. Median age was 69 years (IQR 58 to 78), and there were more male patients (51.7%) than female patients (48.3%). Most patients were non-Hispanic White (60.6%), followed by Hispanic patients (18.7%) and non-Hispanic Black or African American patients (17.7%) (Table 2.3). The vast majority (97.3%) of patients had Type 2 diabetes, and the most common comorbidities were hypertension (83.1%) and hyperlipidemia (55.6%). Medicare (64.9%), private insurance (18.3%), and Medicaid (7.5%) were the most frequently listed payment sources. Adapted DCSI (aDCSI) scores ranged from 0 to 11, with a

Table 2.3. Characteristics and Adapted Diabetes Complications Severity Index (aDCSI) scores of hospitalized adult patients with diabetes in Florida, USA, 2016-2019.

Characteristic	% (n)	aDCSI<4	aDCSI≥4
Year of admission			
2016	24.4 (258,916)	90.0 (232,982)	10.0 (25,934)
2017	23.9 (253,149)	90.6 (229,394)	9.4 (23,755)
2018	24.8 (263,102)	90.5 (237,982)	9.5 (25,120)
2019	27.0 (285,973)	89.8 (256,833)	10.2 (29,140)
Gender			
Male	51.7 (548,773)	88.7 (486,685)	11.3 (62,088)
Female	48.3 (512,367)	91.8 (470,506)	8.2 (41,861)
Race/ethnicity			
Non-Hispanic American Indian/ Alaska Native	0.13 (1,348)	91.3 (1,231)	8.7 (117)
Non-Hispanic Asian	0.98 (10,128)	92.3 (9,343)	7.7 (785)
Non-Hispanic Black	17.7 (183,600)	89.6 (164,514)	10.4 (19,086)
Non-Hispanic Hawaiian/ Pacific Islander	0.05 (479)	91.0 (436)	9.0 (43)
Non-Hispanic White	60.6 (628,604)	89.6 (562,971)	10.4 (65,633)
Other non-Hispanic	1.9 (20,123)	91.2 (18,350)	8.8 (1,773)
Hispanic	18.7 (193,754)	92.6 (179,394)	7.4 (14,360)
Presence of social security number (SSN)			
SSN provided on admission	95.9 (1,017,333)	90.1 (916,990)	9.9 (100,343)
No SSN on admission	4.1 (43,807)	91.8 (40,201)	8.2 (3,606)
Principal payer			
Medicare	64.9 (689,067)	88.0 (606,108)	12.0 (82,959)
Medicaid	7.5 (79,339)	92.3 (73,229)	7.7 (6,110)
Private	18.3 (193,909)	95.2 (184,498)	4.8 (9,411)
VA[1], TriCare, federal, state or local government	2.7 (28,929)	91.7 (26,523)	8.3 (2,406)
Self-pay (uninsured)	4.7 (49,808)	96.0 (47,792)	4.0 (2,016)
Non-payment	1.5 (16,073)	95.9 (15,406)	4.1 (667)
Other	0.4 (4,015)	90.5 (3,635)	9.5 (380)
Diabetes type			
Type 1	2.7 (28,815)	88.7 (25,557)	11.3 (3,258)
Type 2	97.3 (1,032,325)	90.3 (931,634)	9.7 (100,691)
Diagnosed comorbidities			
Hypertension	83.1 (882,253)	89.0 (784,959)	11.0 (97,294)
Arthritis	14.5 (153,460)	90.7 (139,133)	9.3 (14,327)
Hyperlipidemia	55.6 (590,247)	88.3 (521,237)	11.7 (69,010)
Obesity	26.8 (284,369)	89.8 (255,464)	10.2 (28,905)
Depression	12.6 (133,262)	89.9 (119,797)	10.1 (13,465)
Neighborhood Deprivation Index quartiles			
1 (most deprived)	26.4 (280,228)	90.6 (253,793)	9.4 (26,436)
2	29.9 (317,117)	90.1 (285,679)	9.9 (31,438)
3	25.8 (273,824)	90.0 (246,411)	10.0 (27,413)
4 (least deprived)	17.9 (189,971)	90.2 (171,309)	9.8 (18,662)

[1]Veterans Affairs

median of 1 and IQR of 0 to 2. Approximately one-tenth (9.8%) of patients in the study had an aDCSI score of 4 or higher.

The number of patients from each ZCTA ranged from 1 to 5,162 with a median of 907 and IQR of 402 to 1,625. Summary statistics of ZCTA-level characteristics, all of which were non-normally distributed, are displayed in Table 2.4. In 2016, the median numbers of primary care physicians and licensed pharmacies were 6 (IQR 1.7 to 13.6) and 3.1 (IQR 1.3 to 5.5) per 10,000 population, respectively. The percentage of residents with educational attainment below the high school level ranged from 0 to 62.5%, with a median of 10.3%. Other socioeconomic characteristics of ZCTAs also varied widely; for instance, the median unemployment rate was 5.1%, but ranged from 0 to 78.8%. Median value of owner-occupied housing units ranged from $12,800 to $1,208,3300 (median $188,740, IQR $130,420 to $273,460). There was a higher median percentage of females in professional occupations (37.9%) compared to males (28.8%), but the percentage of males in management positions (median 10.6%) tended to be higher than females (median 8.0%). The median percentage of households in poverty was 8.9%, but ranged from 0 to 70.8%. The percentage of non-Hispanic Black residents at the ZCTA level also ranged widely, from 0 to 100%, with a median of 7.9%. Residential stability within a one-year period tended to be high (median 85.6%, IQR 81.8 to 88.6%).

2.4.2 Neighborhood deprivation index

The neighborhood deprivation index (NDI) included variables from the following domains: education (percentage of residents at least 25 years of age with education

Table 2.4. Characteristics of ZIP code tabulation areas in Florida, USA.

Variable Name and Year	Min.	Quartiles Q1[1]	Median	Q3[2]	Max.
Total population (2015-2019)	104	7,940.5	19,030.5	31,342.5	76,508
Healthcare Access (2016)					
Primary care physicians / 10,000 pop.	0	1.7	6.0	13.6	7,541
Pharmacies / 10,000 pop.	0	1.3	3.1	5.5	390.2
Food Environment (2016)					
Grocery stores / km^2	0	0.003	0.05	0.2	7.6
Convenience stores / km^2	0	0	0.02	0.1	6.7
Limited service restaurants / km^2	0	0.01	0.2	0.8	38.2
Education (2015-2019)					
% ≥ 25 with less than high school education	0	6.3	10.3	16.7	62.5
Employment (2015-2019)					
Unemployment rate in population 16 years and older	0	3.8	5.1	7.0	78.8
% males no longer in work force	0	14.4	19.0	26.1	100
Housing (2015-2019)					
% renter-occupied housing units	0	19.1	27.5	41.2	100
% vacant housing units	0	10.5	16.1	24.0	97.6
% crowded (>1 person/room)	0	0.9	2.0	3.7	47.2
% renter/owner costs >50% of income	0	10.6	13.9	18.2	49.8
Median value, owner-occupied housing units	$12,800	$130,420	$188,740	$273,460	$1,208,300
Occupation (2015-2019)					
% males in management	0	6.9	10.6	14.6	100
% males in professional occupations	0	20.4	28.8	39.4	100
% females in management	0	5.4	8.0	10.8	100
% females in professional occupations	0	31.6	37.9	45.8	100
Poverty (2015-2019)					
% households in poverty	0	5.3	8.9	13.8	70.8
% female-headed households with dependent children	0	3.1	5.1	7.5	66.0
% households earning < $30,000 / year	0	18.5	25.7	33.4	100
% households receiving public assistance or SNAP[3] benefits	0	6.7	13.1	21.2	100
% households with no car	0	2.5	4.5	7.5	41.2
Racial composition (2015-2019)					
% non-Hispanic Black residents	0	2.8	7.9	17.2	100
Residential stability (2015-2019)					
% in same residence as 1 year ago	11.9	81.8	85.6	88.6	100
% 65 years and over	0	13.8	19.2	27.1	87.1

[1]First quartile
[2]Third quartile
[3]Supplemental Nutrition Assistance Program

below the high school level), housing (median value of owner-occupied housing units), occupation (percentage of employed males and females 16 and over with management or professional occupations), poverty (percentage of families with income below the poverty level, percentage of households with annual income less than $30,000, percentage of families with public assistance income or in households receiving Supplemental Nutrition Assistance Program (SNAP) benefits), and residential stability (percentage of residents aged 65 and over). Variable loadings on the first principal component, which were used to construct NDI scores, are displayed in Table 2.5. Across the entire study area, 59.6% of the variance of the ten variables in the index was explained by the first principal component. When PCA was stratified by rurality, the percentage of variance explained was higher for non-rural ZCTAs (65.7%) than for rural ZCTAs (53.6%). Characteristics of the ZCTAs in each NDI quartile are summarized in Table 2.6. Lower values of the index were associated with higher percentages of the population with less than a high school education, families with income below the poverty level, households with annual income less than $30,000, and families receiving public assistance income. Higher median housing values, percentage of employed males and females with professional or management occupations, and percentage of older adults in the population were associated with higher values of the NDI. Therefore, lower values of the index indicate more deprived areas. Fewer patients (17.9%) resided in ZCTAs in the highest (least deprived) NDI quartile compared to all other quartiles (Table 2.3).

Table 2.5. Results of principal components analysis used to construct Neighborhood Deprivation Index, stratified by rurality, for ZIP code tabulation areas (ZCTAs) in Florida, USA, 2016-2019.

Theoretical domains and variable names	Variable loadings on first principal component		
	Rural ZCTAs[1]	Non-rural ZCTAs[1]	All ZCTAs[1]
Education			
% ≥ 25 with less than high school education	-0.78	-0.91	-0.84
Housing			
Median value, owner-occupied housing units	0.68	0.58	0.63
Occupation			
% males in management	0.57	0.73	0.63
% males in professional occupations	0.76	0.77	0.77
% females in management	0.36	0.62	0.48
% females in professional occupations	0.60	0.70	0.67
Poverty			
% of families with income below poverty level	-0.77	-0.90	-0.83
% households with annual income < $30,000	-0.83	-0.89	-0.86
% families with public assistance income or in households receiving SNAP[2] benefits	-0.82	-0.98	-0.89
Residential stability			
% of residents 65 years and older	0.22	0.27	0.24
Percent of variance explained	**53.6%**	**65.7%**	**59.6%**

[1]ZIP code tabulation areas
[2]Supplemental Nutrition Assistance Program

Table 2.6. Median values of ZIP code tabulation area characteristics by Neighborhood Deprivation Index (NDI) quartile, Florida, USA, 2016-2019.

Variable	NDI quartile			
	1 *(most deprived)*	2	3	4 *(least deprived)*
% ≥ 25 with less than high school education	20.6	12.7	8.5	4.4
Median value, owner-occupied housing units	$105,580	$157,250	$207,160	$347,240
% males in management	5.6	8.9	11.8	17.9
% males in professional occupations	16.5	25.8	32.5	47.4
% females in management	5.1	6.7	9.0	12.0
% females in professional occupations	28.7	35.0	41.2	50.5
% families with income below poverty level	17.8	10.8	7.1	4.2
% households with annual income < $30,000	38.4	29.1	22.2	16.0
% families with public assistance income or in households receiving SNAP[1] benefits	27.3	16.8	10.3	4.0
% residents 65 years and older	16.5	19.6	19.7	21.8

[1]Supplemental Nutrition Assistance Program

2.4.3 Population average generalized linear model

Significant individual-level predictors of severe diabetes complications (aDCSI score≥4) included age, gender, race/ethnicity, diabetes type, comorbidities (hypertension, hyperlipidemia, obesity, depression and arthritis), payer, report of an SSN upon admission, and year of admission (Tables 2.7 and 2.8).

Coefficients for linear and quadratic age terms in the final model had opposite signs, such that the odds of severe diabetes complications were higher for older patients, but the magnitude of this effect diminished as age increased. Racial and ethnic differences in the odds of severe diabetes complications differed by gender. For instance, among males, the odds of severe complications were 21% lower for Asian patients compared to non-Hispanic White patients (95% confidence interval [CI]: 0.72, 0.87, $p < 0.0001$), but a significant difference was not observed among female patients ($p = 0.0718$). On the other hand, while Hispanic male patients also had lower odds of severe complications compared to non-Hispanic White male patients (odds ratio [OR] = 0.86, 95% CI: 0.84, 0.89, $p < 0.0001$), the magnitude of the difference between these groups was greater among females (OR = 0.78, 95% CI: 0.76, 0.81, $p < 0.0001$). In contrast, both male (OR = 1.20, 95% CI: 1.17, 1.23, $p < 0.0001$) and female (OR = 1.27, 95% CI: 1.23, 1.31, $p < 0.0001$) non-Hispanic Black patients had higher odds of severe diabetes complications compared to non-Hispanic White patients.

Several clinical factors were associated with the severity of diabetes complications among hospitalized adult patients with diabetes. For instance, the odds of severe diabetes complications were 62% lower for patients with Type 2 compared to

Table 2.7. Predictors of severe diabetes complications among hospitalized adults in Florida, USA, 2016-2019.

Parameters	Coefficient	95% Confidence Interval*		*p*-value
Intercept	-4.416	-4.496	-4.335	< 0.0001
Age	0.040	0.037	0.043	< 0.0001
Age (quadratic)	-0.0002	-0.0002	-0.0002	< 0.0001
Gender				
Male	0.398	0.381	0.416	< 0.0001
Female	Ref.	-	-	-
Race/ethnicity				< 0.0001
Non-Hispanic American Indian/Alaska Native	0.123	-0.151	0.397	0.3777
Non-Hispanic Asian	-0.088	-0.183	0.008	0.0718
Non-Hispanic Black or African American	0.238	0.207	0.268	< 0.0001
Non-Hispanic Hawaiian/ Pacific Islander	0.098	-0.383	0.578	0.6906
Other non-Hispanic	-0.070	-0.149	0.009	0.0812
Hispanic	-0.243	-0.277	-0.210	< 0.0001
Non-Hispanic White	Ref.	-	-	-
Diabetes type				
Type 2	-0.976	-1.017	-0.934	< 0.0001
Type 1	Ref.	-	-	-
Comorbidities				
Hypertension	0.833	0.804	0.862	< 0.0001
Hyperlipidemia	0.258	0.243	0.273	< 0.0001
Obesity	0.211	0.194	0.229	< 0.0001
Depression	0.089	0.069	0.109	< 0.0001
Arthritis	-0.216	-0.237	-0.194	< 0.0001
Principal payer				< 0.0001
Medicare	0.615	0.587	0.642	< 0.0001
Medicaid	0.606	0.568	0.644	< 0.0001
VA[1], TriCare, gov't	0.285	0.233	0.337	< 0.0001
Uninsured	-0.043	-0.096	0.010	0.1104
Non-payment	-0.019	-0.106	0.067	0.6586
Other	0.450	0.337	0.562	< 0.0001
Private	Ref.	-	-	-
Presence of social security number (SSN)				
No SSN on admission	0.105	0.067	0.143	< 0.0001
SSN on admission	Ref.	-	-	-
Admission year				< 0.0001
2017	-0.086	-0.105	-0.066	< 0.0001
2018	-0.067	-0.088	-0.049	< 0.0001
2019	-0.011	-0.030	0.008	0.2613
2016	Ref.	-	-	-
Neighborhood Deprivation Index quartile				
Lower 3 quartiles	0.090	0.064	0.117	< 0.0001
Least deprived quartile	Ref.	-	-	-
Interaction term				< 0.0001
Male				
Non-Hispanic American Indian/ Alaska Native	-0.233	-0.615	0.148	0.2299
Non-Hispanic Asian	-0.147	-0.289	-0.005	0.0421
Non-Hispanic Black or African American	-0.055	-0.092	-0.019	0.0033
Non-Hispanic Hawaiian/ Pacific Islander	-0.198	-0.860	0.464	0.5579
Other non-Hispanic	0.091	-0.011	0.194	0.0817
Hispanic	0.098	0.059	0.136	< 0.0001
Female, non-Hispanic White	Ref.	-	-	-

*Confidence intervals computed using modified sandwich estimate of variance

[1]Veterans Affairs

Table 2.8. Predictors of severe diabetes complications among hospitalized adults in Florida, USA, 2016-2019.

Parameters	Odds Ratio	95% Confidence Interval*		*p*-value
Intercept	**0.012**	0.011	0.013	< 0.0001
Age	**1.041**	1.038	1.044	< 0.0001
Age (quadratic)	**0.9998**	0.9998	0.9998	< 0.0001
Gender & race/ethnicity				
Males				
Non-Hispanic American Indian/Alaska Native	0.896	0.666	1.205	0.4675
Non-Hispanic Asian	**0.791**	0.716	0.873	< 0.0001
Non-Hispanic Black or African American	**1.200**	1.168	1.233	< 0.0001
Non-Hispanic Hawaiian/ Pacific Islander	0.904	0.587	1.395	0.3326
Other non-Hispanic	1.021	0.958	1.089	0.5223
Hispanic	**0.864**	0.840	0.889	< 0.0001
Non-Hispanic White	Ref.	-	-	-
Females				
Non-Hispanic American Indian/Alaska Native	1.131	0.860	1.487	0.3777
Non-Hispanic Asian	0.916	0.833	1.008	0.0718
Non-Hispanic Black or African American	**1.269**	1.230	1.307	< 0.0001
Non-Hispanic Hawaiian/ Pacific Islander	1.103	0.682	1.782	0.6906
Other non-Hispanic	0.932	0.862	1.009	0.0812
Hispanic	**0.784**	0.758	0.811	< 0.0001
Non-Hispanic White	Ref.	-	-	-
Diabetes type				
Type 2	**0.377**	0.362	0.393	< 0.0001
Type 1	Ref.	-	-	-
Comorbidities				
Hypertension	**2.300**	2.234	2.368	< 0.0001
Hyperlipidemia	**1.294**	1.275	1.314	< 0.0001
Obesity	**1.235**	1.214	1.257	< 0.0001
Depression	**1.093**	1.071	1.115	< 0.0001
Arthritis	**0.806**	0.789	0.824	< 0.0001
Principal payer				
Medicare	**1.850**	1.799	1.900	< 0.0001
Medicaid	**1.833**	1.765	1.904	< 0.0001
VA[1], TriCare, gov't	**1.330**	1.262	1.401	< 0.0001
Uninsured	0.958	0.908	1.010	0.1104
Non-payment	0.981	0.899	1.069	0.6586
Other	**1.568**	1.401	1.754	< 0.0001
Private	Ref.	-	-	-
Presence of social security number (SSN)				
No SSN on admission	**1.111**	1.069	1.154	< 0.0001
SSN on admission	Ref.	-	-	-
Admission year				
2017	**0.918**	0.900	0.936	< 0.0001
2018	**0.935**	0.916	0.952	< 0.0001
2019	0.989	0.970	1.008	0.2613
2016	Ref.	-	-	-
Neighborhood Deprivation Index quartile				
Lower 3 quartiles	**1.094**	1.066	1.124	< 0.0001
Least deprived quartile	Ref.	-	-	-

*Confidence intervals computed using modified sandwich estimate of variance
[1]Veterans Affairs

Type 1 diabetes (95% CI: 0.36, 0.39, $p < 0.0001$). Diagnoses of hypertension (OR = 2.30, 95% CI: 2.23, 2.37, $p < 0.0001$), hyperlipidemia (OR = 1.29, 95% CI: 1.27, 1.31, $p < 0.0001$), obesity (OR = 1.24, 95% CI: 1.21, 1.26, $p < 0.0001$) and depression (OR = 1.09, 95% CI: 1.07, 1.11, $p < 0.0001$) were associated with higher odds of severe diabetes complications, while arthritis was associated with lower odds of severe complications (OR = 0.81, 95% CI: 0.79, 0.82, $p < 0.0001$).

Lack of health insurance coverage was not a significant predictor of the severity of diabetes complications when compared to private insurance ($p = 0.1104$). However, patients with Medicare (OR = 1.85, 95% CI: 1.80, 1.90, $p < 0.0001$), Medicaid (OR = 1.83, 95% CI: 1.77, 1.90, $p < 0.0001$), VA and other government insurance (OR = 1.33, 95% CI: 1.26, 1.40, $p < 0.0001$), and other insurance sources (OR = 1.57, 95% CI: 1.40, 1.75, $p < 0.0001$) did have higher odds of severe complications compared to private insurance. Absence of an SSN upon hospital admission was also positively associated with severe diabetes complications (OR = 1.11, 95% CI: 1.07, 1.15, $p < 0.0001$). Patients admitted in 2017 (OR = 0.92, 95% CI: 0.90, 0.94, $p < 0.0001$) and 2018 (OR = 0.94, 95% CI: 0.92, 0.95, $p < 0.0001$) had slightly lower odds of severe complications than those admitted in 2016.

Neighborhood Deprivation Index (NDI) quartile was the only significant ZCTA-level predictor in the final model. Compared to patients living in ZCTAs in the least deprived quartile, patients in all other NDI quartiles had significantly higher odds of severe diabetes complications (OR = 1.09, 95% CI: 1.07, 1.12, $p < 0.0001$). Food environment, healthcare access, and racial composition variables were not significantly associated with severity of diabetes complications.

2.5 Discussion

This study investigated and identified predictors of severe complications among adult patients hospitalized with diabetes in Florida. The odds of severe complications increased with age, a finding that likely reflects duration of the condition, which is associated with macrovascular events in affected patients [68]. The observed association between Type 1 diabetes and severe complications is also likely related to duration of the condition, since Type 1 diabetes tends to have an earlier age of onset than Type 2 diabetes [4]. The diminishing magnitude of the strength of association between older age and severity of complications observed in this study might be due to survival bias since higher aDCSI values are associated with higher risks of death [31,39].

Several comorbidities were positively associated with severe diabetes complications, highlighting the difficulties of managing multiple chronic conditions. Patients with multiple conditions face challenges with coordination and quality of care, financial costs, and adhering to complex self-management recommendations [69]. Hypertension and hyperlipidemia, two important cardiovascular risk factors, were predictors of severe diabetes complications, consistent with findings of a previous study which reported that hypertension and/or hypercholesterolemia in patients with diabetes were predictors of poor health status [70]. Interestingly, having a diagnosis of arthritis was associated with lower odds of severe complications. While most evidence suggests that multiple conditions are associated with poorer quality of care, this may vary depending upon the specific combination of illnesses [69]. Further investigation is warranted to understand the mechanism of the negative association between arthritis and severe diabetes complications observed in this study.

Higher odds of severe diabetes complications were observed among patients with a diagnosis of depression compared to those without this diagnosis. Previous research has identified a bi-directional association between diabetes and depression, and the two conditions share risk factors such as socioeconomic deprivation [71]. The association between depression and severe diabetes complications observed in the current study could reflect the impacts of diabetes complications on quality of life [71]. This finding may also have been driven by poorer adherence to treatment and self-management recommendations among patients with diabetes who also have depression [71]. The association observed in this study underscores the importance of depression screening for patients with diabetes, as well as ensuring linkage to additional care when indicated [71].

There were racial/ethnic and gender disparities in the odds of severe diabetes complications, with non-Hispanic Black patients having significantly higher odds of severe complications than non-Hispanic White patients. In addition to having higher odds of severe complications, non-Hispanic Black patients tended to be younger, with the lowest median age (62 years) of any group in the present study. In comparison, non-Hispanic White patients had a median age of 70 years. These findings are consistent with those of a New York City study that reported younger average age for Black patients with diabetes compared to White patients and lower relative proportions of Black patients in older age groups [45]. The observed disparities in age and odds of severe complications could, in part, reflect earlier onset of diabetes among Black patients in Florida. They may also indicate disparities in the provision and quality of diabetes care [72–74], and may suggest earlier diabetes-related mortality among Black patients [45].

While previous studies have reported lower levels of glycemic control [75] and a higher prevalence of complications [76,77] among Hispanic patients with diabetes compared to White patients, Hispanic patients in this study had lower odds of severe complications, a difference that was most pronounced among females. Previous research investigating predictors of severe diabetes complications in a Medicare population had the opposite finding [66]. This discrepancy could, in part, reflect differences between the compositions of the Hispanic populations of Florida and the U.S. overall. Diabetes prevalence in the Hispanic population in the U.S. varies by country of origin, with the highest diabetes prevalence and diabetes-related mortality rates among those of Mexican descent [75,78,79], who represent a much smaller percentage of the Hispanic population in Florida (13.5%) compared to the U.S. overall (59.5%) [80]. Significantly lower diabetes prevalence and mortality have been reported among Cubans and Cuban Americans, the largest subgroup of the Hispanic population in Florida [80]. Given the evidence of inequalities in diabetes prevalence, control, and outcomes within the Hispanic population, considering this diverse population as a single group may mask important differences between subgroups [79,81]. However, detailed ethnicity information was not recorded in the hospitalization data, precluding more detailed investigation in the current study.

There is mixed evidence regarding the occurrence of diabetes complications among Asian Americans, who experience higher incidence of some complications, such as end-stage renal disease, and lower incidence of others (lower extremity amputations) compared to their non-Hispanic White counterparts [77]. In this study, Asian male patients had lower odds of severe complications compared to non-Hispanic White males, but no such difference was observed for Asian female patients, despite findings of a previous study that reported lower diabetes prevalence among females in all Asian subgroups [82]. The observed finding may reflect gender-based differences in psychosocial factors, health behaviors, and access to healthcare as well as other resources necessary for effective management of the condition [72,83,84]. However, this finding could also be a result of relative sample size in the current study. In 2019, Asian Americans represented 2.6% of Florida's population [33], and Asian patients comprised an even lower percentage of the study population (0.98%, 10,128 patients).

The odds of severe complications were higher among both Medicaid and Medicare patients than those with private insurance. As of July 2022, Florida is one of twelve states that have not adopted the Medicaid eligibility expansion of the Affordable Care Act, and therefore non-elderly, low-income adults in the state must meet additional criteria to be eligible for Medicaid [85]. These criteria include blindness and disability [86], both of which can result from complications of diabetes, which may partially explain the observed association. In addition, given the income eligibility threshold for Medicaid recipients, these patients are likely to face additional financial barriers to securing the resources and care necessary for effective diabetes control, despite having health insurance coverage. The higher odds of severe diabetes complications among Medicare patients compared to those with private insurance may reflect the older age of Medicare-eligible patients, and longer duration of diabetes in these patients. In addition, end-stage renal disease, a potential consequence of diabetic nephropathy [4], is one of the eligibility criteria for Medicare [87], which may also partly explain the observed association.

Lack of health insurance was not significantly associated with having severe diabetes complications when compared to private health insurance coverage. This was somewhat surprising, since health insurance coverage is a predictor of receiving quality diabetes care [73,88]. The reason for this finding is unclear, although it could reflect utilization of care. As inpatient hospitalization carries a large cost burden, those without health insurance coverage may decline necessary care for financial reasons. This may have, in part, accounted for the low level of uninsurance among patients in the study (4.7%) compared to the overall population of Florida, which has the fourth-highest percentage of uninsured individuals in the nation (13.4%), although this difference could also reflect the older age of the hospital patients in this study, most of whom were insured with Medicare. It is also important to note that only patients' health insurance coverage at the time of hospitalization was available, and prior insurance status was unknown. Since diabetes complications may result from cumulative years of inadequate glycemic control and cardiovascular risk factor management [89], health insurance coverage throughout the life course may be a better predictor of this outcome. Regardless, the persistence of disparities in severe diabetes complications despite controlling for health insurance suggests that barriers to diabetes control outside of the healthcare setting should also be investigated. Indeed, socioeconomic disparities in avoidable hospitalizations and lower extremity amputations due to diabetes have been reported in Canada, a country with universal access to healthcare [90].

In addition to the observed association between Medicaid coverage and severe complications, two other findings of this study suggest that socioeconomic position is related to the occurrence of severe diabetes complications. First, the odds of severe complications were higher among patients not reporting a social security number (SSN) than among those that did. It is worth noting that patients who do not report an SSN tend to be from vulnerable groups who may have lower access to healthcare and other important resources than those who do. Such groups may include temporary workers, undocumented immigrants, and those experiencing homelessness [41]. The higher odds of severe diabetes complications in these patients in the current study suggests that they face barriers to effective diabetes management. In addition, neighborhood deprivation, which is a function of educational attainment, housing value, occupation, poverty, and residential stability, was also a predictor of severe diabetes complications. This association underscores the importance of the living environment, which can impact the ability of patients with diabetes to effectively manage the condition and prevent complications. Residents of more deprived neighborhoods may have fewer opportunities for education and employment, and face both social and physical barriers to engaging in recommended health behaviors [91].

2.5.1 Strengths and limitations

This study investigated a large sample of hospitalized adult patients with diabetes in Florida who were diverse with respect to demographic characteristics, health insurance coverage, and socioeconomic status. Previous studies that have investigated claims data from a single insurance payer have limited generalizability to patients with different insurance sources or without health insurance coverage. The use of hospital data in this study also prevented bias associated with self-reporting, a limitation of survey data. In addition, while some studies investigating the association between diabetes-related outcomes and socioeconomic position have substituted area-level measures for individual income, this analysis accounted for the nested nature of the data using population average models estimated with generalized estimating equations [92,93].

However, this study is not without limitations. A limited number of individual-level variables that reflect individual socioeconomic position (health insurance coverage and presence of a Social Security Number) were available for analysis. Study findings may have also been affected by differences in healthcare utilization, since the financial burden of hospitalization may lead patients with limited resources to decline necessary care. Further investigation of emergency department visits and observation stays is warranted to assess the potential impact of healthcare utilization bias on the findings of this study. These limitations notwithstanding, this study provides valuable information for guiding the development and implementation of health programs in Florida to reduce disparities in preventable complications of diabetes in the state.

2.6 Conclusions

This study identified racial, ethnic, gender and socioeconomic disparities in the severity of diabetes complications among hospitalized adult patients in Florida. The disproportionately high risk of severe complications in some groups may reflect earlier diabetes onset as well as challenges to achieving glycemic control and managing cardiovascular risk factors. In addition, study findings highlight the challenge of achieving sustained, effective management of diabetes for patients with multiple chronic conditions and the importance of depression as a predictor of adverse outcomes of diabetes. Since hospitalizations due to diabetes complications are preventable, the findings of this study are useful for guiding health programming aimed at improving health outcomes for patients with diabetes in Florida. Targeting populations with disproportionately high burdens of severe complications using evidence-based interventions to facilitate effective diabetes management in outpatient and community-based settings will help reduce complications, improve quality of life, and decrease premature mortality among patients with diabetes.

CHAPTER 3

Investigation of geographic disparities of diabetes-related hospitalizations in Florida using flexible spatial scan statistics: an ecological study

A version of this chapter has been submitted for publication at *PLOS ONE* and is currently under review. My contributions to this manuscript included study design, data preparation and analysis, preparing figures, and drafting and editing the manuscript. Dr. Agricola Odoi was also involved in the design of the study and revision of the manuscript, and both authors read and approved the final manuscript.

3.1 Abstract

Background: Hospitalizations due to diabetes complications are potentially preventable with effective management of the condition in the outpatient setting. Diabetes-related hospitalization (DRH) rates can provide valuable information about access, utilization, and efficacy of healthcare services. However, little is known about the local geographic distribution of DRH rates in Florida. Therefore, the objectives of this study were to investigate the geographic distribution of DRH rates at the ZIP code tabulation area (ZCTA) level in Florida, identify significant local clusters of high hospitalization rates, and describe characteristics of ZCTAs within the observed spatial clusters.

Methods: Hospital discharge data from 2016 to 2019 were obtained from the Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. Raw and spatial empirical Bayes smoothed DRH rates were computed at the ZCTA level. High-rate DRH clusters were identified using Tango's flexible spatial scan statistic. Choropleth maps were used to display smoothed DRH rates and significant high-rate spatial clusters. Demographic, socioeconomic, and healthcare-related characteristics of cluster and non-cluster ZCTAs were compared using the Wilcoxon rank sum test for continuous variables and Chi-square test for categorical variables.

Results: There was a total of 554,449 diabetes-related hospitalizations during the study period. The statewide DRH rate was 8.5 per 1,000 person-years, but smoothed rates at the ZCTA level ranged from 0 to 101.9. A total of 24 significant high-rate spatial clusters were identified. High-rate clusters had a higher percentage of rural ZCTAs (60.9%) than non-cluster ZCTAs (41.8%). The median percent of non-Hispanic Black residents was significantly ($p < 0.0001$) higher in cluster ZCTAs than in non-cluster ZCTAs. Populations of cluster ZCTAs also had significantly ($p < 0.0001$) lower median income and educational attainment, and higher levels of unemployment and poverty compared to the rest of the state. In addition, median percent of the population with health insurance coverage and number of primary care physicians per capita were significantly ($p < 0.0001$) lower in cluster ZCTAs than in non-cluster ZCTAs.

Conclusions: This study identified geographic disparities of DRH rates at the ZCTA level in Florida. The identification of high-rate DRH clusters provides useful information to guide resource allocation such that communities with the highest burdens are prioritized to reduce the observed disparities. Future research will investigate determinants of hospitalization rates to inform public health planning, resource allocation and interventions.

3.2 Background

Diabetes mellitus, a condition that affects an estimated 37.1 million adults in the United States [1], is characterized by hyperglycemia due to insulin resistance or impaired insulin production [2]. Hyperglycemia in patients with undiagnosed or inadequately controlled diabetes promotes vascular changes, which can lead to long-term complications that account for much of the morbidity and mortality associated with the condition [89]. These include accelerated cardiovascular disease, cerebrovascular disease, peripheral arterial disease, retinopathy, nephropathy and neuropathy [3,89]. Prompt diagnosis, glycemic control, and management of cardiovascular risk factors such as hypertension and dyslipidemia are important to limit the development of these complications [11–13].

In general, hospitalizations due to diabetes complications are considered to be preventable if the condition is managed effectively in the outpatient setting [14]. However, optimal control of diabetes requires tailored patient care and relatively frequent engagement with the healthcare system, and can be challenging due to financial costs and potentially complex self-management requirements [12,13,94]. Thus, surveillance of diabetes-related hospitalization rates can yield important insights with respect to access, utilization, and efficacy of healthcare services [14]. Nationwide reductions in the risks of diabetes-related complications and mortality over the past few decades have been attributed to improvements in clinical care, patient education, and support [95,96]. However, some recent reports suggest stagnation or reversal of this progress [19,97,98], warranting continued careful attention to this problem.

In Florida, the age-adjusted rate of hospitalizations due to diabetes increased by 19% between 2013 and 2018 [26]. During this time period, the annual cost of these hospitalizations rose from $1.8 billion to $3.6 billion [26]. It is essential to curb these trends to reduce the public health and economic impacts of diabetes, which affects over

2.4 million adults in Florida [26]. Rates of inpatient hospitalizations due to diabetes provide an indirect measure that can be used to effectively identify geographic hot-spots of poor glycemic control in the absence of a population-level hemoglobin A1c (HbA1c) registry [99]. This suggests that populations with high hospitalization rates are likely to benefit from interventions to improve diabetes management [99]. Therefore, understanding the local geographic distribution of diabetes-related hospitalization rates is important so that communities with high burdens can be prioritized for resource allocation and implementation of such interventions. However, there is a lack of information regarding the distribution of diabetes-related outcomes in Florida. Furthermore, while county-level geographic disparities in pre-diabetes prevalence, diabetes prevalence, and participation in validated self-management education and support programs have been identified within the state [30,100–102], information at the sub-county level is limited to model-based small area estimates [103] or focused, single-county investigations [104]. Filling this knowledge gap by characterizing the local distribution of diabetes-related hospitalization rates across the state will be essential to reduce disparities of adverse diabetes outcomes. Therefore, the objectives of this study were to investigate the geographic distribution of diabetes-related hospitalization rates at the ZIP code tabulation area (ZCTA) level in Florida, identify significant local clusters of high hospitalization rates, and describe characteristics of ZCTAs within the observed spatial clusters.

3.3 Methods

3.3.1 Ethics approval

This study was approved by the University of Tennessee Institutional Review Board (Number: UTK IRB-22-07182-XP). The study used secondary data collected between January 1, 2016 and December 31, 2019 and provided to the investigators by Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. The study was conducted between 2022 and 2023. Study investigators did not have information that could be used to identify individual participants during or after data collection. In accord with 45 CFR 46.116(f), informed consent was waived by the Institutional Review Board. In addition, the request for waiver of HIPAA authorization for the conduct of the study itself is approved. All data were fully anonymized before sharing with study investigators.

3.3.2 Study area and design

This study was conducted in Florida, which had an estimated population of 20.9 million in 2019, the largest among the states of the Southeastern United States [33]. There are 67 counties and 983 ZIP code tabulation areas (ZCTAs) in the state (Figure 3.1) [32]. Approximately half (46.6%) of these ZCTAs are classified as rural and had a combined population of 6.2 million residents [33,46]. The median age in Florida was 42 years, and the state had the highest percentage of adults aged 65 and older in the U.S. (20.1%) [33]. The estimated prevalence of diagnosed diabetes among adults in Florida in 2019 was 11.7%, but was higher among older adults, reaching 22.5% among those between the ages of 65 and 74, and 24.8% among those aged 75 and older [105]. A

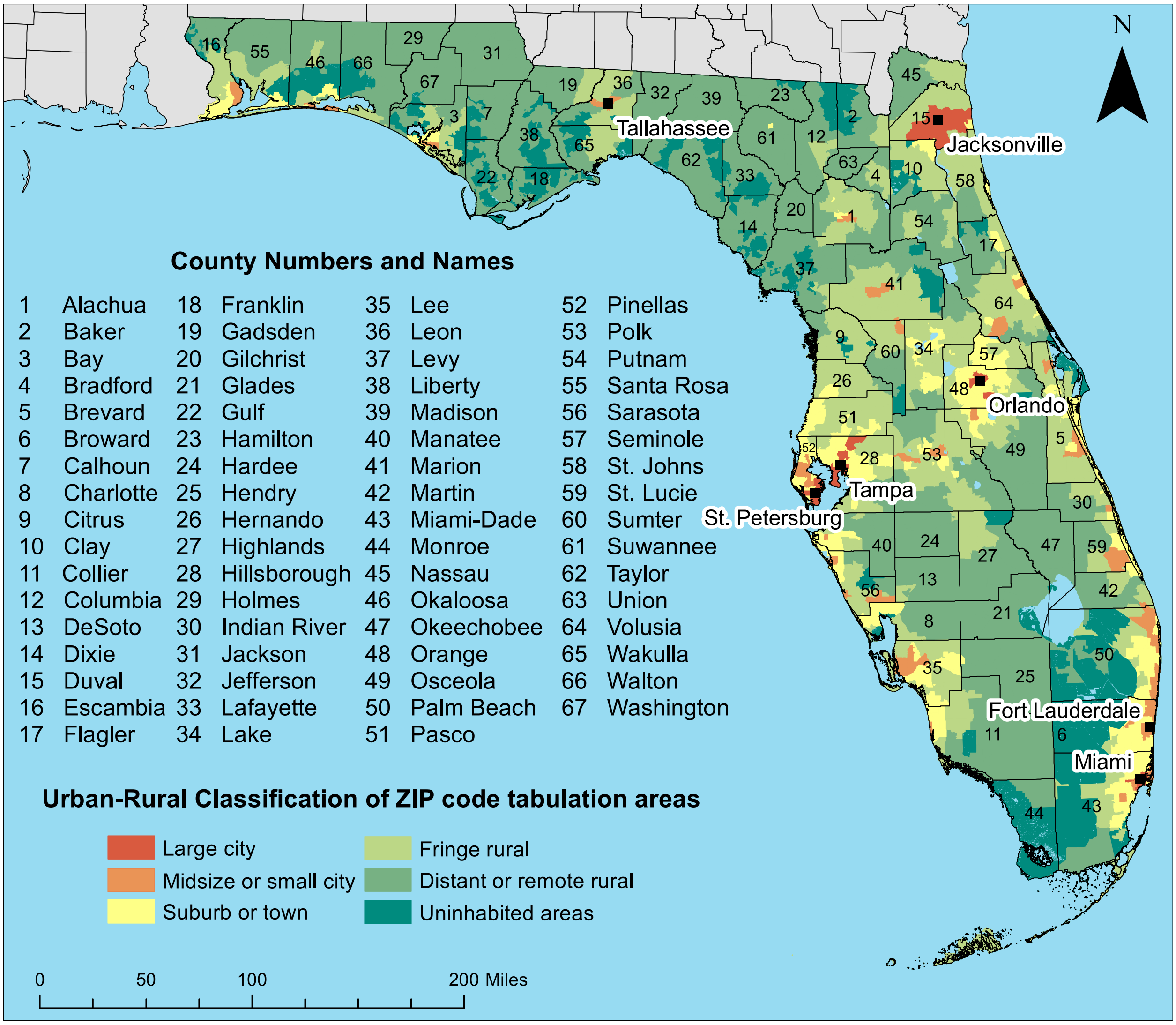

Figure 3.1. Urban-rural classification of ZIP code tabulation areas and geographic distribution of counties and major cities in Florida, USA.

retrospective ecological study design was used to investigate the local geographic distribution of diabetes-related hospitalizations in Florida. Diabetes-related hospitalizations were computed at the ZCTA level, and significant high-rate spatial clusters were identified. Descriptive statistics were used to compare ZCTAs within high-rate clusters with the rest of the state with respect to measures of rurality/urbanization, demographic composition, economic characteristics, educational attainment, healthcare access, and the food environment.

3.3.3 Data sources and preparation

3.3.3.1 Hospital discharge, population and ZCTA data

Hospital discharge data for patients admitted between January 1, 2016 and December 31, 2019 were provided by the Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. The following variables were extracted from the dataset: patient age, admission and discharge dates, ZIP code of residence, all International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) diagnosis codes, and all International Classification of Diseases, Tenth Revision, Procedure Coding System (ICD-10-PCS) procedure codes. Records for patients between the ages of 18 and 100 with diabetes-related hospitalizations were selected for analysis. Patients with diabetes-related hospitalizations were defined as those who met any of the following criteria:

(1) Patients with a principal diagnosis code included in one of the following Agency for Healthcare Research and Quality (AHRQ) Prevention Quality Indicators (PQIs): diabetes with short-term complications (PQI 01), diabetes

with long-term complications (PQI 03), and uncontrolled diabetes (PQI 14) [106–108].

(2) Patients with a diagnosis of Type 1 or Type 2 diabetes mellitus (ICD-10-CM codes E10.x or E11.x) in any diagnosis field and a procedure code for lower-extremity amputation in any procedure field. These included all diagnosis codes included in AHRQ PQI 16 (lower extremity amputation among patients with diabetes) [109], as well as procedure codes for toe amputations in order to maintain consistency with methods used in the Florida Diabetes Advisory Council Diabetes Report [26].

(3) Patients with a diagnosis of Type 1 or Type 2 diabetes mellitus in any diagnosis field, and a principal diagnosis of a complication of diabetes included in the list used to construct the Diabetes Complications Severity Index [31,38].

The ZIP code to ZCTA crosswalk table developed by John Snow, Inc. was used to join patient address ZIP codes to ZIP code tabulation areas (ZCTAs) [44], and diabetes-related hospitalizations were then aggregated to the ZCTA level. The total number of person-years at risk used to compute ZCTA-level diabetes-related hospitalization rates was obtained by summing the adult populations for each year from 2016 to 2019, which were obtained from the U.S. Census Bureau American Community Survey (ACS) 5-year estimates [33,110–112]. In order to limit risk of disclosure and minimize bias from areas with low population counts, values for ZCTAs with fewer than 100 adult residents during any year of the study and/or fewer than 10 diabetes-related hospitalizations were excluded from statistical analyses and suppressed in map figures. Therefore, a total of 933 ZCTAs were included for further analysis.

3.3.3.2 Shape files, grocery store, and physician data

County- and ZCTA-level cartographic boundary shapefiles used for mapping were obtained from the U.S. Census Bureau TIGER Geodatabase and the Florida Geographic Data Library [113,114]. The number of grocery stores at the ZIP code level was obtained from the 2016 U.S. Census Bureau Annual Economic Survey and joined to ZCTAs [49]. Grocery store density was computed using land area obtained from the ZCTA shapefile. Practice address ZIP codes for physicians with a specialty of family practice or internal medicine who had a clear/active license at the time of data accession (01/2021) were obtained from the Florida Department of Health, Division of Medical Quality Assurance's Florida Healthcare Practitioner Data Portal [115]. Practice address ZIP codes were joined to ZCTAs and aggregated to the ZCTA level to compute the number of primary care physicians per 10,000 population.

3.3.3.3 Socioeconomic and demographic data

Socioeconomic and demographic characteristics at the ZCTA level were obtained from ACS 5-year estimates [33,116–120]. These included: population age distribution and racial/ethnic composition, percent ≥ 25 years of age without a high school education, percent ≥ 25 years of age with a bachelor's degree or higher, median household income, median household value, percent of families in poverty, percent unemployed, percent without health insurance coverage, and percent of households without a vehicle. Diabetes prevalence estimates at the ZCTA level were obtained from the Centers for Disease Control and Prevention (CDC) Population-Level Analysis and Community Estimates (PLACES) project [103]. Rural-urban classification of ZCTAs was performed using locale assignments published by the National Center for Education Statistics [46].

3.3.4 Geographic analysis

To adjust for spatial autocorrelation and low populations in some ZCTAs, the ZCTA-level diabetes-related hospitalization rates were smoothed before mapping. The smoothing was performed using the spatial empirical Bayes smoothing approach, employing queen contiguity weights in GeoDa 1.18.0 [121]. This approach shrinks local rate estimates toward the local mean rate within a spatial window containing a given geographic unit and its neighbors [122]. This results in more stable estimates for areas with small populations and large variances, while accounting for the geographic structure of the data [122,123].

Cluster investigation was performed using Tango and Takahashi's flexible spatial scan statistic (FSSS), specifying a Poisson model, implemented in FleXScan v3.1.2 [124]. Under the null hypothesis of no clustering, the number of cases in each region in the study area follows a Poisson distribution with mean proportional to the relative number of person-years at risk in the region [124,125]. To assess whether significant spatial clustering exists, a set of flexibly shaped scanning windows are imposed on each region in the study area. The windows include the individual region as well as all combinations of connected regions up to a specified maximum number of nearest neighbors. A log-likelihood ratio test (LLR) is used to compare the log-likelihood of observing the number of cases that occur within each window with that of the regions outside of it. The regions within the window with the highest value of the LLR comprise the primary cluster. Secondary clusters are identified from the remaining regions in the study area that do not overlap with any cluster with a higher LLR statistic. To increase computational efficiency and avoid including areas that do not have elevated rates in the primary cluster, a restricted LLR statistic was used [125,126]. This takes the individual rate of each region into account and limits candidates for inclusion in the primary cluster to those with elevated risk at a pre-specified α value. In this study, the maximum scanning window size was specified as 30 ZCTAs, and the default α value of 0.2 was selected for restriction of the likelihood ratio test. Monte Carlo simulation with 999 replications was used for statistical inference. Clusters with LLR test p-values $\leq$ 0.05 and rate ratios (RRs) $\geq$ 1.5 were reported.

Smoothed estimates of diabetes-related hospitalization rates and cluster identities were imported into QGIS Opensource software, which was used to perform all cartographic manipulations [127]. Jenks' optimization scheme was used for classification of smoothed diabetes-related hospitalization rate estimates and rate ratios of diabetes-related hospitalization clusters [128].

3.3.5 Descriptive statistical analyses

Descriptive analyses were performed using SAS version 9.4 [37]. The Shapiro-Wilk test was used to assess normality of distribution of continuous variables. Since all continuous variables were non-normally distributed, median and interquartile range (IQR) were used as measures of central tendency and dispersion, respectively. ZCTAs with missing data for any of the variables assessed were excluded from computations of median and IQR for that variable. Variables with missing data were: median household value (14/933, 1.5%), median household income (4/933, 0.4%), percent of families in poverty (2/933, 0.2%), percent of households without a vehicle (1/933, 0.1%). The Wilcoxon rank sum test was used to assess whether median characteristics of non-cluster ZCTAs differed significantly from those of ZCTAs within clusters of high diabetes-related hospitalization rates. The Chi-square test was used to assess whether the distribution of rural-urban ZCTA locale assignments differed between cluster and non-cluster areas.

3.4 Results

3.4.1 Distribution of diabetes-related hospitalization rates

There was a total of 2,581,031 hospitalizations with a diagnosis of Type 1 or Type 2 diabetes among patients aged 18-100 years. Only 554,449 of these hospitalizations met the inclusion criteria for diabetes-related hospitalizations in this study. The statewide diabetes-related hospitalization (DRH) rate was 8.5 per 1,000 person-years, but spatial empirical Bayes (SEB) smoothed rates at the ZCTA level ranged from 0 to 101.9 (Figure 3.2). The highest DRH rates tended to occur in ZCTAs in inland central and northeastern Florida, as well as along the Gulf Coast to the north of the Tampa Bay area (Figures 3.1 and 3.2). In northwest Florida, ZCTAs to the west of Tallahassee as well as those in the rural northwest panhandle also had relatively high rates of diabetes-related hospitalizations (Figures 3.1 and 3.2). While large swaths of ZCTAs with high DRH rates tended to occur in relatively rural parts of the state, the distribution of DRH

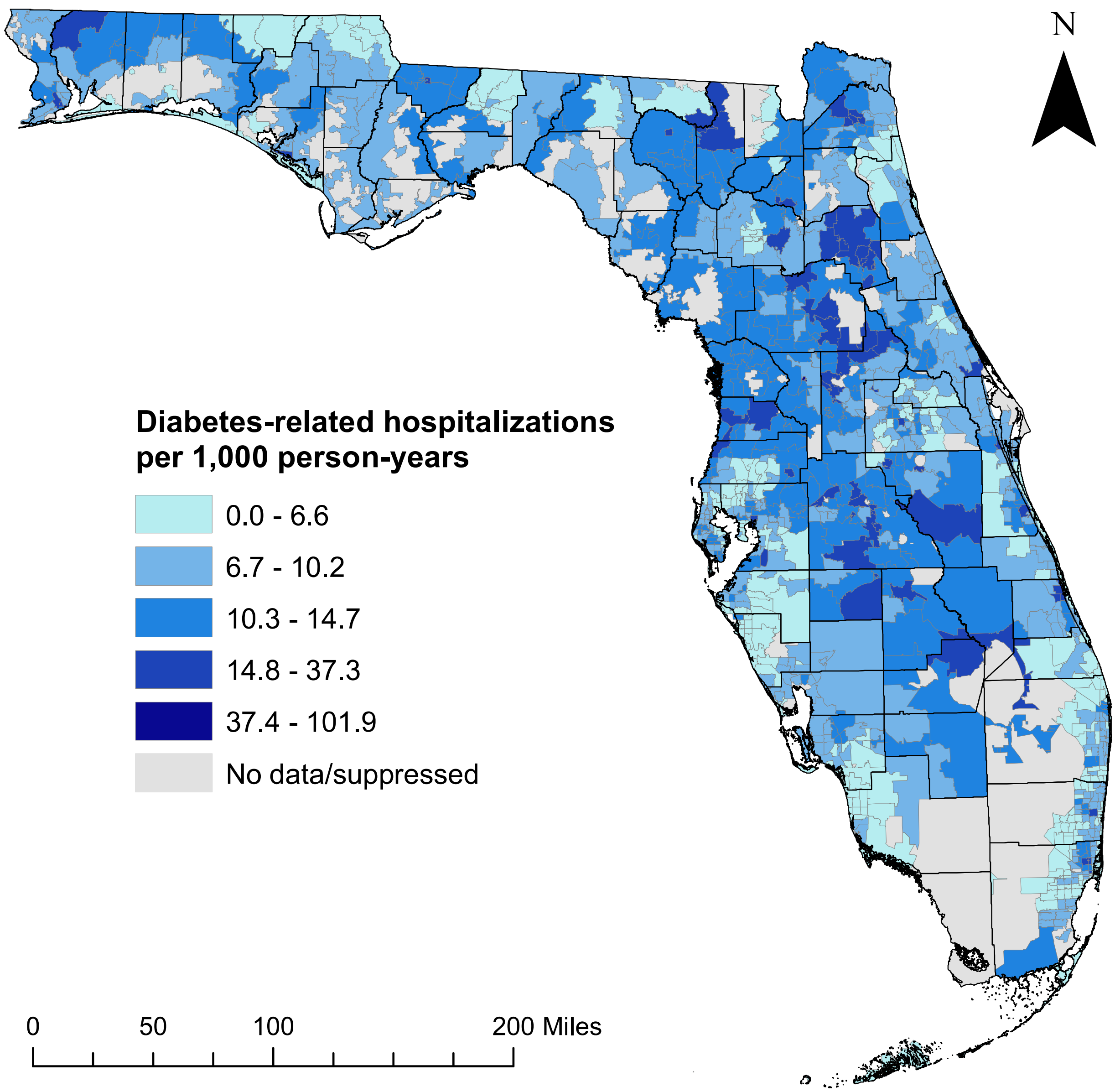

Figure 3.2. Geographic distribution of spatial empirical Bayes smoothed diabetes-related hospitalization (DRH) rates at the ZIP code tabulation area level in Florida, 2016-2019.

rates exhibited marked variation within some metropolitan areas (Figure 3.3). For instance, a group of ZCTAs extending from central Jacksonville to the northern and western fringes of the city was characterized by relatively high DRH rates compared to those in southeastern Jacksonville and closer to the Atlantic Coast. High rates of DRH were also evident in southeastern coastal Florida, an area that consists largely of urban and suburban ZCTAs (Figure 3.3). Two distinct groups of ZCTAs with high DRH rates were present in this area, one in the city of Fort Lauderdale and the other in northern Miami. Both areas were surrounded by ZCTAs with relatively low DRH rates.

3.4.2 Significant spatial clusters of high rates of diabetes-related hospitalizations

Geographic locations and rate ratios of significant high-rate spatial clusters of diabetes-related hospitalizations are displayed in Figure 3.4. The DRH rate of the primary cluster was 14.0 per 1,000 person-years (Table 3.1). The rate ratio (RR) of this cluster was 1.65, implying that the rate of diabetes-related hospitalizations within the cluster was 1.65 times that of the state. The primary cluster was also the largest cluster, and was comprised of 24 ZCTAs in central Florida to the east of Tampa and southwest of Orlando (Figures 3.1 and 3.4). Most of these ZCTAs were located in Polk County, but the cluster also included portions of Osceola, Highlands, and Hardee Counties (Figures 3.1 and 3.4). The majority (79.2%) were classified as fringe or distant rural ZCTAs.

In addition to the primary cluster, 23 secondary clusters were identified, with rate ratios ranging from 1.51 to 2.48 (Table 3.1 and Figure 3.4). A total of 179 ZCTAs (19.2% of the 933 ZCTAs included in the analysis) were included in high-rate clusters. The primary cluster in central Florida was bordered by several secondary clusters that had

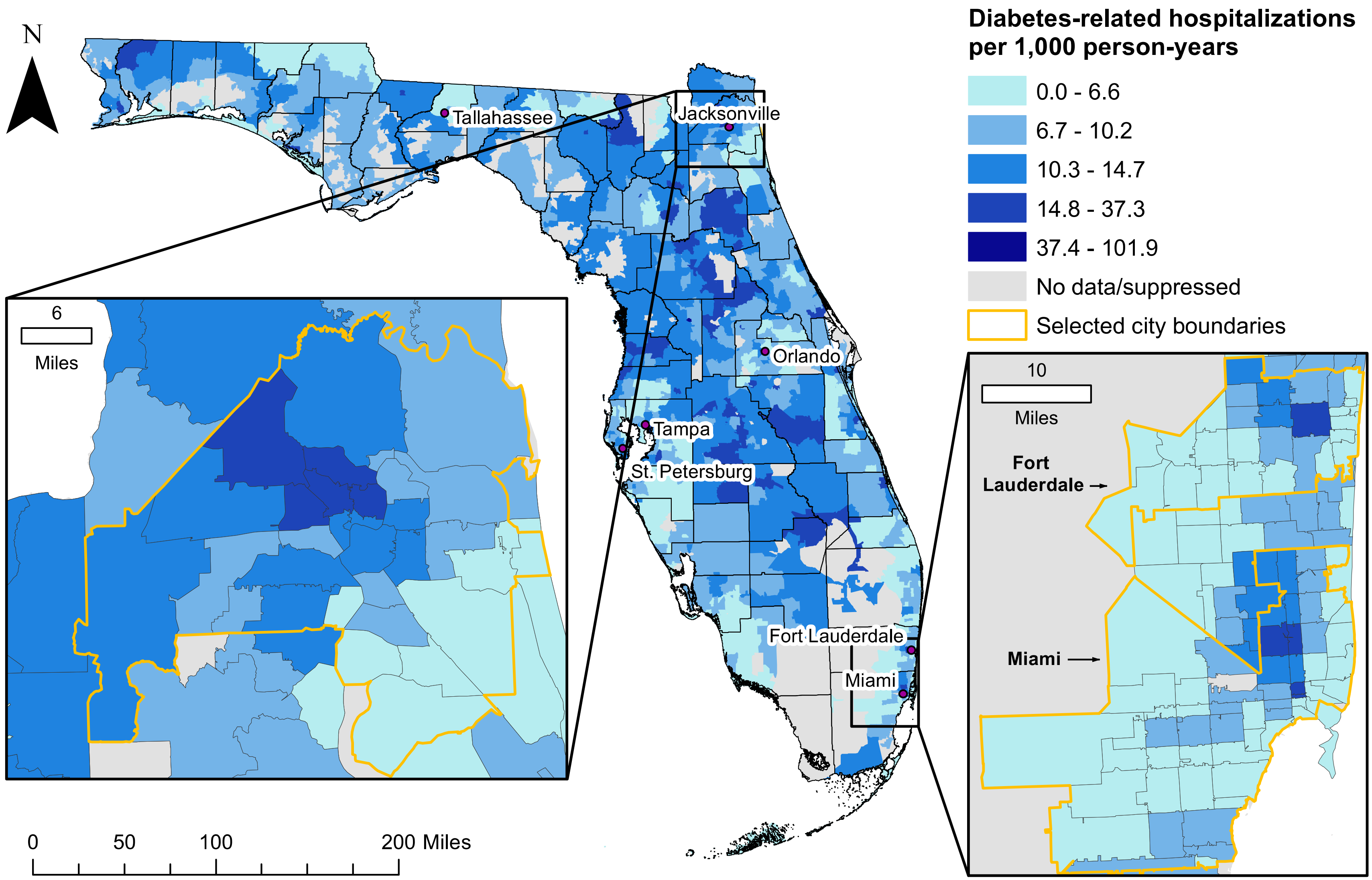

Figure 3.3. Geographic distribution of spatial empirical Bayes smoothed diabetes-related hospitalization (DRH) rates in selected metropolitan areas in Florida, 2016-2019.

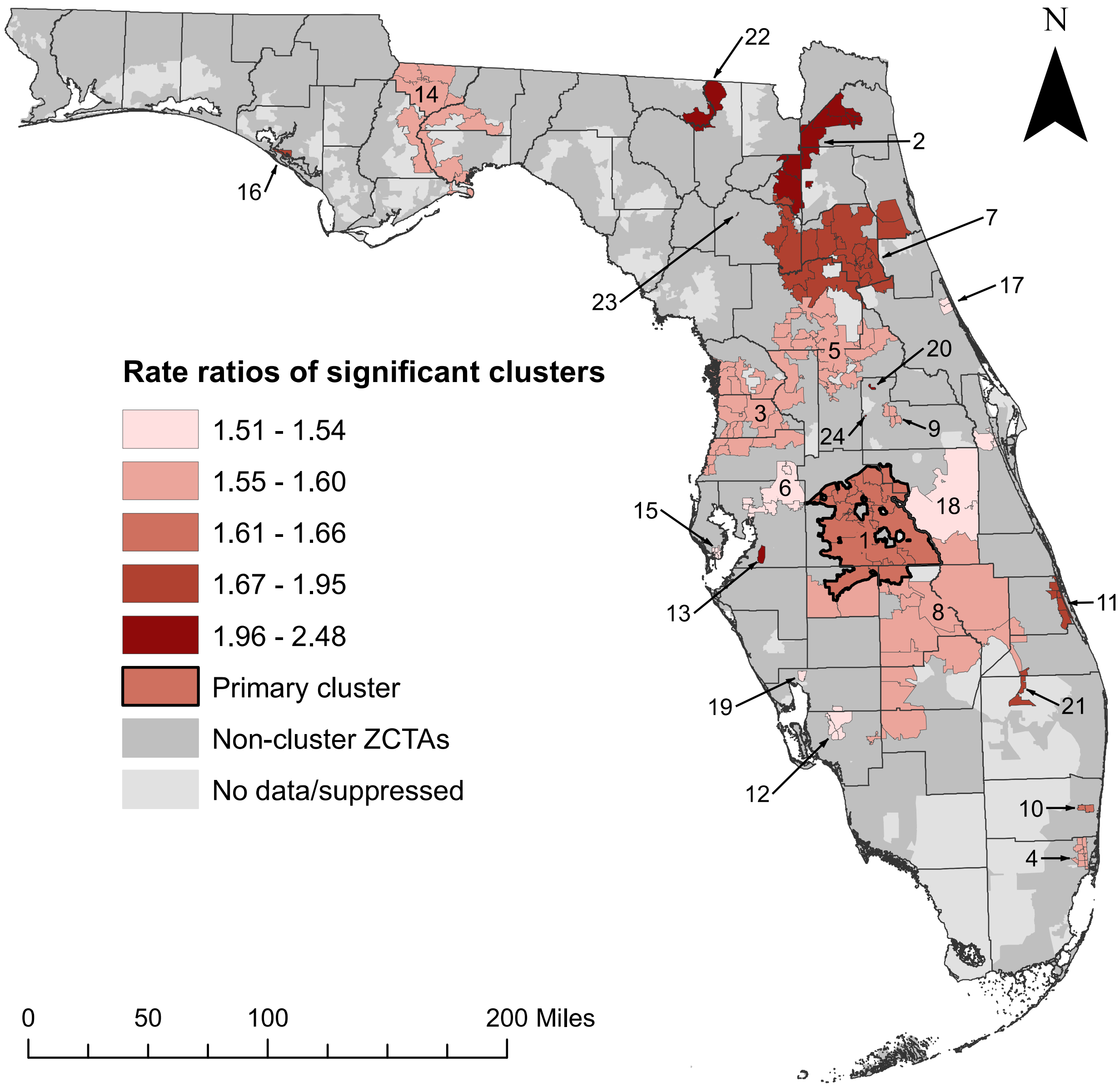

Figure 3.4. Significant high-rate spatial clusters of diabetes-related hospitalizations at the ZIP code tabulation area level in Florida, 2016-2019.

Table 3.1. Significant high-rate spatial clusters of diabetes-related hospitalizations at the ZIP code tabulation area level in Florida, 2016-2019.

Cluster	Location: Region	Location: Counties	Size[1]	Number of cases: Observed	Number of cases: Expected	Rate[2]	RR[3]	*p*
1	Central	Polk, Osceola, Highlands, Hardee	24	19915	12099.6	14.0	1.65	0.001
2	Northeast	Duval, Nassau, Baker, Union, Bradford, Clay	11	9029	4222.6	18.2	2.14	0.001
3	East Central	Pasco, Hernando, Citrus, Sumter	21	18349	11620.8	13.4	1.58	0.001
4	Southeast	Miami-Dade	12	16438	10286.3	13.6	1.60	0.001
5	Central	Sumter, Lake, Marion	23	14427	9081.4	13.5	1.59	0.001
6	West Central	Hillsborough, Pasco	11	11227	7390.5	12.9	1.52	0.001
7	Northeast	St. Johns, Putnam, Alachua, Bradford, Marion, Volusia	21	5601	3124.3	15.3	1.79	0.001
8	South Central	Glades, Hendry, Lee, Highlands, Hardee, Okeechobee, St. Lucie, Martin, Osceola	12	6976	4361.9	13.6	1.60	0.001
9	Central	Orange	4	6879	4318.5	13.6	1.59	0.001
10	Southeast	Broward	2	5568	3360.8	14.1	1.66	0.001
11	Southeast	St. Lucie	5	4724	2735.2	14.7	1.73	0.001
12	Southwest	Lee, Charlotte	4	4156	2693.4	13.1	1.54	0.001
13	West Central	Hillsborough	1	1466	706.1	17.7	2.08	0.001
14	Northwest	Gadsden, Leon, Liberty, Wakulla, Franklin	11	3224	2024.7	13.6	1.59	0.001
15	West Central	Pinellas	3	3032	1986.4	13.0	1.53	0.001
16	Northwest	Bay	1	1212	620.2	16.6	1.95	0.001
17	East Central	Volusia	2	2405	1596.3	12.8	1.51	0.001
18	East Central	Osceola, Brevard	4	1733	1126.4	13.1	1.54	0.001
19	Southwest	Charlotte	1	1427	940.9	12.9	1.52	0.001
20	Central	Orange	1	201	81.2	21.1	2.48	0.001
21	Southeast	Palm Beach, Martin	2	398	217.4	15.6	1.83	0.001
22	Northeast	Columbia, Hamilton, Suwannee	1	127	62.8	17.2	2.02	0.001
23	Northeast	Alachua	1	65	26.7	20.7	2.44	0.002
24	Central	Orange	1	56	22.9	20.9	2.45	0.006

[1]Number of ZIP code tabulation areas
[2]Diabetes-related hospitalization rate per 1,000 person-years
[3]Rate ratio

rate ratios ranging from 1.55 to 1.60 (Table 3.1 and Figure 3.4). The large secondary cluster to the south of the primary cluster encompassed the majority of Highlands and Okeechobee Counties, and included rural ZCTAs in several other counties in inland south-central Florida (Figures 3.1 and 3.4).

There were several large clusters to the north of the primary cluster, spanning a mostly rural area that extended northeast from west central Florida (Figure 3.4). Cluster 2 had a rate ratio of 2.14, and was composed of 11 ZCTAs, including 6 “large city” ZCTAs in Jacksonville, the most populous city in Florida (Table 3.1; Figures 3.4 and 3.5). The Jacksonville area cluster was relatively large and had one of the highest rate ratios identified in this study. However, high-rate clusters were also identified in several other metropolitan areas in Florida. In southeastern coastal Florida, high-rate clusters were identified in Miami (RR = 1.60) and Fort Lauderdale (RR = 1.66) (Table 3.1 and Figure 3.5). Tampa, St. Petersburg, and Orlando were among the other cities that contained ZCTAs in high-rate clusters (Figures 3.4 and 3.5). In addition, there was a relatively large cluster (Cluster 14) with a rate ratio of 1.59 that extended west from southern Tallahassee, the state’s capital (Table 3.1; Figures 3.4 and 3.5).

3.4.3 Characteristics of cluster vs. non-cluster ZCTAs

The median diabetes prevalence estimate for ZCTAs within high-rate clusters of diabetes-related hospitalizations was 15.1% (IQR 13.8-16.7), which was significantly higher than that of ZCTAs outside of high-rate clusters (11.9%, IQR 10.2-13.5, $p < 0.0001$) (Table 3.2). The characteristics of ZCTAs in high-rate clusters differed significantly ($p < 0.0001$) from those that were not in clusters with respect to their level

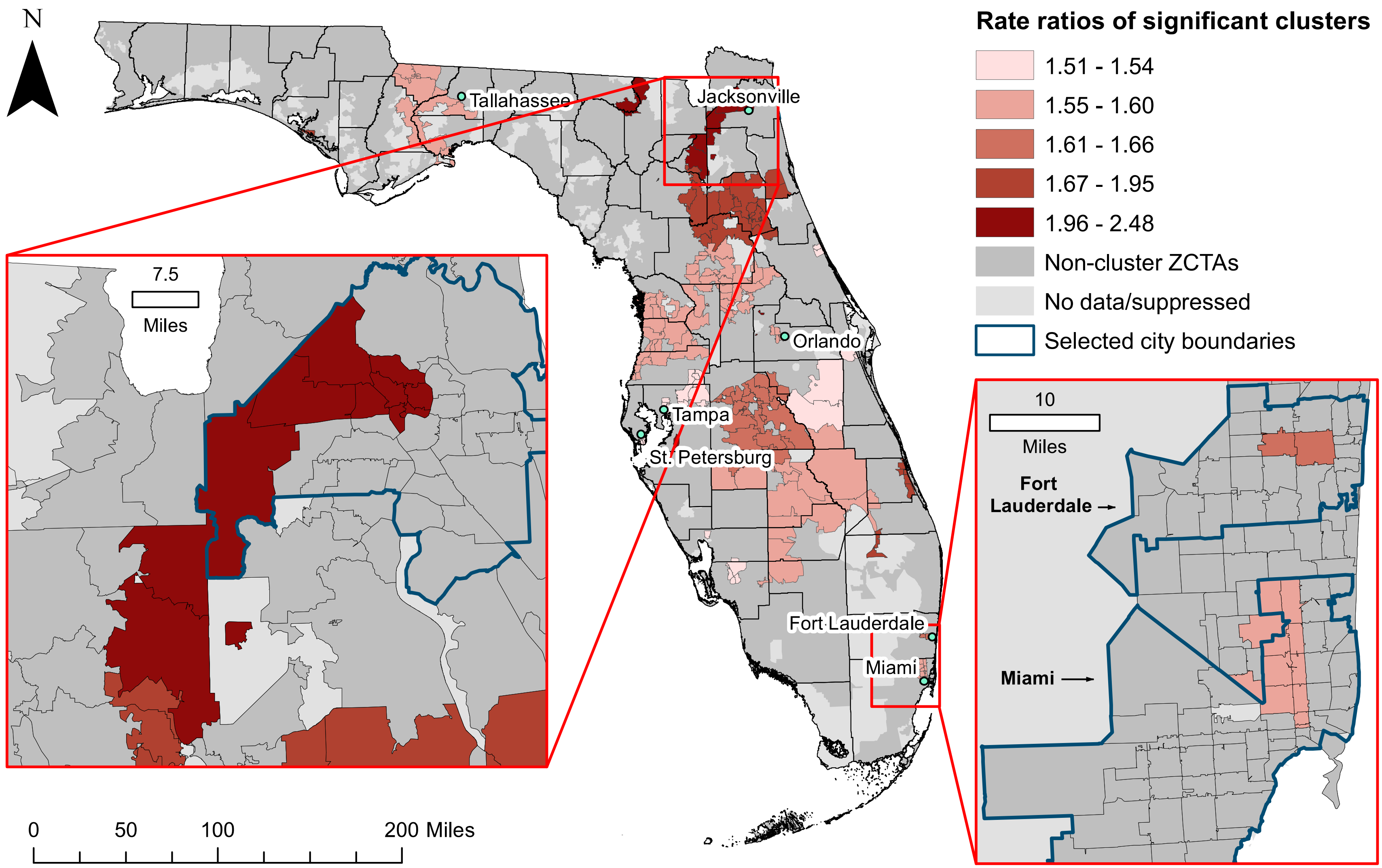

Figure 3.5. Significant high-rate spatial clusters of diabetes-related hospitalizations in selected metropolitan areas in Florida, 2016-2019.

Table 3.2. Comparison of characteristics of ZIP code tabulation areas within and outside of clusters of diabetes-related hospitalizations in Florida, 2016-2019.

Variable	Median (interquartile range) Cluster ZCTAs[1]	Non-cluster ZCTAs[1]	*p*[*]
Diabetes prevalence estimate (percent)	15.5 (13.8 – 16.7)	11.9 (10.2 – 13.5)	< 0.0001
Rurality/urbanization[**]			
Rural	60.9 (109)	41.8 (315)	
Suburban/town	24.0 (43)	38.7 (292)	< 0.0001
City	15.1 (27)	19.5 (147)	
Demographic characteristics			
Percent non-Hispanic Black	13.7 (4.4 – 38.4)	7.4 (2.8 – 15.2)	< 0.0001
Percent Hispanic	10.6 (5.1 – 20.8)	10.4 (5.1 – 24.3)	0.3409
Percent 65 years of age and older	20.8 (15.2 – 27.8)	18.9 (13.8 – 26.8)	0.0567
Median age	42.4 (36.8 – 51.1)	42.6 (38.0 – 50.3)	0.4720
Economic characteristics			
Median household income	\$42,060 (\$36,551 – \$48,214)	\$57,816 (\$48,153 – 72,159)	< 0.0001
Percent of families in poverty	14.0 (9.7 – 19.4)	7.9 (3.2 – 11.8)	< 0.0001
Percent unemployed	7.3 (5.4 – 9.0)	4.9 (3.7 – 6.4)	< 0.0001
Percent of households without a vehicle	6.4 (4.3 – 11.1)	4.2 (2.5 – 6.9)	< 0.0001
Median household value	\$115,800 (\$95,400 – 154,200)	\$215,650 (\$156,600 – \$294,100)	< 0.0001
Educational attainment			
Percent ≥25 years of age without a high school education	16.7 (12.2 – 21.2)	9.1 (5.6 – 14.6)	< 0.0001
Percent ≥25 years of age with a bachelor's degree or higher	15.3 (11.9 – 19.2)	28.5 (19.6 – 41.3)	< 0.0001
Healthcare access			
Percent without health insurance coverage	13.9 (10.9 – 17.8)	11.0 (8.1 – 15.0)	< 0.0001
Primary care physicians per 10,000 population	3.3 (0.5 – 10.0)	7.3 (2.6 – 14.3)	< 0.0001
Food environment			
Grocery stores per 100 square kilometers	1.8 (0 – 15.4)	6.4 (0.6 – 23.0)	0.0005

[1]ZIP code tabulation areas
[*]*p*-value for Chi-square test (categorical variable) or Wilcoxon rank sum test (continuous variables)
[**]Percent and frequency presented for categorical variable

of rurality/urbanization. High-rate clusters had a higher percentage of rural ZCTAs (60.9%) than non-cluster ZCTAs (41.8%). The majority of ZCTAs in non-cluster areas were either classified as suburbs/towns (38.7%) or cities (19.5%), while 24.0% of the ZCTAs within high-rate clusters were suburbs or towns and 15.1% were cities.

Populations of cluster and non-cluster ZCTAs also exhibited significant differences with respect to racial composition, economic indicators, educational attainment, and healthcare and food access (Table 3.2). The median percentage of non-Hispanic Black residents was significantly ($p < 0.0001$) higher within cluster ZCTAs (13.7%) than non-cluster ZCTAs (7.4%). Populations of ZCTAs within high-rate clusters had significantly ($p < 0.0001$) lower median household income ($42,060) than those of non-cluster ZCTAs ($57,816). In addition, the median percentage of families in poverty was significantly ($p < 0.0001$) higher in cluster ZCTAs (14.0%) than non-cluster ZCTAs (7.9%). The median unemployment rate and percentage of households without access to a vehicle were also significantly ($p < 0.0001$) higher for populations of cluster ZCTAs than those of non-cluster ZCTAs.

Compared to non-cluster ZCTAs, populations of ZCTAs within high-rate clusters tended to have lower levels of educational attainment. The median percentage of adults aged 25 and older without a high school education was significantly ($p < 0.0001$) higher within cluster ZCTAs (16.7%) than non-cluster ZCTAs (9.1%). In addition, the median percentage of adults with a bachelor's degree or higher was significantly ($p < 0.0001$) lower within cluster ZCTAs (15.3%) than non-cluster ZCTAs (28.5%). The median percentage of the population without health insurance coverage was significantly ($p < 0.0001$) higher within cluster ZCTAs (13.9%) than non-cluster ZCTAs (11.0%).

Furthermore, the median number of primary care physicians per capita was significantly ($p < 0.0001$) lower in cluster ZCTAs (3.3 per 10,000 population) than non-cluster ZCTAs (7.3 per 10,000 population). Finally, median density of grocery stores was also significantly ($p = 0.0005$) lower in cluster ZCTAs (1.8 per 100 km^2) than in non-cluster ZCTAs (6.4 per 100 km^2).

3.5 Discussion

This study identified significant high-rate spatial clusters of diabetes-related hospitalizations (DRH) at the ZCTA level in Florida, and provides evidence of geographic disparities of DRH rates within the state. Interventions that aim to alleviate the excess burden of DRH in the identified hotspots have the potential to reduce these inequities.

Previous research in Florida identified county-level geographic disparities in pre-diabetes and diabetes prevalence [30,100–102]. The locations of those identified high-prevalence diabetes clusters and the high-rate DRH clusters identified in this study exhibited some overlap, particularly in south-central Florida and near Tallahassee [30,101,102]. Populations of cluster ZCTAs also tended to have higher diabetes prevalence than those of non-cluster ZCTAs, suggesting that the observed disparities in hospitalization rates may, in part, reflect the burden of diabetes in the population. However, differences between the distribution of DRH rates and diabetes prevalence were also apparent in some parts of the state. This could be indicative of disparities in diabetes care and management. This is consistent with findings of previous research in the US [83,129]. For instance, compared to patients with diabetes from other parts of the country, those from the Southern US are less likely to receive HbA1c testing, are more likely to report foregoing medical care due to cost, and are more likely to experience hypoglycemia [83,129].

The identified local clusters in this study are important for guiding targeted efforts to improve glycemic control and cardiovascular risk factor management among patients with diabetes in communities with high DRH rates. Exploring characteristics of clusters and their populations can also inform needs-based planning to improve outcomes in these communities. For instance, the largest high-rate DRH clusters were primarily located in rural parts of Florida, consistent with findings of other US studies that have reported rural-urban disparities in diabetes outcomes [130,131]. This could, in part, reflect a higher burden of diabetes and risk factors such as overweight/obesity and tobacco use among rural populations compared to those of urban areas [132–136]. High DRH rates in rural areas may also reflect challenges in obtaining outpatient care and effective diabetes self-management for rural patients. For example, limited public transportation in rural areas could pose a barrier to attending appointments or obtaining medications in a timely manner. This challenge may be exacerbated by other resource limitations of ZCTAs within high-rate clusters. For instance, cluster ZCTAs tended to have greater distances between grocery stores (which often contain pharmacies), fewer primary care physicians per capita, and populations with more limited vehicle access than the rest of the state. Previous research in Florida reported a negative association between the percentage of rural residents and county-level rates of participation in diabetes self-management education (DSME) programs [30]. In addition, nationwide studies have reported that patients with diabetes in rural areas are less likely to receive routine HbA1c testing, foot and eye examinations than those in metropolitan areas [74,132].

While high-rate clusters tended to occur in rural rather than urban areas, it is worth noting that the distribution of DRH rates within some of the major cities in Florida varied significantly, and high-rate clusters were identified in several metropolitan areas. This is consistent with findings of studies in other states that reported geographic disparities within urban areas. Examples include hotspots of diabetes-related emergency department visits in central Los Angeles County in California [137], and diabetes-specific inpatient hospitalizations and emergency department visits in New York City [99]. In this study, one of the most notable high-rate clusters occurring in a metropolitan area included part of Jacksonville, located in Duval County in northeastern Florida. An analysis of 2007 data also reported sub-county level disparities in diabetes prevalence, emergency department visits, hospitalizations, and deaths in Duval County [104]. Compared to the rest of the county, residents of central Jacksonville had higher burdens of all the outcomes investigated in that study [104]. The current study found that these central ZCTAs also had relatively high hospitalization rates between 2016 and 2019, and were part of a significant spatial cluster. This suggests that there are persistent geographic disparities with respect to diabetes complications at the sub-county level, and highlights the value of ongoing data collection and analysis at the local level to inform resource allocation.

ZCTAs located in high-rate clusters of diabetes-related hospitalizations tended to have higher proportions of non-Hispanic Black residents compared to the rest of the state. This is consistent with findings of the aforementioned Duval County study [104].

The proportion of non-Hispanic Black residents has also been reported to be a predictor of county-level pre-diabetes [100] and diabetes prevalence in statewide investigations in Florida [102]. Racial disparities with respect to diabetes-related quality of care and management have been reported in numerous studies in the United States, and may contribute to disparities in adverse outcomes [73,74,88,129,138]. Black patients with diabetes have lower odds of receiving HbA1c testing, blood pressure testing, and foot examination at recommended intervals, are less likely to have blood pressure and HbA1c control, and are more than twice as likely to have diabetes-related hospital admissions initiated in the emergency department compared to White patients [73,74,88,129,138]. A Georgia study reported that non-Hispanic Black patients with diabetes had significantly higher rates of hospital discharges and longer hospital stays than non-Hispanic White patients [139].

High-rate DRH clusters were characterized by relative socioeconomic disadvantage when compared to the rest of the state, with populations of cluster ZCTAs having lower median income and educational attainment in addition to higher levels of poverty and unemployment than those of non-cluster ZCTAs. Socioeconomic position can impact diabetes management through pathways such as health behaviors and health literacy, social support, stress, competing demands, and area-level structural factors such as built environment resources [91]. Cost barriers may contribute to medication underuse and foregone medical care among patients with diabetes [83,140,141]. Populations of high-rate DRH clusters in this study also tended to have lower levels of health insurance coverage compared to those of non-cluster ZCTAs. Lack of insurance coverage may result in delayed detection of diabetes and initiation of appropriate treatment [142]. Furthermore, patients with diabetes who do not have health insurance coverage are less likely to receive diagnostic testing and examinations at recommended intervals compared to those with private insurance [73,74,88,129].

3.5.1 Strengths and limitations

To our knowledge, this is the first statewide study investigating geographic disparities of diabetes-related hospitalization rates at the sub-county level in Florida. This study was conducted using Tango's flexible spatial scan statistic (FSSS), a robust technique for the detection of high risk/rate spatial clusters [124]. Tango's FSSS can be used to detect either circular or irregularly shaped clusters and does not suffer from problems of multiple comparisons or pre-selection bias, which are drawbacks of some other cluster detection methods. In addition, the use of hospital discharge data over a four-year period in this study provided a sufficient sample size for investigating the distribution of diabetes-related hospitalization rates at a relatively small geographic unit of analysis (ZIP code tabulation areas).

However, this study was not without limitations. Direct estimates of diabetes prevalence are not available at the ZCTA level, so diabetes-related hospitalization rates presented in this study are not adjusted for the burden of diabetes in the population. Additionally, this study does not account for patients whose illness warrant hospitalization but do not receive it, for reasons such as travel time to the nearest hospital, or declining care due to cost of hospitalization. Finally, this investigation was limited to the state of Florida, and the findings of descriptive analyses comparing cluster and non-cluster ZCTAs may not generalize to other areas. However, the techniques used in the present study can be employed in other states to identify and describe high-rate clusters of diabetes-related hospitalizations and other potentially preventable hospitalizations. Despite the above limitations, the findings of this study are valuable for guiding health planning and future research.

3.6 Conclusions

This study identified geographic disparities of DRH rates at the ZCTA level in Florida. High-rate clusters tended to: have greater proportions of non-Hispanic Black residents, be in rural areas, have relatively fewer grocery stores and primary care physicians, have populations with low income, low educational attainment, and low employment rates compared to the rest of the state. The identification of high-rate DRH clusters in this study provides useful information to guide resource allocation such that communities with the highest burdens of these potentially preventable hospitalizations are prioritized to reduce the observed disparities. Future research will investigate determinants of hospitalization rates to inform public health planning, resource allocation and interventions.

CHAPTER 4

Determinants of disparities of diabetes-related hospitalization rates in Florida: a retrospective ecological study using a multiscale geographically weighted regression approach

A version of this chapter has been submitted for publication at *International Journal of Health Geographics* and is currently under review. My contributions to this manuscript included study design, data preparation and analysis, preparing figures, and drafting and editing the manuscript. Dr. Agricola Odoi was also involved in the design of the study and revision of the manuscript, and both authors read and approved the final manuscript.

4.1 Abstract

Background: Early diagnosis, control of blood glucose levels and cardiovascular risk factors, and regular screening are essential to prevent or delay complications of diabetes. However, most adults with diabetes do not meet recommended targets, and some populations have disproportionately high rates of potentially preventable diabetes-related hospitalizations. Understanding the factors that contribute to geographic disparities can guide resource allocation and help ensure that future interventions are designed to meet the specific needs of these communities. Therefore, the objectives of this study were (1) to identify determinants of diabetes-related hospitalization rates at the ZIP code tabulation area (ZCTA) level in Florida, and (2) assess if the strengths of these relationships vary by geographic location and at different spatial scales.

Methods: Diabetes-related hospitalization (DRH) rates were computed at the ZCTA level using data from 2016 to 2019. A global ordinary least squares regression model was fit to identify socioeconomic, demographic, healthcare-related, and built environment characteristics associated with log-transformed DRH rates. A multiscale geographically weighted regression (MGWR) model was then fit to investigate and describe spatial heterogeneity of regression coefficients.

Results: Populations of ZCTAs with high rates of diabetes-related hospitalizations tended to have higher proportions of older adults ($p < 0.0001$) and non-Hispanic Black residents ($p = 0.003$). In addition, DRH rates were associated with higher levels of unemployment ($p = 0.001$), uninsurance ($p < 0.0001$), and lack of access to a vehicle ($p = 0.002$). Population density and median household income had significant ($p < 0.0001$) negative associations with DRH rates. Non-stationary variables exhibited spatial heterogeneity at local (percent non-Hispanic Black, educational attainment), regional (age composition, unemployment, health insurance coverage), and statewide scales (population density, income, vehicle access).

Conclusions: The findings of this study underscore the importance of socioeconomic resources and rurality in shaping population health. Understanding the spatial context of the observed relationships provides valuable insights to guide needs-based, locally-focused health planning to reduce disparities in the burden of potentially avoidable hospitalizations.

4.2 Background

In the United States, the prevalence of diabetes among adults is estimated to be as high as 14.7%, and is projected to increase to 17.9% by 2060 [1,28]. Early diagnosis, control of blood glucose levels and cardiovascular risk factors, and regular screening for complications are key components of diabetes care to prevent or delay complications and reduce the risk of major clinical events that necessitate hospitalization [11,143–

145]. However, fewer than 1 in 4 US adults with diagnosed diabetes meet recommended targets for glucose, blood pressure, and lipid levels [146]. Despite prior improvements in achieving these goals, the percentage of adults with diabetes meeting glycemic and blood pressure targets have declined since the early 2010s, while the percentage with lipid control has plateaued [146–148]. In addition, rates of lower extremity amputations due to diabetes and diabetes-associated hospitalizations in the US have increased over the course of the past decade [97,149]. In 2017, $69.7 billion in healthcare expenditures in the US were attributed to hospital inpatient stays by patients with diabetes [150].

There is evidence of geographic disparities in access and utilization of diabetes care, as well as burden of diabetes and diabetes-related complications in the United States [15,16,83,129,131]. A contiguous region in the Southeastern US has been termed the Diabetes Belt due to the disproportionately high diabetes prevalence in this region compared to the rest of the country [15,16]. However, despite the relatively high burden of the condition, those with diabetes in the Southern US have lower odds of receiving hemoglobin A1c (HbA1c) testing at recommended intervals, and higher odds of foregoing necessary medical care due to cost compared to other regions [83,129]. In addition, patients with diabetes in the South have higher odds of experiencing hypoglycemic events, and higher odds of death during a diabetes-related hospitalization compared to other parts of the country [129,131].

In Florida, the most populous state in the Southeastern US, over 2 million adults have been diagnosed with diabetes [17], and it is estimated that an additional 546,000 Floridians have diabetes that is yet to be diagnosed [18]. Within the state, there is significant geographic variation in the distribution of diabetes prevalence [30,101,102]. In addition, recent research has identified local geographic hotspots of diabetes-related hospitalization (DRH) rates [151], indicating that some communities in the state bear a disproportionately high burden of potentially preventable diabetes complications. Communities in these hotspots also face a major financial burden; in 2018, the median cost of a hospital stay due to diabetes in Florida was $40,718 [26]. In order to reduce the observed disparities in DRH rates, it is important to close gaps in adherence to preventive practices and utilization of diabetes care [146,147]. Identifying predictors of hospitalization rates will provide useful information to guide public health planning and evidence-based interventions to address barriers to achieving diabetes care targets. Furthermore, understanding the spatial context of these relationships can help guide resource allocation and ensure that future interventions are designed to meet the specific needs of these communities. Therefore, the objectives of this study were (1) to identify determinants of diabetes-related hospitalization rates at the ZIP code tabulation area (ZCTA) level in Florida, and (2) assess if the strengths of these relationships vary by geographic location and at different spatial scales.

4.3 Methods

4.3.1 Ethics approval

This study was approved by the University of Tennessee Institutional Review Board (Number: UTK IRB-22-07182-XP). In accordance with 45 CFR 46.116(f), informed consent was waived by the Institutional Review Board. In addition, the request for waiver of HIPAA authorization for the conduct of the study was approved.

4.3.2 Study design and setting

This retrospective ecological study was conducted in the Southeastern US state of Florida. In 2019, the state had an estimated adult population of 16.7 million, 4.2 million of whom were aged 65 and older [33]. There are 983 ZIP code tabulation areas (ZCTAs), which are areal representations of post office ZIP codes, in Florida (Figure 3.1) [32]. In 2019, the estimated diabetes prevalence among Florida adults was 11.7%, compared to 9.3% for the US overall [105]. However, prevalence estimates at the ZCTA level in Florida ranged from 1.0% to 24.5% [152]. The main outcome measure in this study was ZCTA-level diabetes-related hospitalization (DRH) rates among adults 18 years of age and older during the period from 2016 to 2019. Factors investigated for potential associations with DRH rates were socioeconomic, demographic, healthcare-related, and built environment characteristics.

4.3.3 Data sources

Hospital inpatient data files were provided by the Florida Agency for Health Care Administration through a Data Use Agreement with the Florida Department of Health. All other data used in the study were obtained from publicly available sources. Model-based small area estimates of diabetes prevalence were obtained from the Centers for Disease Control and Prevention (CDC) Population-Level Analysis and Community Estimates (PLACES) project [103]. Population size, socioeconomic and demographic characteristics were obtained from the US Census Bureau American Community Survey 5-year estimates [48,116–120]. Built environment variables assessed included food retailers and fitness/recreational facilities. Data on these variables were obtained from the 2016 US Census Bureau ZIP Code Business patterns [49]. Address ZIP codes for pharmacies and practices of internal medicine and family practice physicians were obtained from the Florida Department of Health, Division of Medical Quality Assurance's Florida Healthcare Practitioner Data Portal [115]. Locale assignments for rural-urban classification of ZCTAs were obtained from the National Center for Education Statistics [46]. Cartographic boundary shapefiles used for mapping were downloaded from the U.S. Census Bureau TIGER Geodatabase and the Florida Geographic Data Library [113,114].

4.3.4 Data preparation

4.3.4.1 Diabetes-related hospitalizations

Records of diabetes-related hospitalizations for patients aged 18 to 100 years with home address ZIP codes in Florida and admission dates between January 1, 2016 and December 31, 2019 were extracted from the hospital discharge data. The inclusion criteria for diabetes-related hospitalizations for this study were based on the Agency for Healthcare Research and Quality (AHRQ) Prevention Quality Indicators, the Diabetes Complications Severity Index (DCSI), and reporting by the Florida Diabetes Advisory Council [26,31,38,106–109]. Diabetes-related hospitalizations were defined as those with: a principal diagnosis code for diabetes with short-term complications, long-term complications, or uncontrolled diabetes [106–108]; a procedure code for lower-extremity amputation (including toe amputations) in any field and a diagnosis of Type 1 or Type 2 diabetes mellitus in any field [26,109]; or a principal diagnosis of a diabetes complication included in the DCSI and a diagnosis of Type 1 or Type 2 diabetes mellitus in any field [31,38].

Patient address ZIP codes were joined to ZCTAs using the crosswalk table developed by John Snow, Inc., and aggregated to the ZCTA level [44]. Rates of diabetes-related hospitalizations were computed by dividing the number of diabetes-related hospitalizations by the total number of person-years at risk. The median age of patients with diabetes-related hospitalizations for each ZCTA was also computed. After exclusion of ZCTAs with fewer than 10 diabetes-related hospitalizations or populations of fewer than 100 adult residents to minimize disclosure risk and small number bias, 933 ZCTAs remained for further analysis.

4.3.4.2 Socioeconomic, demographic, healthcare-related and built environment variables

The following socioeconomic and demographic variables were considered as potential predictor variables: population density, median age, median household income and household value, percent of the population that were 65 years or older, Hispanic or non-Hispanic Black, 25 years or older without a high school education, 25 years or older with a bachelor's degree or higher, percent of families with income below the poverty level, percent of unemployed residents, percent without health insurance coverage, and percent of households without a vehicle.

North American Industry Classification System (NAICS) codes were used to extract the number of businesses in each ZIP code classified as: convenience stores (NAICS code 445120), limited service restaurants (NAICS code 722211), supermarkets

(NAICS code 445110), fruit and vegetable markets (NAICS code 445230), warehouse clubs (NAICS 452910), and fitness and recreational sports centers (NAICS 713940). The John Snow, Inc. crosswalk was used to join ZIP codes of food retailers, fitness/recreational centers, pharmacies, and primary care practices to ZCTAs [44]. A ZCTA-level version of the modified retail food environment index (mRFEI), which measures the percent of "healthy" food retailers in an area [153], was also computed. Businesses included in the category of healthy food retailers were supermarkets, produce markets, and warehouse clubs, while those included in the "less healthy" category included limited service (fast food) restaurants and convenience stores. ZCTA-level densities of food retailers, fitness/recreational facilities, and pharmacies were computed using land area from the ZCTA shapefile. The number of primary care physicians per 10,000 population in each ZCTA was also computed.

4.3.5 Statistical analysis

4.3.5.1 Descriptive statistical analyses

Statistical analysis was performed using SAS version 9.4 [37]. Normality of distribution of continuous ZCTA-level characteristics was assessed using the Shapiro-Wilk test, and median and interquartile range (IQR) were used as measures of central tendency and dispersion for non-normally distributed variables. Diabetes-related hospitalization rates were smoothed in GeoDa 1.18.0 using the spatial empirical Bayes approach with queen contiguity weights [121].

4.3.5.2 Ordinary least squares regression model

An ordinary least squares (OLS) regression model was fit to the data to identify predictors of diabetes-related hospitalization rates. Due to the highly skewed distribution of ZCTA-level DRH rates, natural log transformation of the outcome measure was performed. In addition, all continuous variables were standardized to have a mean of 0 and standard deviation of 1 to facilitate comparison with the results of the MGWR analysis described in the following section. To identify candidate variables for inclusion in the multivariable model-building process, univariable associations between potential predictors and log-transformed DRH rates were first assessed. A significance level of 0.15 was used to identify variables for consideration in the multivariable model.

To prevent problems with multicollinearity, Spearman's rank correlation coefficient was used to identify pairs of highly correlated ($|r_s| \geq 0.7$) variables, from which one variable was selected as a potential predictor for inclusion in the model-building process. Variable selection for the multivariable OLS regression model was performed using manual backwards elimination, using a critical *p*-value of 0.05. During the model-building process, collinearity between explanatory variables was assessed using variance inflation factor (VIF), with VIF $\geq$ 10 indicating multicollinearity [65]. Confounding was assessed by examining the magnitude of changes in coefficient estimates as each variable was removed from the model. A variable was considered to be a potential confounder if its removal resulted in a 20% or greater change in the coefficient estimate of another variable in the model, and retained regardless of statistical significance.

4.3.5.3 Multiscale geographically weighted regression model

Global regression models assume that relationships between an outcome variable and its determinants do not vary by geographic location within a given study area [154]. However, violations of this assumption may occur with geographical data, resulting in model misspecification. Therefore, a multiscale geographically weighted regression (MGWR) analysis was performed to assess for spatial variability in regression coefficients and determine the optimal model to assess these relationships [155–158]. Rather than computing a single coefficient that estimates the average association between an explanatory and outcome variable for the entire study area, geographically weighted regression models estimate a regression coefficient for each location in the study area [154]. Model parameters for each geographic unit are estimated using a local subset of observations that are weighted by their distance from that location [154]. The weight assigned to a given observation depends on the type of weighting function selected, and its bandwidth determines the size of the local subset of observations used to estimate model parameters [154]. Multiscale GWR differs from standard and semiparametric GWR in that a unique kernel bandwidth is computed for each explanatory variable in the model [155–158]. In standard GWR, a single bandwidth is computed and used for all explanatory variables in the model [155–158]. Semiparametric GWR allows for specification of variables as either global (stationary) or local (spatially non-stationary), with a single bandwidth computed and used for all local variables in the model [155–158].

The multiscale GWR analysis was implemented using the *mgwr* package in Python, specifying the explanatory variables as those selected for the final global multivariable OLS model [159]. To enable comparison of bandwidth values, continuous variables were standardized to have a mean of 0 and standard deviation of 1 [155–159]. An adaptive bi-square weighting kernel was selected as the weighting scheme. This method is useful when geographic units within the study area vary in size, because the radius of the kernel depends on a fixed number of nearest neighbors rather than a fixed distance [155,160]. Optimal bandwidths were selected using the Golden section search method and the bias-corrected Akaike's Information Criterion (AICc) as the optimization criterion. Covariate-specific critical *t*-values, corrected for multiple testing by adjusting for the effective number of parameters, were used to identify ZCTAs with statistically significant relationships between each explanatory variable and the dependent variable [156,159]. An explanatory variable was considered to exhibit significant spatial non-stationarity if the interquartile range of its coefficient estimates from the MGWR model was greater than twice the standard error of its coefficient estimate from the global OLS model [161].

The optimal bandwidths of the variables in the MGWR model were examined to determine whether a simpler, alternate GWR model should be considered [157,158]. For example, spatial non-stationarity and similar bandwidths for all variables would suggest a standard GWR model may be appropriate [157,158]. A subset of stationary variables, with the remainder exhibiting non-stationarity and having similar bandwidths, would suggest a semiparametric GWR model should be considered [157,158]. Model fit of the global and local models was compared using AICc values. Residual plots were generated to assess the distribution of the standardized residuals from the final model, assess for heteroskedasticity, and identify outliers.

4.3.6 Cartographic displays

Smoothed diabetes-related hospitalization rates and diabetes prevalence estimates obtained from CDC PLACES data were displayed in choropleth maps using ArcGIS [103,162]. In addition, choropleth maps were generated to show the ZCTA-level distribution of explanatory variables from the final MGWR model and to display local coefficients for non-stationary variables. The class ranges used for display of continuous variables in map figures were determined using Jenks' natural breaks classification scheme, except for population density, which was displayed using a quantile map [128].

4.4 Results

4.4.1 Descriptive analyses

There were 554,449 diabetes-related hospitalizations in Florida between 2016 and 2019. The median ZCTA-level diabetes prevalence was 12.5% (interquartile range [IQR] 10.6 – 14.3%), and the median rate of diabetes-related hospitalizations was 8.4 per 1,000 person-years (IQR 6.0 – 11.4) (Table 4.1). The median age of patients with diabetes-related hospitalizations was 67 years (IQR 64 – 70 years).

The geographic distributions of diabetes prevalence and DRH rates are displayed in Figure 4.1. Rural areas, such as the region surrounding Tallahassee, north-central Florida between Orlando and Jacksonville, and south-central Florida, tended to have relatively high diabetes prevalence. In addition, there were densely populated, urban ZCTAs in Miami, Fort Lauderdale, Tampa, Orlando, and Jacksonville that had relatively high diabetes prevalence. Similarly, rural ZCTAs in north-central Florida tended to have high DRH rates, as did many of the rural ZCTAs in south-central Florida.

Table 4.1. Summary statistics of characteristics of ZIP code tabulation areas in Florida, 2016-2019.

Theoretical domains & variables	Median	IQR[1]	n
Health outcomes			
Diabetes prevalence	12.5	10.6 - 14.3	933
DRH[2] rate per 1,000 person-years	8.4	6.0 - 11.4	933
Median age of DRH[2] patients	67.0	64.0 - 70.0	933
*Rurality/urbanization**			
Population density	471.4	83.3 - 1200.5	933
Rural/urban designation*			
Rural	45.4	-	424
Suburban/town	35.9	-	335
City	18.7	-	174
Demographic characteristics			
Median age	42.5	37.8 - 50.5	933
Percent 65 years of age and older	19.3	14.2 - 26.9	933
Percent non-Hispanic Black	8.0	3.0 - 17.5	933
Percent Hispanic	10.4	5.1 - 23.6	933
Economic characteristics			
Median household income	$53,988	$44,239 - $68,382	929
Median household value	$191,500	$135,400 - 274,100	919
Percent of families with income below FPL[3]	8.9	5.4 - 13.7	931
Percent unemployed	5.2	3.9 - 7.1	933
Percent of households without a vehicle	4.6	2.6 - 7.6	932
Educational attainment			
Percent aged ≥25 years without a high school education	10.4	6.4 - 16.5	933
Percent aged ≥25 years with a bachelor’s degree or higher	25.1	16.2 - 37.7	933
Healthcare access			
Percent without health insurance	11.7	8.4 - 15.7	933
Primary care physicians per 10,000 population	6.4	1.97 - 13.8	933
Pharmacies per 100 km^2	13.4	1.1 - 52.8	933
Built environment resources			
Healthy food retailers per 100 km^2	6.6	0.6 - 24.8	933
Less healthy food retailers per 100 km^2	26.5	2.4 - 105.3	933
Modified retail food environment index	20.0	11.8 - 27.5	933
Recreational facilities per 100 km^2	2.4	0 - 12.3	933

*Percent and frequency presented for categorical variable
[1]Interquartile range
[2]Diabetes-related hospitalization
[3]Federal poverty level

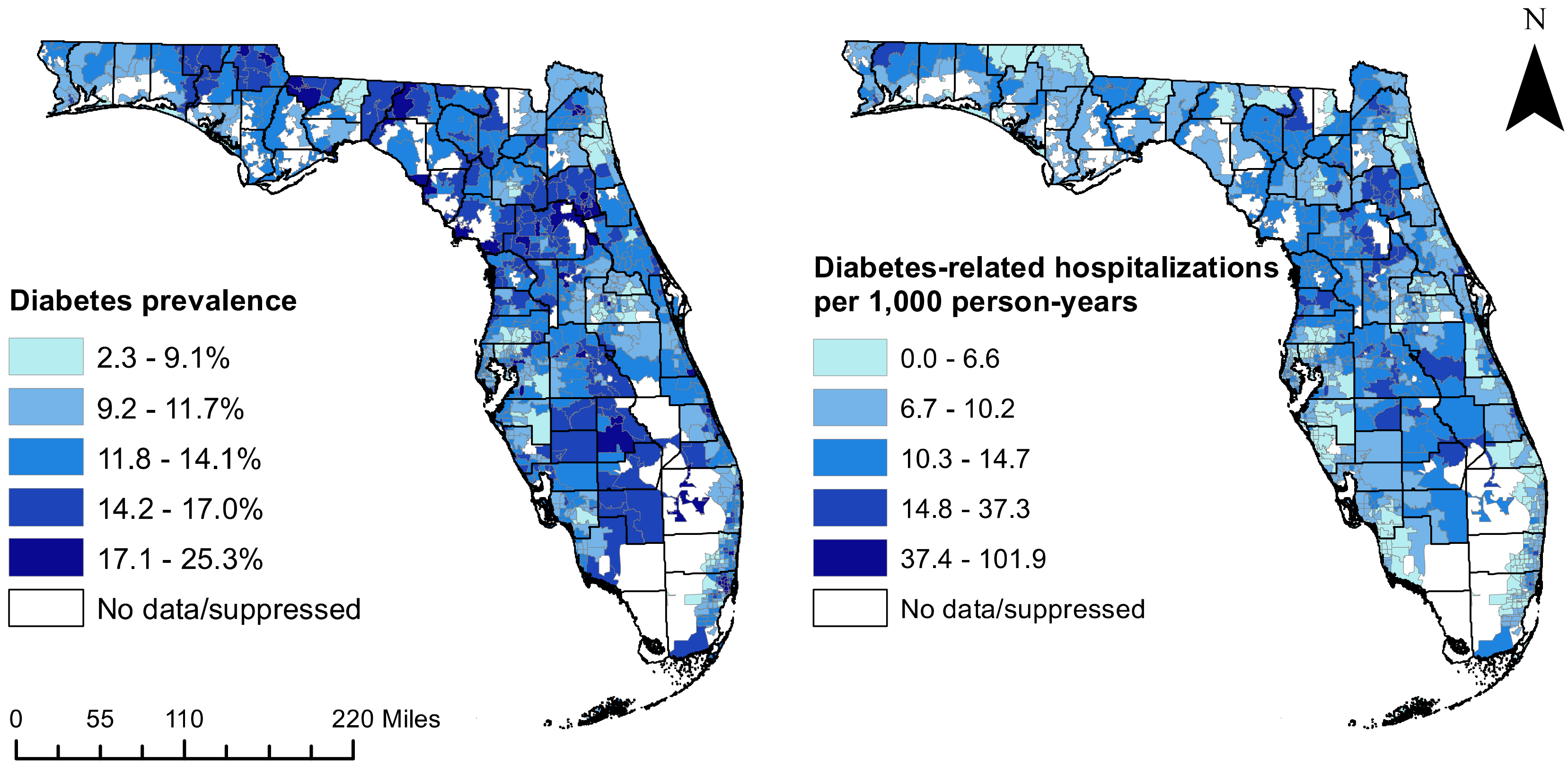

Figure 4.1. Geographic distribution of ZCTA-level diabetes prevalence estimates and smoothed diabetes-related hospitalization rates in Florida, 2016-2019.

In addition, the central urban ZCTAs of Miami, Fort Lauderdale, and Jacksonville had relatively high DRH rates. Diabetes-related hospitalization rates were comparatively lower in the suburban ZCTAs surrounding large metropolitan areas. There were some differences between the spatial patterns of diabetes prevalence and DRH rates. For example, many of the rural ZCTAs in Holmes and Jackson Counties to the east of Tallahassee had high diabetes prevalence, but relatively low rates of diabetes-related hospitalizations compared to the rest of the state.

Summary statistics of ZCTA-level characteristics are displayed in Table 4.1. The study area was largely comprised of ZCTAs classified as either rural (45.4%) or suburbs/towns (35.9%), with the remaining 18.7% classified as cities. The median percentage of older adults (those aged $\geq$ 65 years) was 19.3%. ZCTA populations had a median of 8.0% non-Hispanic Black residents, and 10.4% Hispanic residents. Median household income at the ZCTA level was $53,988, but ranged from $13,375 to $170,673. The median percent of families with income below the poverty level was 8.9%, and the median unemployment rate was 5.2%. The median percent of adults with educational attainment below the high school level was 10.4%, and a median of 25.4% of adults had a bachelor's degree or higher. The median percent of the population without health insurance coverage at the ZCTA level was 11.7%, but ranged from 0% to 50.4%. Built environment characteristics such as density of pharmacies, food retailers, and recreational centers were highly correlated ($|r_s| > 0.7$) with one another, and pharmacy and food retailer density were also highly correlated with population density and rural-urban classification.

4.4.2 Predictors of diabetes-related hospitalization rates

4.4.2.1 Global ordinary least squares regression model

Results of the final global multivariable ordinary least squares regression model are displayed in Table 4.2. Explanatory variables that had statistically significant, positive associations with log-transformed diabetes-related hospitalization rates included the percent of the population aged 65 and older ($p < 0.0001$), percent of non-Hispanic Black residents ($p = 0.003$), unemployment ($p = 0.001$), percent without health insurance coverage ($p < 0.0001$), and percent of households without access to a vehicle ($p = 0.002$). Population density ($p < 0.0001$) and median household income ($p < 0.0001$) had significant negative associations with DRH rates. Associations between DRH rates and the percent of Hispanic residents and percent without a high school education were not significantly associated with the outcome, but were retained in the model because ethnicity and educational attainment have previously been identified as predictors of self-management behaviors, access to healthcare, and diabetes-related outcomes in both individual-level and ecological studies [45,66,73,74,76,83,84,141,148,163–166].

The geographic distributions of the predictor variables included in the global OLS model are displayed in Figure 4.2. Populations of ZCTAs along the Gulf Coast, south of the Tampa Bay area, and in the rural region to the north of Tampa and northeast of Orlando had the highest percentages of adults aged 65 and older, while the percentage of older adults in populations of major cities was relatively low. The percent of non-Hispanic Black residents tended to be highest in populations of ZCTAs surrounding Tallahassee, as well as in large cities such as Jacksonville, Orlando, Miami, and Fort

Table 4.2. Predictors of log-transformed ZCTA-level diabetes-related hospitalization rates in Florida, 2016-2019.

Parameter	Coefficient (SE[1])	*p*-value	VIF[2]
Intercept	-0.010 (0.023)	0.664	0
Population density	-0.240 (0.031)	< 0.0001	1.850
Percent 65 and older	0.125 (0.027)	< 0.0001	1.436
Percent non-Hispanic Black	0.085 (0.029)	0.003	1.636
Percent Hispanic	-0.020 (0.031)	0.518	1.879
Median household income	-0.458 (0.034)	< 0.0001	2.242
Percent without a high school education	0.041 (0.036)	0.253	2.535
Unemployment rate	0.092 (0.027)	0.001	1.207
Percent without health insurance	0.118 (0.032)	< 0.0001	1.962
Percent without access to a vehicle	0.097 (0.032)	0.002	2.020

[1]Standard error
[2]Variance inflation factor

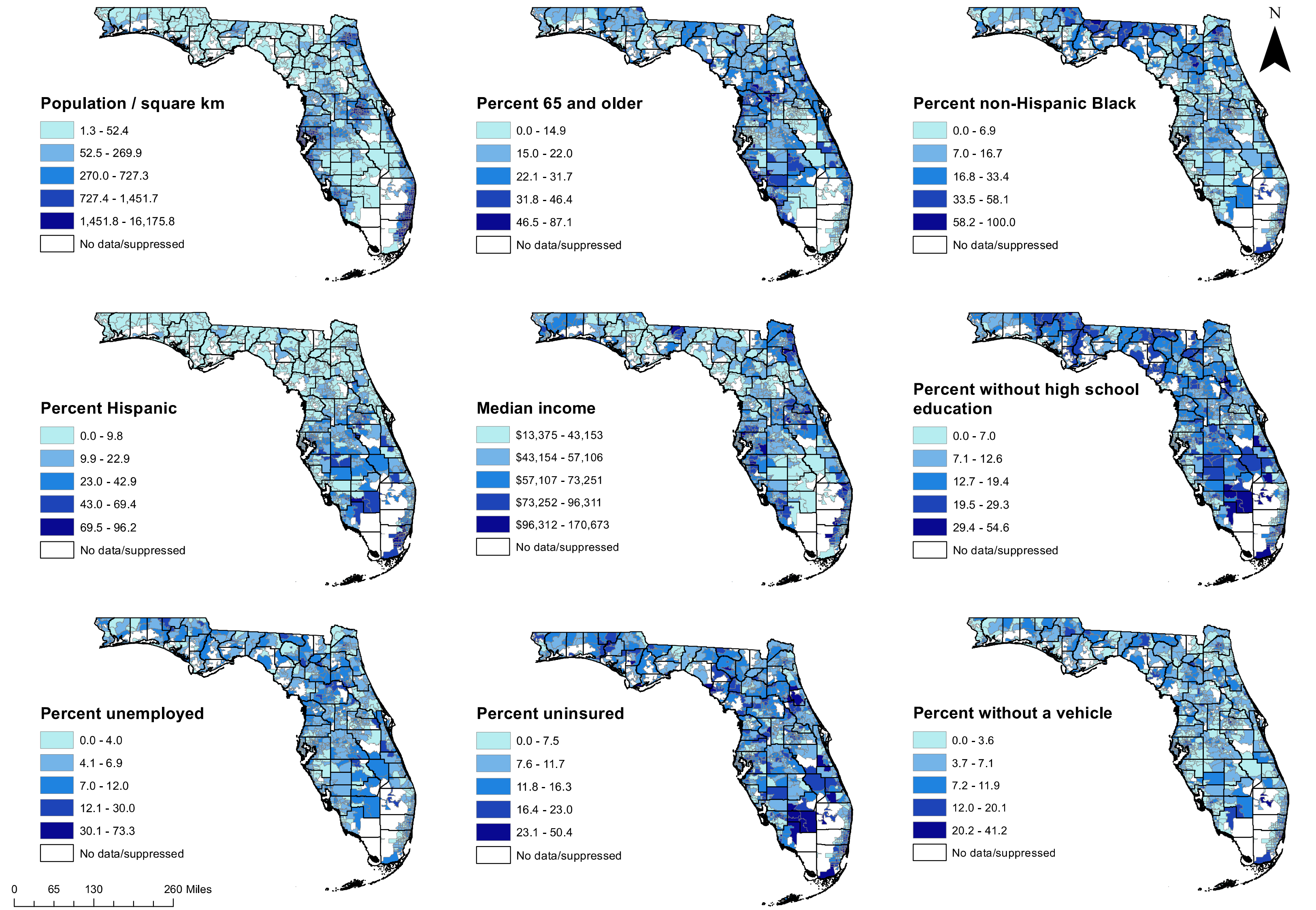

Figure 4.2. Geographic distribution of predictors of ZCTA-level diabetes-related hospitalization rates in Florida, 2016-2019.

Lauderdale. The percent of Hispanic residents was lowest in populations of ZCTAs in northern Florida and the panhandle, and tended to be higher in central and south Florida. There were similarities in the distribution of several socioeconomic variables, including median household income, the unemployment rate, vehicle access, and educational attainment. Suburban and fringe rural ZCTAs adjacent to urban areas tended to have higher income, educational attainment, employment rates, and vehicle access, while these were often lower in distant or remote rural areas as well as some of the most densely populated urban ZCTAs in major cities such as Miami and Jacksonville.

4.4.2.2 Multiscale geographically weighted regression model

Results of the multiscale geographically weighted regression model are displayed in Tables 4.3-4.5. The interquartile ranges of the local regression coefficients in the MGWR model were greater than twice the standard errors of the coefficients from the global model for all parameters except the percent of Hispanic residents (Table 4.3). These findings indicate that the coefficients for the intercept and all other explanatory variables in the model exhibited significant spatial non-stationarity, varying in strength based upon geographic location in the study area.

Since the bandwidths in an MGWR model control the number of local observations used to compute regression coefficients, their values indicate the spatial scale at which the associations between explanatory variables and the outcome vary within the study area [155–157]. A variable with a small bandwidth relative to the number of units in the study area has a large effective number of parameters (ENP) and

Table 4.3. Assessment of spatial non-stationarity of regression coefficients in MGWR model predicting log-transformed diabetes-related hospitalization rates.

Parameter	SE[1] (OLS[2])	IQR[3] (MGWR[4])	IQR[3] – 2(SE[1])
Intercept	0.023	0.489	0.443
Population density	0.031	0.287	0.225
Percent 65 and older	0.027	0.190	0.136
Percent non-Hispanic Black	0.029	0.257	0.199
Percent Hispanic	0.031	0.010	-0.052
Median household income	0.034	0.157	0.089
Percent without a high school education	0.036	0.362	0.290
Unemployment rate	0.027	0.177	0.123
Percent without health insurance	0.032	0.343	0.279
Percent without access to a vehicle	0.032	0.108	0.044

[1]Standard error
[2]Global ordinary least squares regression model
[3]Interquartile range
[4]Multiscale geographically weighted regression model

Table 4.4. Summary of MGWR model predicting log-transformed ZCTA-level diabetes-related hospitalization rates.

Parameter	Bandwidth	ENP[1]	Critical *t*-value	Number (%) of ZCTAs with significant coefficients
Intercept	25	83.657	3.445	148 (15.9)
Population density	315	4.052	2.507	739 (79.5)
Percent 65 and older	146	10.034	2.815	763 (82.1)
Percent non-Hispanic Black	27	63.952	3.370	111 (12.8)
Percent Hispanic	920	1.114	2.009	0 (0)
Median household income	275	5.040	2.584	739 (79.5)
Percent without a high school education	54	30.521	3.158	207 (22.3)
Unemployment rate	199	7.805	2.732	207 (22.3)
Percent without health insurance	81	20.167	3.034	301 (32.4)
Percent without access to a vehicle	446	3.703	2.475	421 (45.3)

[1]Effective number of parameters

Table 4.5. Distribution of local coefficients from MGWR model predicting log-transformed ZCTA-level diabetes-related hospitalization rates.

Parameter	Local coefficients		
	Minimum	Median	Maximum
Intercept	-0.713	0.038	0.756
Population density	-0.577	-0.244	-0.093
Percent 65 and older	0.022	0.294	0.590
Percent non-Hispanic Black	-1.035	0.186	1.118
Percent Hispanic	-0.006	0.008	0.013
Median household income	-0.449	-0.341	-0.057
Percent without a high school education	-0.355	0.195	0.649
Unemployment rate	-0.112	0.068	0.234
Percent without health insurance	-0.170	0.075	0.714
Percent without access to a vehicle	0.011	0.075	0.188

greater spatial heterogeneity, while a bandwidth approaching the total number of observations and ENP close to 1 indicate little spatial variation in the strength of the association [155–157]. The optimal bandwidths identified in this study varied, suggesting that simpler standard or semiparametric GWR models would not adequately describe the spatial variation in the observed associations (Table 4.4). Comparison of the AICc values from the global OLS model (AICc = 1951.469) and the MGWR model (AICc = 1414.473) indicated that the MGWR model had better fit to the data than the global model.

The geographic distributions of coefficient estimates for explanatory variables with significant spatial non-stationarity from the final MGWR model are presented in Figures 4.3 and 4.4. For each model parameter, the map on the left shows the distribution of coefficient estimates for all ZCTAs in the study area, while the map on the right shows only statistically significant estimates, with correction for multiple hypothesis testing. Parameter estimates with the lowest bandwidths relative to the number of units in the study area, implying regression coefficients with the most spatial heterogeneity, included the intercept (BW = 25), percent of non-Hispanic Black residents (BW = 27), and educational attainment (BW = 54) (Table 4.4). This spatial heterogeneity is apparent in the maps of the regression coefficients, which exhibited a great deal of local variation and were only significant in a subset of ZCTAs in the study area (Figures 4.3 and 4.4).

Another subset of explanatory variables had associations with DRH rates that varied at a more regional spatial scale, as evidenced by their bandwidth values and the geographic distribution of their regression coefficients. These included population age composition (BW = 146), the unemployment rate (BW = 199), and percent without

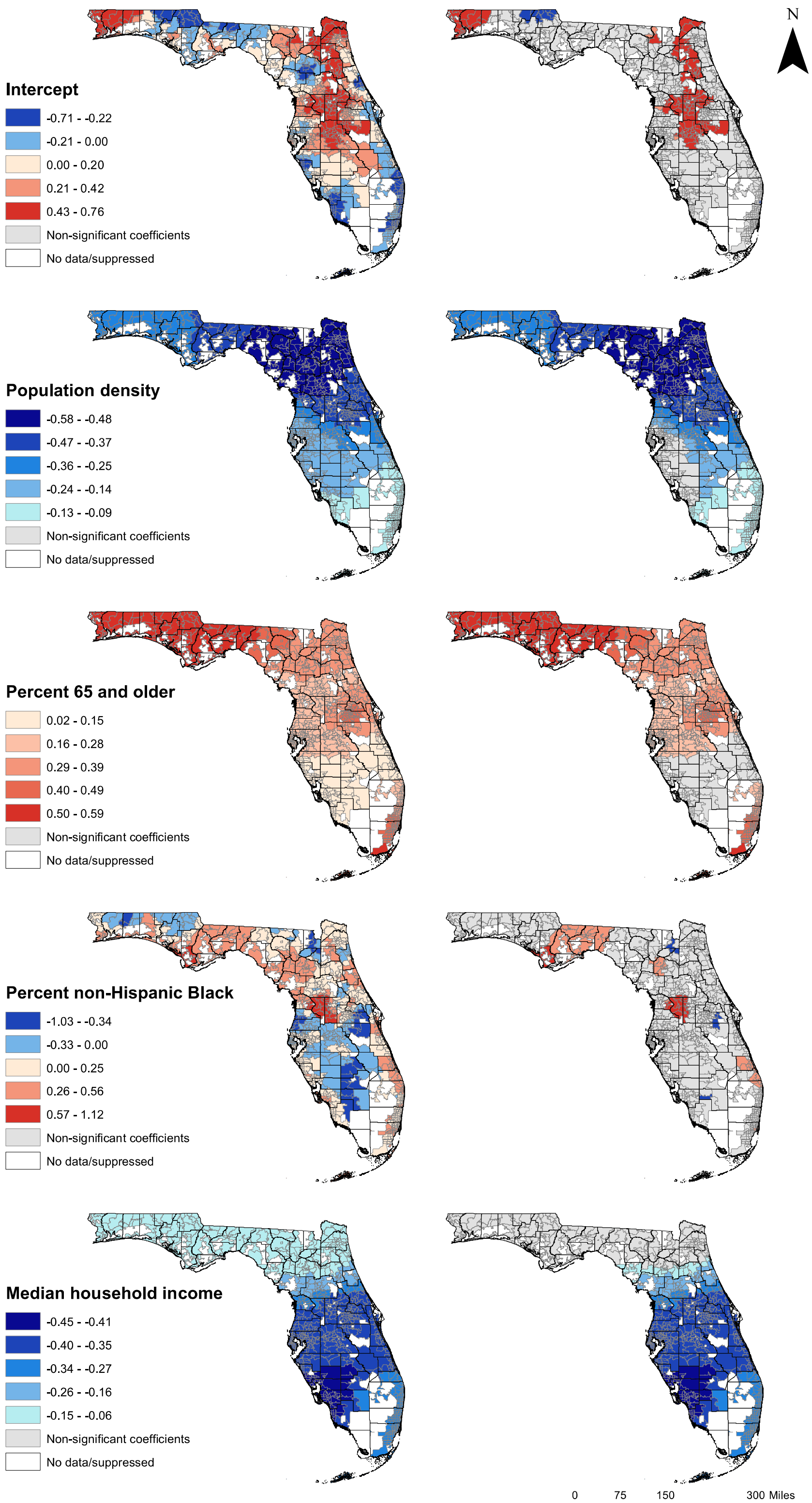

Figure 4.3. Distribution of all (left) and significant (right) local coefficients of predictors of diabetes-related hospitalization rates.

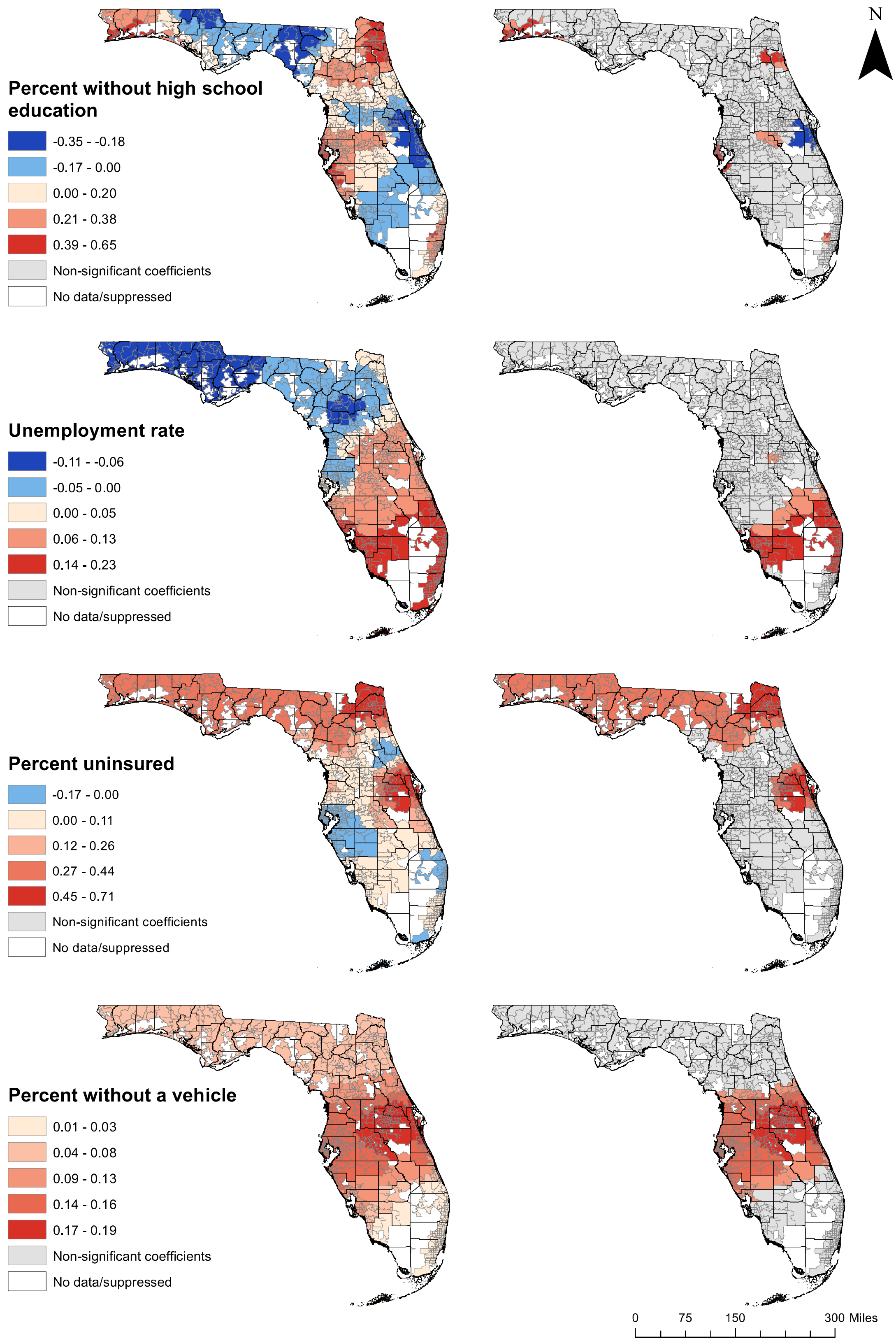

Figure 4.4. Distribution of all (left) and significant (right) local coefficients of predictors of diabetes-related hospitalization rates.

health insurance coverage (BW = 81) (Table 4.4). The percent of adults aged 65 and older was significantly associated with DRH rates in 82.1% of the ZCTAs in the study area, with the strongest associations in the panhandle, the Orlando area, and south of Fort Lauderdale (Figure 4.3). Significant associations between the unemployment rate and DRH rates occurred primarily in southern Florida, and were also observed in southwest Orange County, including part of the Orlando area (Figure 4.4). Health insurance coverage was a significant predictor of DRH rates in about one-third (32.4%) of ZCTAs, with the strongest associations in the Jacksonville and Orlando areas (Figure 4.4).

Non-stationary variables with the largest bandwidths, implying less heterogeneity of regression coefficients, included population density (BW = 315), median income (BW = 275), and vehicle access (BW = 446) (Table 4.4). The variation in the strengths of their associations with DRH rates occurred at a larger spatial scale, with less heterogeneity within the study area. For instance, the negative association between population density and DRH rates, which was significant in most of the study area, was strongest in northern Florida and gradually decreased in magnitude toward the southern and western parts of the state (Figure 4.3). Median household income was also negatively associated with DRH rates in most of the state, with the strongest associations observed in Southwest Florida (Figure 4.3). The percent of households that lacked access to a vehicle was a significant predictor of DRH rates across central Florida (Figure 4.4).

4.5 Discussion

This study identified determinants of local (ZCTA-level) geographic disparities of diabetes-related hospitalization rates in Florida. Identified significant determinants included population demographic composition, socioeconomic characteristics, and rurality. This study also demonstrated the use of multiscale geographically weighted regression as a tool for describing the spatial variation in the associations between these determinants and DRH rates. The observed associations differed in both strength and direction based on geographic location within the state, and exhibited differing levels of spatial heterogeneity.

Populations with high DRH rates tended to have higher proportions of older adults, an association that was significant in most of the state. At the individual level, age is a risk factor for diabetes as well as macrovascular complications such as stroke and myocardial infarction, so this finding was not surprising [3,68]. To some extent, the positive association between DRH rates and the percent of adults over the age of 65 may also reflect utilization of hospital services, because this population has fewer gaps in health insurance coverage due to Medicare eligibility [87,167]. The strength and statistical significance of the association between population age composition and DRH rates varied based upon geographic location. Weak and/or no associations, particularly in areas with relatively high incomes and percentages of older adults, may, in part, reflect the presence of active retirement communities and self-selecting populations of healthy older adults. It is also worth noting that earlier age of onset of Type 2 diabetes is a predictor of adverse diabetes-related outcomes, independent of duration of disease

[148,168–170], and patients with diabetes-related hospitalizations in this study tended to be younger in areas with high DRH rates, consistent with previous research [45]. Thus, it is possible that the association between population age composition and DRH rates was attenuated in some parts of the state, particularly those with disproportionately high DRH rates, due to the elevated risk profile of younger patients with Type 2 diabetes.

Significant, ZCTA-level associations between household income and DRH rates were observed across most of the study area. This finding may be due to a combination of individual- and area-level processes, and is consistent with previous research. Patients with diabetes who report lower income levels are more likely to forego medical care due to cost, and less likely to receive routine HbA1c testing, cholesterol testing, and eye examinations [74,83,88]. Furthermore, neighborhood-level income and poverty are associated with heart disease, renal disease, and lower extremity amputations [171,172], and perceived neighborhood safety is a predictor of treatment nonadherence among adults with diabetes [173]. County-level associations between socioeconomic status and the burden of diabetes complications and ambulatory care sensitive hospitalizations have also been reported in the US [174–176]. Population-level educational attainment and unemployment were associated with DRH rates in smaller subsets of the study area after controlling for income and the other variables in the model. Among those with diabetes, educational attainment below the high school level has previously been associated with healthcare quality and utilization in global models [73,83,141]. Educational attainment and unemployment may also be associated with other factors such as income and health insurance [177], which may explain the lack of association observed in many parts of the study area.

Interestingly, significant associations between insurance coverage and diabetes-related hospitalizations were mostly observed in northern Florida, where income was not significantly associated with DRH rates. The observed association between health insurance coverage and DRH rates is not surprising; at the individual level, health insurance is a predictor of linkage to care, diagnostic testing, screening for complications, and glycemic control among patients with diabetes [74,88,148]. Furthermore, patients without health insurance are at higher risk of diabetes-related hospital deaths than those with insurance [131]. The strength of the coefficients for health insurance coverage exhibited regional variation, consistent with findings of a study that used MGWR to investigate determinants of mortality rates in the US [178]. Regional variation in the strength of association between health insurance coverage and DRH rates could reflect differences in the availability of resources for uninsured individuals within the state, such as county health programs and services [177]. In addition, the finding that income was a stronger determinant of DRH rates than insurance coverage in some areas may reflect cost barriers to healthcare access and effective self-management experienced by many patients despite having health insurance coverage.

Population density, which was used as a measure of rurality in this study, was significantly associated with DRH rates, with more densely populated areas tending to have lower rates of hospitalizations. It is worth noting that population density was selected from a group of highly correlated variables, which included pharmacy and food retailer densities, for inclusion in the modeling process. Thus, the observed association between rurality and DRH rates may reflect the availability of built environment resources to some extent. Previous research also suggests that quality of care is worse for rural patients with diabetes than for those living in metropolitan areas [74]. Rural populations in Florida also tend to have lower rates of participation in diabetes self-management education programs [30].

Transportation barriers may also contribute to rural-urban disparities in health outcomes by creating additional time demands for patients. A review of transportation barriers to healthcare access found that access to a vehicle was consistently identified as a predictor of access to care, while there was less evidence in support of distance to providers as a barrier to receiving care [179]. Furthermore, patients who experience transportation barriers to health care tend to utilize emergency department services more frequently than those who do not report such barriers [180]. This is in line with the findings of our study, which identified vehicle access, but not density of primary care physicians, as a significant predictor of diabetes-related hospitalization rates, suggesting that increasing the physician workforce alone is not sufficient to close gaps in access and utilization of care. The geographic variation in the observed association between vehicle access and DRH rates may reflect differences in the availability of alternate forms of transportation. Regional differences in transportation barriers to health care have previously been reported in the US, with residents of the South and Midwest being more likely to report such barriers than those from other parts of the country [180].

Despite controlling for population-level socioeconomic characteristics, the percent of non-Hispanic Black residents remained a significant predictor of DRH rates in certain parts of the state, with most of these associations being positive. At the individual level, previous studies have reported that Black patients with diabetes are less likely than White patients to receive recommended diagnostic testing and examinations [73,74,88] and more likely to forego necessary medical care due to cost [83]. Furthermore, non-Hispanic Black patients with diabetes are less likely to achieve diabetes management targets [148], and tend to have more severe complications [66]. Ecological studies in the US, which have investigated burdens of end-stage renal disease, stroke, and diabetes-related lower extremity amputations, have reported similar findings [171,174,176]. The degree of spatial heterogeneity in the association observed in the current study highlights the importance of locally-focused interventions to close gaps in access, quality, and utilization of diabetes-related care in order to reduce inequities in diabetes outcomes.

Since predictor variables were standardized prior to regression modeling, local intercept coefficients from the MGWR model represent the expected value of the outcome (log-transformed DRH rates) in each ZCTA when all of the predictor variables are equal to their mean value. The map of significant local intercept parameter estimates indicates that there are elevated DRH rates, mostly in ZCTAs in the central and northeastern part of the state, as well as a few ZCTAs in the panhandle with lower DRH rates than expected, after controlling for the explanatory variables in the model. Many of the ZCTAs in central and northeast Florida that had significant, positive intercept parameter estimates were also part of high-rate DRH clusters. This finding suggests that there may be additional drivers of the excess DRH rates in these areas that were not identified in this study.

4.5.1 Strengths and Limitations

To our knowledge, this is the first study to investigate determinants of geographic disparities of diabetes-related hospitalization rates at the sub-county level using multiscale geographically weighted regression. Multiscale geographically weighted regression provides a more detailed understanding of the spatial heterogeneity of these associations than standard GWR, which assumes that all processes operate at the same spatial scale within the study area [155–159]. Understanding the spatial context of the observed relationships provides valuable insights to guide health planning aimed at improving diabetes management and outcomes at the population level. However, this study is not without limitations. Relatively small sample sizes in some ZCTAs may have reduced statistical power to detect significant local associations, particularly for variables that had a high degree of spatial heterogeneity and large effective number of parameters. Models predicting diabetes-related hospitalization rates were not adjusted for underlying diabetes prevalence, comorbidities, or health behaviors, since direct estimates of these measures are not available at the ZCTA level, and the use of small area estimates could have introduced bias into the analysis [181]. Despite these limitations, the findings of this study are useful for guiding evidence-based interventions by identifying determinants of diabetes-related hospitalization rates, which have been shown to reflect population-level glycemic control [99].

4.6 Conclusions

Addressing barriers to diabetes-related care and effective management of the condition, particularly in communities disproportionately burdened by adverse outcomes, is essential for reducing disparities. The findings of this study underscore the importance of socioeconomic resources and rurality in shaping population health. In addition, this study highlights the usefulness of multiscale geographically weighted regression as a tool for investigating spatially variable determinants of diabetes-related hospitalizations, which exhibited different levels of heterogeneity within the study area. Knowledge of the determinants most strongly associated with DRH rates in a given location can help guide the development of needs-based policies and interventions that address barriers to achieving diabetes care targets in order to reduce the burden of potentially avoidable hospitalizations.

CHAPTER 5

Summary, Discussions, and Conclusions

This research investigated disparities of potentially preventable hospitalizations due to diabetes and its complications in Florida. Understanding these disparities is particularly relevant to public health in Florida, where geographic disparities in diabetes prevalence have persisted over the past decade, and substantial increases in diabetes-related hospitalizations, amputations, and hospital costs have been reported [26,29,30,102]. The overall goal of this work was to provide information to guide evidence-based health planning to improve diabetes management in high-risk populations and reduce inequities in adverse outcomes of diabetes in the state.

This research identified socioeconomic, racial, ethnic, and gender disparities in the severity of diabetes complications among hospitalized adult patients in Florida. Additionally, significant, high-rate spatial clusters of diabetes-related hospitalizations were identified, indicating that certain communities bear disproportionately high burdens of diabetes hospitalizations. The determinants of the observed disparities included demographic composition, socioeconomic resources, and rurality. The strengths of associations between the identified determinants and diabetes-related hospitalization rates differed based on geographic location within the state. Elevated blood glucose levels promote vascular changes in patients with diabetes, and cumulative effects of the condition contribute to the development of micro- and macrovascular complications over time [89]. Therefore, disparities in hospitalization rates and severity of complications could reflect differences in factors such as age of onset or duration of diabetes, as well as barriers to achieving effective management of the condition.

A number of comorbidities (hypertension, hyperlipidemia, obesity, and depression) were positively associated with severity of diabetes complications. This finding highlights the importance of managing cardiovascular risk factors for patients with diabetes, who may be faced with the challenge of managing multiple chronic conditions. Furthermore, the observed association between depression and severe complications contributes to the growing body of evidence linking depression and diabetes outcomes [71]. Racial disparities in the severity of complications, as well as the age of hospitalized patients, were also identified, with non-Hispanic Black patients having the highest odds of severe complications of any group in the study, and a substantially younger median age than non-Hispanic White patients. This finding could reflect earlier onset of the condition, which is an independent predictor of adverse diabetes-related outcomes, as well as disparities in glycemic control [168–170]. Future research is warranted to investigate the observed age disparity and identify potential avenues for intervention.

Indicators of individual socioeconomic position that were associated with the severity of diabetes complications included having Medicaid (vs. private insurance) and not reporting a social security number (SSN). While there is a large body of evidence regarding the impact of socioeconomic position on health outcomes, few studies have specifically investigated the availability of an SSN in the database as a predictor of outcomes in hospitalized patients. However, findings of this research indicated that patients with an SSN in their hospital record differed from those who did not with respect to several clinical and sociodemographic characteristics. Furthermore, patients who do not report an SSN may be from vulnerable groups with less access to care and health-promoting resources [41]. Findings of this work suggest that future studies of ambulatory care sensitive hospitalizations should consider controlling for this variable rather than excluding this group of patients. Socioeconomic status at the local level, as measured using the Neighborhood Deprivation Index (NDI), was also associated with the severity of diabetes complications, suggesting that place of residence may be associated with diabetes management and outcomes.

The geographic distribution and determinants of diabetes-related hospitalizations were investigated using ecological studies to identify disparities at the population level and provide further insights about potential associations with place-based characteristics. One of the strengths of this research was the use of Tango's flexible spatial scan statistic (FSSS), a robust technique for the detection of high risk/rate spatial clusters, which permitted the detection of both circular and irregularly shaped clusters of diabetes-related hospitalizations [124]. Since the analysis was conducted at a relatively fine geographic scale, it permitted the assessment of spatial patterns that would have been masked at a larger unit of analysis, such as the county level. In addition to relatively large spatial clusters of high DRH rates in rural areas, smaller clusters were identified within more densely populated, urban areas. This information can be used to help implement more focused intervention strategies to improve access to care and diabetes management.

A multiscale geographically weighted regression approach was used to investigate spatially variable determinants of hospitalization rates, with local socioeconomic, healthcare-related, and built environment characteristics considered as potential predictors. The use of this MGWR approach is another strength of this work, as it provides a detailed understanding of the spatial heterogeneity of the regression coefficients of the identified predictors [155–159]. Understanding the spatial context of the observed relationships provides valuable insights to guide health planning aimed at improving diabetes management and outcomes at the population level. Several of the variables identified as determinants of DRH rates in this study have previously been identified as predictors of quality of diabetes care at the individual level. These included variables such as rurality and income, which were significant predictors of DRH rates in large parts of the study area, and had regression coefficients that exhibited relatively little geographic variation. Other predictors of hospitalization rates, such as the percent of non-Hispanic Black residents and the percent of the population without health insurance coverage, had associations that exhibited comparatively higher levels of spatial heterogeneity. The regional variation in the strength of association between health insurance coverage and DRH rates suggests that increasing county programs and services for uninsured individuals, particularly in parts of the state where strong associations were observed, may be an effective strategy for reducing disparities [177]. Vehicle access has been identified as a predictor of access to healthcare in previous research [179], and was also associated with diabetes-related hospitalization rates in this study, particularly in central Florida. The observed geographic differences in the associations between the identified determinants and DRH rates imply that population needs differ based on location within the state. The information provided by this research provides useful insights to guide health planning and interventions that aim to reduce the burden of these potentially preventable hospitalizations.

The challenges encountered in this research largely relate to the availability of data sources that capture socioeconomic and health information at the same level, although this is a frequently cited limitation of public health research and is not unique to this work. A limited number of individual-level variables that reflect individual socioeconomic position were available in the hospital records used in these analyses. Data sources that include individual health information and socioeconomic data, such as health surveys, can be costly to obtain, may include self-reported health information, and often are not spatially representative at smaller geographic units of analysis. On the other hand, while population-level socioeconomic data are publicly available, small-scale geographic data with direct estimates of diabetes prevalence, comorbidities, or health behaviors, are also not currently available in Florida. In some areas, allocating resources to purchase larger sample sizes for routinely collected health surveys, such as the Behavioral Risk Factor Surveillance System, may be worthwhile to support further investigations of diabetes-related outcomes at the local level [104]. For instance, such investigations may be warranted in areas that had disproportionately high burdens of diabetes-related hospitalizations despite controlling for the explanatory variables from the final MGWR model in this study.

Despite these challenges, the findings of this work are valuable for guiding public health planning and further research. To my knowledge, this is the first study to investigate predictors of the severity of diabetes complications among hospitalized patients in Florida, and the first statewide investigation of geographic disparities and determinants of diabetes-related hospitalization rates at the sub-county level. Future studies will need to investigate emergency department visits and observation stays so as to assess the potential impact of healthcare utilization bias on these findings. In addition, further research is warranted to examine age disparities with respect to diabetes and diabetes-related hospitalizations in Florida, considering the findings of previous research that suggests younger adults with diabetes have a higher risk profile than those with a later age of onset of the condition [168–170].

In conclusion, this work identified disparities in the severity of diabetes complications and diabetes-related hospitalization rates in Florida. In addition, individual- and area-level determinants of severe complications and spatially variable determinants of diabetes-related hospitalization rates were reported. The identification of high-rate DRH clusters in this study can inform resource allocation to prioritize communities with disproportionately high burdens of adverse diabetes outcomes. Strategies to improve diabetes prevention, early diagnosis, control and risk factor management among populations with high burdens of these outcomes will be important to reduce the observed disparities. The findings of this research provide valuable information for guiding the development and implementation of locally-focused strategies to improve access, utilization, and quality of diabetes care in Florida.

References

1. Centers for Disease Control and Prevention. National Diabetes Statistics Report website [Internet]. 2022. Available from: https://www.cdc.gov/diabetes/data/statistics-report/index.html
2. American Diabetes Association Professional Practice Committee. Classification and Diagnosis of Diabetes: Standards of Medical Care in Diabetes—2022. Diabetes Care [Internet]. 2022 Jan 1;45(Supplement_1):S17–38. Available from: https://diabetesjournals.org/care/article/45/Supplement_1/S17/138925/2-Classification-and-Diagnosis-of-Diabetes
3. Deshpande AD, Harris-Hayes M, Schootman M. Epidemiology of Diabetes and Diabetes-Related Complications. Phys Ther [Internet]. 2008 Nov 1;88(11):1254–64. Available from: https://academic.oup.com/ptj/article/88/11/1254/2858146
4. Forbes JM, Cooper ME. Mechanisms of diabetic complications [Internet]. Vol. 93, Physiological Reviews. Physiol Rev; 2013. p. 137–88. Available from: https://pubmed.ncbi.nlm.nih.gov/23303908/
5. Corriere M, Rooparinesingh N, Kalyani RR. Epidemiology of diabetes and diabetes complications in the elderly: An emerging public health burden. Curr Diab Rep [Internet]. 2013 Dec;13(6):805–13. Available from: https://jhu.pure.elsevier.com/en/publications/epidemiology-of-diabetes-and-diabetes-complications-in-the-elderl-3
6. Baena-Díez JM, Peñafiel J, Subirana I, Ramos R, Elosua R, Marín-Ibañez A, et al. Risk of cause-specific death in individuals with diabetes: A competing risks analysis. Diabetes Care [Internet]. 2016 Nov 1;39(11):1987–95. Available from: http://www.diabetesjournals
7. Shao H, Yang S, Fonseca V, Stoecker C, Shi L. Estimating Quality of Life Decrements Due to Diabetes Complications in the United States: The Health Utility Index (HUI) Diabetes Complication Equation. Pharmacoeconomics [Internet]. 2019 Jul 1;37(7):921–9. Available from: https://pubmed.ncbi.nlm.nih.gov/30778865/
8. Hayes A, Arima H, Woodward M, Chalmers J, Poulter N, Hamet P, Clarke P. Changes in Quality of Life Associated with Complications of Diabetes: Results from the ADVANCE Study. Value Heal. 2016 Jan 1;19(1):36–41.
9. Alva M, Gray A, Mihaylova B, Clarke P. The Effect of Diabetes Complications on Health-Related Quality of Life: the Importance of Longitudinal Data to Address Patient Heterogeneity. Health Econ [Internet]. 2014 Apr 1;23(4):487–500. Available from: https://onlinelibrary.wiley.com/doi/full/10.1002/hec.2930
10. Heron M. National Vital Statistics Reports, Volume 70, Issue 9 - Deaths: Leading Causes for 2019 [Internet]. Vol. 70, National Vital Statistics Reports. 2021. Available from: https://www.cdc.gov/nchs/products/index.htm.
11. Konig M, Mary Lamos E, Aleskow Stein S, N. Davis S. An Insight into the Recent Diabetes Trials: What is the Best Approach to Prevent Macrovascular and Microvascular Complications? Curr Diabetes Rev. 2013;9:371–81.
12. American Diabetes Association. Glycemic Targets: Standards of Medical Care in Diabetes—2021. Diabetes Care [Internet]. 2021 Jan 1;44(Supplement 1):S73–84. Available from: https://care.diabetesjournals.org/content/44/Supplement_1/S73
13. American Diabetes Association. Cardiovascular Disease and Risk Management: Standards of Medical Care in Diabetes—2021. Diabetes Care [Internet]. 2021 Jan

1;44(Supplement 1):S125–50. Available from: https://care.diabetesjournals.org/content/44/Supplement_1/S125
14. Ansari Z. The concept and usefulness of ambulatory care sensitive conditions as indicators of quality and access to primary health care [Internet]. Vol. 13, Australian Journal of Primary Health. CSIRO; 2007. p. 91–110. Available from: https://www.publish.csiro.au/py/py07043
15. Barker LE, Kirtland KA, Gregg EW, Geiss LS, Thompson TJ. Geographic Distribution of Diagnosed Diabetes in the U.S.: A Diabetes Belt. Am J Prev Med [Internet]. 2011 Apr 1;40(4):434–9. Available from: https://www.sciencedirect.com/science/article/pii/S0749379711000353
16. Shrestha SS, Kirtland KA, Thompson TJ, Barker L, Gregg EW, Geiss L. Spatial Clusters of County-Level Diagnosed Diabetes and Associated Risk Factors in the United States. Open Diabetes J [Internet]. 2012;5:29–37. Available from: https://benthamopen.com/contents/pdf/TODIAJ/TODIAJ-5-29.pdf
17. Centers for Disease Control and Prevention Division of Diabetes Translation. U.S. Diabetes Surveillance System [Internet]. 2022. Available from: https://gis.cdc.gov/grasp/diabetes/diabetesatlas-surveillance.html#
18. Dall TM, Yang W, Gillespie K, Mocarski M, Byrne E, Cintina I, Beronja K, Semilla AP, Iacobucci W, Hogan PF. The Economic Burden of Elevated Blood Glucose Levels in 2017: Diagnosed and Undiagnosed Diabetes, Gestational Diabetes Mellitus, and Prediabetes. Diabetes Care [Internet]. 2019 Sep 1;42(9):1661–8. Available from: https://diabetesjournals.org/care/article/42/9/1661/36300/The-Economic-Burden-of-Elevated-Blood-Glucose
19. Gregg EW, Hora I, Benoit SR. Resurgence in Diabetes-Related Complications [Internet]. Vol. 321, JAMA - Journal of the American Medical Association. American Medical Association; 2019. p. 1867–8. Available from: https://www.cdc.gov/diabetes/data.
20. Shrestha SS, Zhang P, Hora I, Geiss LS, Luman ET, Gregg EW. Factors contributing to increases in diabetes-related preventable hospitalization costs among U.S. Adults during 2001–2014. Diabetes Care [Internet]. 2019 Jan 1;42(1):77–84. Available from: http://care.diabetesjournals.org/lookup/suppl/
21. Yang W, Dall TM, Beronjia K, Lin J, Semilla AP, Chakrabarti R, Hogan PF, Petersen MP. Economic costs of diabetes in the U.S. in 2017. Diabetes Care. 2018 May 1;41(5):917–28.
22. Nouwen A, Adriaanse MC, Dam K van, Iversen MM, Viechtbauer W, Peyrot M, Caramlau I, Kokoszka A, Kanc K, Groot M de, Nefs G, Pouwer F. Longitudinal associations between depression and diabetes complications: a systematic review and meta-analysis. Diabet Med [Internet]. 2019 Dec 1;36(12):1562–72. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/dme.14054
23. Agency for Healthcare Research and Quality. Prevention Quality Indicator 01 (PQI 01) Diabetes Short-Term Complications Admission Rate [Internet]. 2016. Available from: www.qualityindicators.ahrq.gov
24. Agency for Healthcare Research and Quality. Prevention Quality Indicator 03 (PQI 03) Diabetes Long-Term Complications Admission Rate [Internet]. 2016. Available from: www.qualityindicators.ahrq.gov
25. Agency for Healthcare Research and Quality. Prevention Quality Indicators (PQI)

Overview [Internet]. 2020. Available from: https://www.qualityindicators.ahrq.gov/Modules/pqi_resources.aspx
26. Florida Diabetes Advisory Council. 2021 Florida Diabetes Report. 2021.
27. Bureau of Economic and Business Research. Florida Population Studies Population Projections by Age, Sex, Race, and Hispanic Origin for Florida and Its Counties, 2025-2045, With Estimates for 2020 [Internet]. 2021 Jun. Available from: www.bebr.ufl.edu
28. Lin J, Thompson TJ, Cheng YJ, Zhuo X, Zhang P, Gregg E, Rolka DB. Projection of the future diabetes burden in the United States through 2060. Popul Heal Metrics 2018 161 [Internet]. 2018 Jun 15;16(1):1–9. Available from: https://pophealthmetrics.biomedcentral.com/articles/10.1186/s12963-018-0166-4
29. Lord J, Roberson S, Odoi A. Investigation of geographic disparities of pre-diabetes and diabetes in Florida. BMC Public Health [Internet]. 2020 Aug 12;20(1). Available from: https://pubmed.ncbi.nlm.nih.gov/32787830/
30. Khan MM, Roberson S, Reid K, Jordan M, Odoi A. Geographic disparities and temporal changes of diabetes prevalence and diabetes self-management education program participation in Florida. PLoS One [Internet]. 2021 Jul 16;16(7):e0254579. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0254579
31. Young BA, Lin E, Von Korff M, Simon G, Ciechanowski P, Ludman EJ, Everson-Stewart S, Kinder L, Oliver M, Boyko EJ, Katon WJ. Diabetes Complications Severity Index and risk of mortality, hospitalization, and healthcare utilization. Am J Manag Care [Internet]. 2008 Jan;14(1):15–24. Available from: /pmc/articles/PMC3810070/?report=abstract
32. U.S. Census Bureau. Florida: Guide to 2010 State and Local Census Geography [Internet]. 2021. Available from: https://www.census.gov/geographies/reference-files/2010/geo/state-local-geo-guides-2010/florida.html
33. U.S. Census Bureau. American Community Survey 5-year Estimates, 2015-2019: Demographic and Housing Estimates [Internet]. 2019. Available from: https://data.census.gov/table?q=dp05&tid=ACSDP5Y2019.DP05
34. U.S. Census Bureau. American Community Survey 5-year Estimates, 2015-2019: Poverty Status in the Past 12 Months [Internet]. 2019. Available from: https://data.census.gov/cedsci/table?q=florida acs 2019 poverty&tid=ACSST5Y2019.S1701
35. U.S. Census Bureau. American Community Survey 5-year Estimates, 2015-2019: Selected Characteristics of Health Insurance Coverage [Internet]. 2019. Available from: https://data.census.gov/cedsci/table?q=florida acs 2019 health insurance
36. Florida Department of Health. FLHealthCHARTS: Community Health Assessment Resource Tool Set [Internet]. 2022. Available from: https://www.flhealthcharts.gov/charts/ChronicDiseases/default.aspx
37. SAS Institute Inc. SAS version 9.4. Cary, NC, USA: SAS Institute; 2017.
38. Glasheen WP, Renda A, Dong Y. Diabetes Complications Severity Index (DCSI)—Update and ICD-10 translation. J Diabetes Complications. 2017 Jun 1;31(6):1007–13.
39. Chang HY, Weiner JP, Richards TM, Bleich SN, Segal JB. Validating the adapted Diabetes Complications Severity Index in claims data. Am J Manag Care

[Internet]. 2012 Nov 1;18(11):721–6. Available from: https://europepmc.org/article/med/23198714
40. Wicke FS, Glushan A, Schubert I, Köster I, Lübeck R, Hammer M, Beyer M, Karimova K. Performance of the Adapted Diabetes Complications Severity Index Translated to ICD-10. Am J Manag Care [Internet]. 2019;25(2):e45–9. Available from: https://www.ajmc.com/view/performance-of-the-adapted-diabetes-complications-severity-index-translated-to-iicd10i
41. Jung J, Uejio CK, Adeyeye TE, Kintziger KW, Duclos C, Reid K, Jordan M, Spector JT, Insaf TZ. Using social security number to identify sub-populations vulnerable to the health impacts from extreme heat in Florida, U.S. Environ Res. 2021 Nov 1;202:111738.
42. Wright G, Hulett D. Transitive Record Linkage in SAS using Hash Objects [Internet]. 2010. Available from: https://www.lexjansen.com/wuss/2010/databases/2997_2_DDI-Wright.PDF
43. Wright G. Probabilistic Record Linkage in SAS [Internet]. 2011. Available from: https://www.lexjansen.com/wuss/2011/data/Papers_Wright_G_76128.pdf
44. John Snow Inc. ZIP Code to ZCTA Crosswalk [Internet]. 2017. Available from: https://maps.udsmapper.org/zcta-crosswalk.cfm
45. Lee DC, Young T, Koziatek CA, Shim CJ, Osorio M, Vinson AJ, Ravenell JE, Wall SP. Age Disparities Among Patients With Type 2 Diabetes and Associated Rates of Hospital Use and Diabetic Complications. Prev Chronic Dis [Internet]. 2019 Aug 1;16(8):180681. Available from: /pmc/articles/PMC6716392/
46. National Center for Education Statistics. Education Demographic and Geographic Estimates: ZCTA Locale Assignments [Internet]. 2019. Available from: https://nces.ed.gov/programs/edge/Geographic/ZCTAAssignments
47. Florida Department of Health. Health Care Practitioner Data Portal [Internet]. Available from: https://mqa-internet.doh.state.fl.us/downloadnet/GeneralInformation.aspx
48. U.S. Census Bureau. American Community Survey 5-year Estimates, 2015-2019: Demographic and Housing Estimates. 2019.
49. U.S. Census Bureau. Annual Economic Surveys ZIP Code Business Statistics: Zip Code Business Patterns by Employment Size Class, 2016 [Internet]. 2016. Available from: https://data.census.gov/cedsci/table?g=0100000US.861000&y=2016&n=445110&tid=ZBP2016.CB1600ZBP&hidePreview=false
50. U.S. Census Bureau. Annual Economic Surveys Geographic Area Series: County Business Patterns by Employment Size Class and Legal Form of Organization, 2016 [Internet]. 2016. Available from: https://data.census.gov/cedsci/table?g=0400000US12.050000&y=2016&n=445110&tid=CBP2016.CB1600CBP&hidePreview=false
51. United States Census Bureau. TIGER/Line Geodatabases. 2019; Available from: https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-geodatabase-file.html
52. Messer LC, Laraia BA, Kaufman JS, Eyster J, Holzman C, Culhane J, Elo I, Burke JG, O'Campo P. The development of a standardized neighborhood deprivation index. J Urban Heal [Internet]. 2006 Nov 21;83(6):1041–62. Available from:

https://link.springer.com/article/10.1007/s11524-006-9094-x
53. Duru OK, Schmittdiel JA, Dyer WT, Parker MM, Uratsu CS, Chan J, Karter AJ. Mail-Order Pharmacy Use and Adherence to Diabetes-Related Medications. Am J Manag Care [Internet]. 2010 Jan;16(1):33. Available from: /pmc/articles/PMC3015238/
54. Doubeni CA, Schootman M, Major JM, Torres Stone RA, Laiyemo AO, Park Y, Lian M, Messer L, Graubard BI, Sinha R, Hollenbeck AR, Schatzkin A. Health status, neighborhood socioeconomic context, and premature mortality in the United States: The national institutes of health-AARP diet and health study. Am J Public Health [Internet]. 2012 Apr 7;102(4):680–8. Available from: https://ajph.aphapublications.org/doi/10.2105/AJPH.2011.300158
55. Signorello LB, Cohen SS, Williams DR, Munro HM, Hargreaves MK, Blot WJ. Socioeconomic status, race, and mortality: A prospective cohort study. Am J Public Health [Internet]. 2014 Dec 1;104(12):e98–107. Available from: https://ajph.aphapublications.org/doi/10.2105/AJPH.2014.302156
56. Murchison AP, Hark L, Pizzi LT, Dai Y, Mayro EL, Storey PP, Leiby BE, Haller JA. Non-adherence to eye care in people with diabetes. BMJ Open Diabetes Res Care [Internet]. 2017 Jul 1;5(1):e000333. Available from: https://drc.bmj.com/content/5/1/e000333
57. Akwo EA, Kabagambe EK, Harrell FE, Blot WJ, Bachmann JM, Wang TJ, Gupta DK, Lipworth L. Neighborhood Deprivation Predicts Heart Failure Risk in a Low-Income Population of Blacks and Whites in the Southeastern United States. Circ Cardiovasc Qual Outcomes [Internet]. 2018 Jan 1;11(1):4052. Available from: https://www.ahajournals.org/doi/abs/10.1161/CIRCOUTCOMES.117.004052
58. O’ Lenick CR, Chang HH, Kramer MR, Winquist A, Mulholland JA, Friberg MD, Sarnat SE. Ozone and childhood respiratory disease in three US cities: evaluation of effect measure modification by neighborhood socioeconomic status using a Bayesian hierarchical approach. Environ Heal A Glob Access Sci Source [Internet]. 2017 Apr 5;16(1):1–15. Available from: https://ehjournal.biomedcentral.com/articles/10.1186/s12940-017-0244-2
59. Mehra R, Shebl FM, Cunningham SD, Magriples U, Barrette E, Herrera C, Kozhimannil KB, Ickovics JR. Area-level deprivation and preterm birth: Results from a national, commercially-insured population. BMC Public Health [Internet]. 2019 Feb 27;19(1):1–16. Available from: https://link.springer.com/articles/10.1186/s12889-019-6533-7
60. Sauer J, Stewart K, Dezman ZDW. A spatio-temporal Bayesian model to estimate risk and evaluate factors related to drug-involved emergency department visits in the greater Baltimore metropolitan area. J Subst Abuse Treat. 2021 Dec 1;131:108534.
61. van Buuren S, Groothuis-Oudshoorn K. mice: Multivariate Imputation by Chained Equations in R. J Stat Softw. 2011;45(3):1–67.
62. White IR, Royston P, Wood AM. Multiple imputation using chained equations: Issues and guidance for practice. Stat Med [Internet]. 2011 Feb 20;30(4):377–99. Available from: https://onlinelibrary.wiley.com/doi/full/10.1002/sim.4067
63. Lee KJ, Carlin JB. Multiple imputation in the presence of non-normal data. Stat Med [Internet]. 2017 Feb 20;36(4):606–17. Available from:

https://onlinelibrary.wiley.com/doi/full/10.1002/sim.7173
64. Hardin JW, Hilbe JM. Generalized Estimating Equations. Second. New York: CRC Press; 2012. 161–212 p.
65. Dohoo I, Martin W, Stryhn H. Methods in Epidemiologic Research. Charlottetown, Prince Edward Island, Canada: VER, inc.; 2012. 645–674 p.
66. Hazel-Fernandez L, Li Y, Nero D, Moretz C, Slabaugh L, Meah Y, Baltz J, Costantino M, Patel NC, Bouchard J. Racial/Ethnic and Gender Differences in Severity of Diabetes-Related Complications, Health Care Resource Use, and Costs in a Medicare Population. Popul Health Manag [Internet]. 2015 Apr 1;18(2):115–22. Available from: https://www.liebertpub.com/doi/10.1089/pop.2014.0038
67. Robitzsch A, Grund S. miceadds: Some Additional Multiple Imputation Functions, Especially for “mice.” 2022.
68. Zoungas S, Woodward M, Li Q, Cooper ME, Hamet P, Harrap S, Heller S, Marre M, Patel A, Poulter N, Williams B, Chalmers J. Impact of age, age at diagnosis and duration of diabetes on the risk of macrovascular and microvascular complications and death in type 2 diabetes. Diabetol 2014 5712 [Internet]. 2014 Sep 17;57(12):2465–74. Available from: https://link.springer.com/article/10.1007/s00125-014-3369-7
69. Vogeli C, Shields AE, Lee TA, Gibson TB, Marder WD, Weiss KB, Blumenthal D. Multiple Chronic Conditions: Prevalence, Health Consequences, and Implications for Quality, Care Management, and Costs. J Gen Intern Med 2007 223 [Internet]. 2007 Nov 16;22(3):391–5. Available from: https://link.springer.com/article/10.1007/s11606-007-0322-1
70. Natarajan S, Nietert PJ. Hypertension, diabetes, hypercholesterolemia, and their combinations increased health care utilization and decreased health status. J Clin Epidemiol. 2004 Sep 1;57(9):954–61.
71. Holt RIG, De Groot M, Golden SH. Diabetes and depression. Curr Diab Rep [Internet]. 2014 Apr 18;14(6):1–9. Available from: https://link.springer.com/article/10.1007/s11892-014-0491-3
72. Yu MK, Lyles CR, Bent-Shaw LA, Young BA. Sex disparities in diabetes process of care measures and self-care in high-risk patients. J Diabetes Res. 2013;2013.
73. Canedo JR, Miller ST, Schlundt D, Fadden MK, Sanderson M. Racial/Ethnic Disparities in Diabetes Quality of Care: the Role of Healthcare Access and Socioeconomic Status. J Racial Ethn Heal Disparities [Internet]. 2018 Feb 1;5(1):7–14. Available from: https://link.springer.com/article/10.1007/s40615-016-0335-8
74. Pu J, Chewning B. Racial difference in diabetes preventive care. Res Soc Adm Pharm. 2013 Nov 1;9(6):790–6.
75. Schneiderman N, Llabre M, Cowie CC, Barnhart J, Carnethon M, Gallo LC, Giachello AL, Heiss G, Kaplan RC, LaVange LM, Teng Y, Villa-Caballero L, Avilés-Santa ML. Prevalence of Diabetes Among Hispanics/Latinos From Diverse Backgrounds: The Hispanic Community Health Study/Study of Latinos (HCHS/SOL). Diabetes Care [Internet]. 2014 Aug 1;37(8):2233–9. Available from: https://diabetesjournals.org/care/article/37/8/2233/30019/Prevalence-of-Diabetes-Among-Hispanics-Latinos

76. Osborn CY, De Groot M, Wagner JA. Racial and ethnic disparities in diabetes complications in the northeastern United States: The role of socioeconomic status. J Natl Med Assoc [Internet]. 2013;105(1):51–8. Available from: https://pubmed.ncbi.nlm.nih.gov/23862296/
77. Haw JS, Shah M, Turbow S, Egeolu M, Umpierrez G. Diabetes Complications in Racial and Ethnic Minority Populations in the USA. Curr Diabetes Reports 2021 211 [Internet]. 2021 Jan 9;21(1):1–8. Available from: https://link.springer.com/article/10.1007/s11892-020-01369-x
78. Kposowa AJ. Mortality from Diabetes by Hispanic Groups: Evidence from the US National Longitudinal Mortality Study. Int J Popul Res. 2013 Oct 26;2013:1–12.
79. Smith CAS, Barnett E. Diabetes-related mortality among Mexican Americans, Puerto Ricans, and Cuban Americans in the United States. Rev Panam Salud Publica [Internet]. 2005;18(6):381–7. Available from: https://pubmed.ncbi.nlm.nih.gov/16536924/
80. United States Census Bureau. Hispanic or Latino Origin by Specific Origin [Internet]. 2021. Available from: https://data.census.gov/cedsci/table?q=hispanic ethnicity country of origin florida&tid=ACSDT1Y2021.B03001
81. López L, Golden SH. A New Era in Understanding Diabetes Disparities Among U.S. Latinos—All Are Not Equal. Diabetes Care [Internet]. 2014 Aug 1;37(8):2081–3. Available from: https://diabetesjournals.org/care/article/37/8/2081/29679/A-New-Era-in-Understanding-Diabetes-Disparities
82. Choi SE, Liu M, Palaniappan LP, Wang EJ, Wong ND. Gender and ethnic differences in the prevalence of type 2 diabetes among Asian subgroups in California. J Diabetes Complications. 2013 Sep 1;27(5):429–35.
83. Towne SD, Bolin J, Ferdinand A, Nicklett EJ, Smith ML, Ory MG. Assessing Diabetes and Factors Associated with Foregoing Medical Care among Persons with Diabetes: Disparities Facing American Indian/Alaska Native, Black, Hispanic, Low Income, and Southern Adults in the U.S. (2011–2015). Int J Environ Res Public Heal 2017, Vol 14, Page 464 [Internet]. 2017 Apr 26;14(5):464. Available from: https://www.mdpi.com/1660-4601/14/5/464/htm
84. Misra R, Lager J. Ethnic and gender differences in psychosocial factors, glycemic control, and quality of life among adult type 2 diabetic patients. J Diabetes Complications [Internet]. 2009 Jan;23(1):54–64. Available from: https://pubmed.ncbi.nlm.nih.gov/18413181/
85. Kaiser Family Foundation. Status of State Medicaid Expansion Decisions: Interactive Map [Internet]. 2022. Available from: https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/
86. Florida Department of Children and Families. SSI-Related Medicaid Fact Sheet [Internet]. 2022. Available from: https://www.myflfamilies.com/service-programs/access/docs/ssifactsheet.pdf
87. U.S. Department of Health and Human Services. Who is eligible for Medicare? [Internet]. 2014. Available from: https://www.hhs.gov/answers/medicare-and-medicaid/who-is-eligible-for-medicare/index.html
88. Hu R, Shi L, Rane S, Zhu J, Chen CC. Insurance, racial/ethnic, SES-related

disparities in quality of care among US adults with diabetes. J Immigr Minor Heal [Internet]. 2014;16(4):565–75. Available from: https://pubmed.ncbi.nlm.nih.gov/24363118/
89. Orasanu G, Plutzky J. The Pathologic Continuum of Diabetic Vascular Disease. J Am Coll Cardiol [Internet]. 2009 Feb 3;53(5 SUPPL.):S35–42. Available from: https://www.jacc.org/doi/10.1016/j.jacc.2008.09.055
90. Booth GL, Hux JE. Relationship Between Avoidable Hospitalizations for Diabetes Mellitus and Income Level. Arch Intern Med [Internet]. 2003 Jan 13;163(1):101. Available from: http://archinte.jamanetwork.com/article.aspx?doi=10.1001/archinte.163.1.101
91. Brown AF, Ettner SL, Piette J, Weinberger M, Gregg E, Shapiro MF, Karter AJ, Safford M, Waitzfelder B, Prata PA, Beckles GL. Socioeconomic Position and Health among Persons with Diabetes Mellitus: A Conceptual Framework and Review of the Literature. Epidemiol Rev [Internet]. 2004 Jul 1;26(1):63–77. Available from: https://academic.oup.com/epirev/article/26/1/63/384189
92. Booth GL, Hux JE. Relationship between avoidable hospitalizations for diabetes mellitus and income level. Arch Intern Med [Internet]. 2003 Jan 13;163(1):101–6. Available from: https://jamanetwork.com/
93. Schmittdiel JA, Dyer WT, Marshall CJ, Bivins R. Using Neighborhood-Level Census Data to Predict Diabetes Progression in Patients with Laboratory-Defined Prediabetes. Perm J [Internet]. 2018;22:18–096. Available from: /pmc/articles/PMC6175602/?report=abstract
94. American Diabetes Association. Facilitating Behavior Change and Well-being to Improve Health Outcomes: Standards of Medical Care in Diabetes - 2021. Diabetes Care [Internet]. 2021 Jan 1;44(Supplement 1):S53–72. Available from: https://care.diabetesjournals.org/content/44/Supplement_1/S53
95. Gregg EW, Li Y, Wang J, Rios Burrows N, Ali MK, Rolka D, Williams DE, Geiss L. Changes in Diabetes-Related Complications in the United States, 1990–2010. N Engl J Med [Internet]. 2014 Apr 17;370(16):1514–23. Available from: http://www.nejm.org/doi/10.1056/NEJMoa1310799
96. Wang J, Imai K, Engelgau MM, Geiss LS, Wen C, Zhang P. Secular trends in diabetes-related preventable hospitalizations in the United States, 1998-2006. Diabetes Care [Internet]. 2009 Jul 1;32(7):1213–7. Available from: http://creativecommons.
97. Geiss LS, Li Y, Hora I, Albright A, Rolka D, Gregg EW. Resurgence of diabetes-related nontraumatic lower-extremity amputation in the young and middle-aged adult U.S. Population. Diabetes Care [Internet]. 2019 Jan 1;42(1):50–4. Available from: https://doi.org/10.2337/dc18-1380
98. Benoit S, Zhang Y, Geiss L, Gregg E, Albright A. Trends in Diabetic Ketoacidosis Hospitalizations and In-Hospital Mortality - United States, 2000-2014. MMWR Morb Mortal Wkly Rep [Internet]. 2018 Mar 30;67(12):362–5. Available from: https://pubmed.ncbi.nlm.nih.gov/29596400/
99. Lee D, Jiang Q, Tabaei B, Elbel B, Koziatek C, Konty K, Wu W. Using Indirect Measures to Identify Geographic Hot Spots of Poor Glycemic Control: Cross-sectional Comparisons With an A1C Registry. Diabetes Care [Internet]. 2018 Jul 1;41(7):1438–47. Available from: https://pubmed.ncbi.nlm.nih.gov/29691230/

100. Lord J, Roberson S, Odoi A. Geographic disparities, determinants, and temporal changes in the prevalence of pre-diabetes in Florida. PeerJ [Internet]. 2021 Jan 13;9:e10443. Available from: http://doi.org/10.7717/peerj.10443
101. Lord J, Roberson S, Odoi A. Investigation of geographic disparities of pre-diabetes and diabetes in Florida. BMC Public Health [Internet]. 2020 Dec 12;20(1):1226. Available from: https://bmcpublichealth.biomedcentral.com/articles/10.1186/s12889-020-09311-2
102. Lord J, Roberson S, Odoi A. A retrospective investigation of spatial clusters and determinants of diabetes prevalence: scan statistics and geographically weighted regression modeling approaches. PeerJ. 2023.
103. Centers for Disease Control and Prevention. PLACES: Local Data for Better Health, ZCTA Data 2020 release [Internet]. 2021. Available from: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-ZCTA-Data-2020/qnzd-25i4
104. Livingood WC, Razaila L, Reuter E, Filipowicz R, Butterfield RC, Lukens-Bull K, Edwards L, Palacio C, Wood DL. Using Multiple Sources of Data to Assess the Prevalence of Diabetes at the Subcounty Level, Duval County, Florida, 2007. Prev Chronic Dis [Internet]. 2010;7(5). Available from: /pmc/articles/PMC2938402/
105. Centers for Disease Control and Prevention Division of Diabetes Translation. US Diabetes Surveillance System [Internet]. 2022. Available from: https://gis.cdc.gov/grasp/diabetes/diabetesatlas-surveillance.html#
106. Agency for Healthcare Research and Quality. Prevention Quality Indicator 01 (PQI 01) Diabetes Short Term Complications Admission Rate [Internet]. 2022. Available from: https://qualityindicators.ahrq.gov/Downloads/Modules/PQI/V2022/TechSpecs/PQI_01_Diabetes_Short-term_Complications_Admission_Rate.pdf
107. Agency for Healthcare Research and Quality. Prevention Quality Indicator 03 (PQI 03) Diabetes Long Term Complications Admission Rate [Internet]. 2022. Available from: https://qualityindicators.ahrq.gov/Downloads/Modules/PQI/V2022/TechSpecs/PQI_03_Diabetes_Long-term_Complications_Admission_Rate.pdf
108. Agency for Healthcare Research and Quality. Prevention Quality Indicator 14 (PQI 14) Uncontrolled Diabetes Admission Rate [Internet]. 2022. Available from: https://qualityindicators.ahrq.gov/Downloads/Modules/PQI/V2022/TechSpecs/PQI_14_Uncontrolled_Diabetes_Admission_Rate.pdf
109. Agency for Healthcare Research and Quality. Prevention Quality Indicator 16 (PQI 16) Lower Extremity Amputation Among Patients with Diabetes Rate [Internet]. 2022. Available from: https://qualityindicators.ahrq.gov/Downloads/Modules/PQI/V2022/TechSpecs/PQI_16_Lower_Extremity_Amputation_among_Patients_with_Diabetes_Rate.pdf
110. U.S. Census Bureau. American Community Survey 5-year Estimates, 2012-2016: Demographic and Housing Estimates [Internet]. 2016. Available from: https://data.census.gov/table?q=dp05&g=0400000US12$8600000&tid=ACSDP5Y2016.DP05
111. U.S. Census Bureau. American Community Survey 5-year Estimates, 2013-2017: Demographic and Housing Estimates [Internet]. 2017. Available from:

https://data.census.gov/table?q=dp05&g=0400000US12$8600000&tid=ACSDP5Y2017.DP05
112. U.S. Census Bureau. American Community Survey 5-year Estimates, 2014-2018: Demographic and Housing Estimates [Internet]. 2018. Available from: https://data.census.gov/table?q=dp05&g=0400000US12$8600000&tid=ACSDP5Y2018.DP05
113. U.S. Census Bureau. MAF/TIGER Geodatabase Census Mapping files - Cartographic Boundary Files. 2018; Available from: https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html
114. University of Florida GeoPlan Center. Florida Geographic Data Library [Internet]. 2022. Available from: https://fgdl.org/zips/geospatial_data/current/
115. Florida Department of Health. Health Care Practitioner Data Portal [Internet]. 2021. Available from: https://mqa-internet.doh.state.fl.us/downloadnet/GeneralInformation.aspx
116. U.S. Census Bureau. American Community Survey 5-year estimates, 2015-2019: Selected Housing Characteristics. 2019.
117. U.S. Census Bureau. American Community Survey 5-year estimates, 2015-2019: Educational Attainment. 2019.
118. U.S. Census Bureau. American Community Survey 5-year estimates, 2015-2019: Employment Status. 2019.
119. U.S. Census Bureau. American Community Survey 5-year estimates, 2015-2019: Poverty Status in the Past 12 Months of Families. 2019.
120. U.S. Census Bureau. American Community Survey 5-year estimates, 2015-2019: Selected Characteristics of Health Insurance Coverage in the United States. 2019.
121. Anselin L, Syabri I, Kho Y. GeoDa: An Introduction to Spatial Data Analysis. Geogr Anal. 2006 Jan 1;38(1):5–22.
122. Pfeiffer D, Robinson T, Stevenson M, Stevens K, Rogers D, Clements A. Spatial Analysis in Epidemiology. New York, NY: Oxford University Press; 2008. 70–74 p.
123. Leyland AH, Davies CA. Empirical Bayes methods for disease mapping. Stat Methods Med Reseach [Internet]. 2016 Jul 2;14(1):17–34. Available from: https://journals.sagepub.com/doi/abs/10.1191/0962280205sm387oa
124. Tango T, Takahashi K. A flexibly shaped spatial scan statistic for detecting clusters. Int J Health Geogr [Internet]. 2005;4:11. Available from: http://doi.wiley.com/10.1002/sim.5478
125. Tango T, Takahashi K. A flexible spatial scan statistic with a restricted likelihood ratio for detecting disease clusters. Stat Med [Internet]. 2012 Dec 30;31(30):4207–18. Available from: https://onlinelibrary.wiley.com/doi/full/10.1002/sim.5478
126. Tango T. A Spatial Scan Statistic with a Restricted Likelihood Ratio. Japanese J Biometrics. 2008;29(2):75–95.
127. QGIS.org. QGIS Geographic Information System. QGIS Association; 2022.
128. Jenks G. The Data Model Concept in Statistical Mapping. Int Yearb Cartogr. 1967;7:186–90.
129. Tan X, Lee LK, Huynh S, Pawaskar M, Rajpathak S. Sociodemographic

disparities in the management of type 2 diabetes in the United States. https://doi.org/101080/0300799520201756764 [Internet]. 2020 Jun 2;36(6):967–76. Available from: https://www.tandfonline.com/doi/abs/10.1080/03007995.2020.1756764
130. Brennan MB, Powell WR, Kaiksow F, Kramer J, Liu Y, Kind AJH, Bartels CM. Association of Race, Ethnicity, and Rurality With Major Leg Amputation or Death Among Medicare Beneficiaries Hospitalized With Diabetic Foot Ulcers. JAMA Netw Open [Internet]. 2022 Apr 1;5(4):e228399–e228399. Available from: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2791437
131. Ferdinand AO, Akinlotan MA, Callaghan T, Towne SD, Bolin J. Diabetes-related hospital mortality in the U.S.: A pooled cross-sectional study of the National Inpatient Sample. J Diabetes Complications. 2019 May 1;33(5):350–5.
132. Krishna S, Gillespie KN, McBride TM. Diabetes Burden and Access to Preventive Care in the Rural United States. J Rural Heal [Internet]. 2010;26:3–11. Available from: https://onlinelibrary-wiley-com.proxy.lib.utk.edu/doi/pdf/10.1111/j.1748-0361.2009.00259.x
133. O'Connor A, Wellenius G. Rural–urban disparities in the prevalence of diabetes and coronary heart disease. Public Health. 2012 Oct 1;126(10):813–20.
134. Ziller EC, Lenardson JD, Paluso NC, Talbot JA, Daley A. Rural-urban differences in the decline of adolescent cigarette smoking. Am J Public Health [Internet]. 2019 May 1;109(5):771–3. Available from: https://ajph.aphapublications.org/doi/10.2105/AJPH.2019.304995
135. Doogan NJ, Roberts ME, Wewers ME, Stanton CA, Keith DR, Gaalema DE, Kurti AN, Redner R, Cepeda-Benito A, Bunn JY, Lopez AA, Higgins ST. A growing geographic disparity: Rural and urban cigarette smoking trends in the United States. Prev Med (Baltim). 2017 Nov 1;104:79–85.
136. Parker MA, Weinberger AH, Eggers EM, Parker ES, Villanti AC. Trends in Rural and Urban Cigarette Smoking Quit Ratios in the US From 2010 to 2020. JAMA Netw Open [Internet]. 2022 Aug 1;5(8):e2225326–e2225326. Available from: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2794885
137. Curtis AJ, Lee WAA. Spatial patterns of diabetes related health problems for vulnerable populations in Los Angeles. Int J Health Geogr [Internet]. 2010 Aug 27;9(1):1–10. Available from: https://ij-healthgeographics.biomedcentral.com/articles/10.1186/1476-072X-9-43
138. Ferdinand AO, Akinlotan MA, Callaghan T, Towne SD, Bolin JN. Factors affecting the likelihood of a hospitalization following a diabetes-related emergency department visit: A regional and urban-rural analysis. J Diabetes [Internet]. 2020 Sep 1;12(9):686–96. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/1753-0407.13066
139. Cook CB, Naylor DB, Hentz JG, Miller WJ, Tsui C, Ziemer DC, Waller LA. Disparities in diabetes-related hospitalizations: relationship of age, sex, and race/ethnicity with hospital discharges, lengths of stay, and direct inpatient charges - PubMed. Ethn Dis [Internet]. 2006;16(1):126–31. Available from: https://pubmed.ncbi.nlm.nih.gov/16599360/
140. Gao CC, Espinoza Suarez NR, Toloza FJK, Malaga Zuniga AS, McCarthy SR, Boehmer KR, Yao L, Fu S, Brito JP. Patients' Perspective About the Cost of

Diabetes Management: An Analysis of Online Health Communities. Mayo Clin Proc Innov Qual Outcomes. 2021 Oct 1;5(5):898–906.
141. Ng BP, LaManna JB, Samuel D. Towne J, Peach BC, He Q, Park C. Factors Associated With Avoiding Health Care Among Community-Dwelling Medicare Beneficiaries With Type 2 Diabetes. Prev Chronic Dis [Internet]. 2020 Oct 15;17. Available from: /pmc/articles/PMC7587306/
142. Zhang X, Geiss LS, Cheng YJ, Beckles GL, Gregg EW, Kahn HS. The Missed Patient With Diabetes: How access to health care affects the detection of diabetes. Diabetes Care [Internet]. 2008 Sep 1;31(9):1748–53. Available from: https://diabetesjournals.org/care/article/31/9/1748/27934/The-Missed-Patient-With-DiabetesHow-access-to
143. American Diabetes Association Professional Practice Committee. Prevention or Delay of Type 2 Diabetes and Associated Comorbidities: Standards of Medical Care in Diabetes—2022. Diabetes Care [Internet]. 2022 Jan 1;45(Supplement 1):S39–45. Available from: https://diabetesjournals.org/care/article/45/Supplement_1/S39/138909/3-Prevention-or-Delay-of-Type-2-Diabetes-and
144. American Diabetes Association Professional Practice Committee. Glycemic Targets: Standards of Medical Care in Diabetes—2022. Diabetes Care [Internet]. 2022 Jan 1;45(Supplement_1):S83–96. Available from: https://diabetesjournals.org/care/article/45/Supplement_1/S83/138927/6-Glycemic-Targets-Standards-of-Medical-Care-in
145. American Diabetes Association Professional Practice Committee. Cardiovascular Disease and Risk Management: Standards of Medical Care in Diabetes—2022. Diabetes Care [Internet]. 2022 Jan 1;45(Supplement_1):S144–74. Available from: https://diabetesjournals.org/care/article/45/Supplement_1/S144/138910/10-Cardiovascular-Disease-and-Risk-Management
146. Fang M, Wang D, Coresh J, Selvin E. Trends in Diabetes Treatment and Control in U.S. Adults, 1999–2018. N Engl J Med [Internet]. 2021 Jun 10;384(23):2219–28. Available from: https://www.nejm.org/doi/full/10.1056/NEJMsa2032271
147. Ali MK, Bullard KM, Saaddine JB, Cowie CC, Imperatore G, Gregg EW. Achievement of Goals in U.S. Diabetes Care, 1999–2010. N Engl J Med [Internet]. 2013 Apr 25;368(17):1613–24. Available from: https://www.nejm.org/doi/full/10.1056/NEJMsa1213829
148. Kazemian P, Shebl FM, McCann N, Walensky RP, Wexler DJ. Evaluation of the Cascade of Diabetes Care in the United States, 2005-2016. JAMA Intern Med [Internet]. 2019 Oct 1;179(10):1376–85. Available from: https://jamanetwork.com/journals/jamainternalmedicine/fullarticle/2740801
149. Rubens M, Ramamoorthy V, Saxena A, McGranaghan P, McCormack-Granja E. Recent Trends in Diabetes-Associated Hospitalizations in the United States. J Clin Med [Internet]. 2022 Nov 1;11(22):6636. Available from: https://www.mdpi.com/2077-0383/11/22/6636/htm
150. American Diabetes Association. Economic Costs of Diabetes in the U.S. in 2017. Diabetes Care [Internet]. 2018 Mar 22;41(5):917–28. Available from: http://www.ncbi.nlm.nih.gov/pubmed/29567642
151. Lord J, Odoi A. Investigation of geographic disparities of diabetes-related

hospitalizations in Florida using flexible spatial scan statistics: an ecological study. Unpublished.
152. Centers for Disease Control and Prevention. PLACES: Local Data for Better Health, ZCTA data 2021 release [Internet]. 2022. Available from: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-ZCTA-Data-2021/s85h-9xpy
153. Centers for Disease Control and Prevention. Census Tract Level State Maps of the Modified Retail Food Environment Index (mRFEI). 2011.
154. Brunsdon C, Fotheringham S, Charlton M. Geographically Weighted Regression. J R Stat Soc Ser D (The Stat [Internet]. 1998 Sep 1;47(3):431–43. Available from: http://doi.wiley.com/10.1111/1467-9884.00145
155. Fotheringham AS, Yang W, Kang W. Multiscale Geographically Weighted Regression (MGWR). Ann Am Assoc Geogr [Internet]. 2017 Nov 2;107(6):1247–65. Available from: https://www.tandfonline.com/doi/abs/10.1080/24694452.2017.1352480
156. Oshan TM, Smith JP, Fotheringham AS. Targeting the spatial context of obesity determinants via multiscale geographically weighted regression. Int J Heal Geogr 2020 191 [Internet]. 2020 Apr 5;19(1):1–17. Available from: https://link.springer.com/articles/10.1186/s12942-020-00204-6
157. Comber A, Brunsdon C, Charlton M, Dong G, Harris R, Lu B, Lü Y, Murakami D, Nakaya T, Wang Y, Harris P. The GWR route map: a guide to the informed application of Geographically Weighted Regression. 2020 Apr 13; Available from: https://arxiv.org/abs/2004.06070v2
158. Comber A, Brunsdon C, Charlton M, Dong G, Harris R, Lu B, Lü Y, Murakami D, Nakaya T, Wang Y, Harris P. A Route Map for Successful Applications of Geographically Weighted Regression. Geogr Anal [Internet]. 2023 Jan 1;55(1):155–78. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/gean.12316
159. Oshan TM, Li Z, Kang W, Wolf LJ, Fotheringham AS. mgwr: A Python Implementation of Multiscale Geographically Weighted Regression for Investigating Process Spatial Heterogeneity and Scale. ISPRS Int J Geo-Information 2019, Vol 8, Page 269 [Internet]. 2019 Jun 8;8(6):269. Available from: https://www.mdpi.com/2220-9964/8/6/269/htm
160. Fotheringham AS, Brunsdon C, Charlton M. Geographically Weighted Regression : The Analysis of Spatially Varying Relationships. Chichester, UK: John Wiley & Sons; 2002.
161. Fotheringham AS, Brunsdon C, Charlton M. Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Wiley; 2002.
162. ESRI. ArcGIS Desktop 10.6.1. Redlands, CA; 2017.
163. Akinlotan MA, Primm K, Bolin JN, Cheres ALF, Lee JS, Callaghan T, Ferdinand AO. Racial, Rural, and Regional Disparities in Diabetes-Related Lower-Extremity Amputation Rates, 2009–2017. Diabetes Care [Internet]. 2021 Sep 1;44(9):2053–60. Available from: https://diabetesjournals.org/care/article/44/9/2053/138862/Racial-Rural-and-Regional-Disparities-in-Diabetes
164. Lee DC, Yi SS, Athens JK, Vinson AJ, Wall SP, Ravenell JE. Using Geospatial

Analysis and Emergency Claims Data to Improve Minority Health Surveillance. J Racial Ethn Heal Disparities [Internet]. 2018 Aug 1;5(4):712–20. Available from: https://link.springer.com/article/10.1007/s40615-017-0415-4
165. Shrestha SS, Thompson TJ, Kirtland KA, Gregg EW, Beckles GL, Luman ET, Barker LE, Geiss LS. Changes in Disparity in County-Level Diagnosed Diabetes Prevalence and Incidence in the United States, between 2004 and 2012. PLoS One [Internet]. 2016 Aug 1;11(8):e0159876. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0159876
166. Smalls BL, Gregory CM, Zoller JS, Egede LE. Assessing the relationship between neighborhood factors and diabetes related health outcomes and self-care behaviors. BMC Heal Serv Res 2015 151 [Internet]. 2015 Oct 1;15(1):1–11. Available from: https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-015-1086-7
167. Cha AE, Cohen RA. Demographic Variation in Health Insurance Coverage: United States, 2020. Natl Health Stat Report. 2022 Feb 1;2022(169):1–15.
168. Al-Saeed AH, Constantino MI, Molyneaux L, D'Souza M, Limacher-Gisler F, Luo C, Wu T, Twigg SM, Yue DK, Wong J. An Inverse Relationship Between Age of Type 2 Diabetes Onset and Complication Risk and Mortality: The Impact of Youth-Onset Type 2 Diabetes. Diabetes Care [Internet]. 2016 May 1;39(5):823–9. Available from: https://diabetesjournals.org/care/article/39/5/823/30800/An-Inverse-Relationship-Between-Age-of-Type-2
169. Zheng L, Chen X, Luo T, Ran X, Hu J, Cheng Q, Yang S, Wu J, Li Q, Wang Z. Early-Onset Type 2 Diabetes as a Risk Factor for End-Stage Renal Disease in Patients With Diabetic Kidney Disease. Prev Chronic Dis [Internet]. 2020 Jul 1;17. Available from: /pmc/articles/PMC7367068/
170. Wong J, Molyneaux L, Constantino M, Twigg SM, Yue DK. Timing is everything: age of onset influences long-term retinopathy risk in type 2 diabetes, independent of traditional risk factors. Diabetes Care [Internet]. 2008 Oct 1;31(10):1985–90. Available from: http://creativecommons.
171. Lee DC, Long JA, Sevick MA, Yi SS, Athens JK, Elbel B, Wall SP. The local geographic distribution of diabetic complications in New York City: Associated population characteristics and differences by type of complication. Diabetes Res Clin Pract. 2016 Sep 1;119:88–96.
172. Stevens CD, Schriger DL, Raffetto B, Davis AC, Zingmond D, Roby DH. Geographic Clustering Of Diabetic Lower-Extremity Amputations In Low-Income Regions Of California. Health Aff. 2014 Aug 2;33(8):1383–90.
173. Billimek J, Sorkin DH. Self-reported neighborhood safety and nonadherence to treatment regimens among patients with type 2 diabetes. J Gen Intern Med [Internet]. 2012 Mar 21;27(3):292–6. Available from: https://link.springer.com/article/10.1007/s11606-011-1882-7
174. Margolis DJ, Hoffstad O, Nafash J, Leonard CE, Freeman CP, Hennessy S, Wiebe DJ. Location, Location, Location: Geographic Clustering of Lower-Extremity Amputation Among Medicare Beneficiaries With Diabetes. Diabetes Care [Internet]. 2011 Nov 1;34(11):2363–7. Available from: https://diabetesjournals.org/care/article/34/11/2363/28864/Location-Location-Location-Geographic-Clustering

175. Basu J, Mobley LR, Thumula V. The Small Area Predictors of Ambulatory Care Sensitive Hospitalizations: A Comparison of Changes over Time. http://dx.doi.org/101080/193719182013776316 [Internet]. 2014 Feb 23;29(2):176–88. Available from: https://www.tandfonline.com/doi/abs/10.1080/19371918.2013.776316
176. Firat Bilgel. Spatial distribution of inequalities in end-stage renal disease in the United States. Spat Spatiotemporal Epidemiol [Internet]. 2019 Aug 1;30. Available from: https://pubmed.ncbi.nlm.nih.gov/31421796/
177. Stone LC, Boursaw B, Bettez SP, Larzelere Marley T, Waitzkin H. Place as a predictor of health insurance coverage: A multivariate analysis of counties in the United States. Health Place. 2015 Jul 1;34:207–14.
178. Cupido K, Fotheringham AS, Jevtic P. Local modelling of U.S. mortality rates: A multiscale geographically weighted regression approach. Popul Space Place [Internet]. 2021 Jan 1;27(1):e2379. Available from: https://onlinelibrary.wiley.com/doi/full/10.1002/psp.2379
179. Syed ST, Gerber BS, Sharp LK. Traveling towards disease: transportation barriers to health care access. J Community Health [Internet]. 2013 Oct;38(5):976–93. Available from: https://pubmed.ncbi.nlm.nih.gov/23543372/
180. Wolfe MK, McDonald NC, Holmes GM. Transportation Barriers to Health Care in the United States: Findings From the National Health Interview Survey, 1997-2017. Am J Public Health [Internet]. 2020 Jun 1;110(6):815–22. Available from: https://ajph.aphapublications.org/doi/10.2105/AJPH.2020.305579
181. Kong AY, Zhang X. The Use of Small Area Estimates in Place-Based Health Research. Am J Public Health [Internet]. 2020 Jun 1;110(6):829–32. Available from: https://ajph.aphapublications.org/doi/10.2105/AJPH.2020.305611

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