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Associations of Food Environment, Mediterranean Diet and Obesity in United States: A Geographic Information System (GIS) Analysis

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ASSOCIATIONS OF FOOD ENVIRONMENT, MEDITERRANEAN DIET AND OBESITY IN UNITED STATES: A GEOGRAPHIC INFORMATION SYSTEM (GIS) ANALYSIS

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HEALTH EDUCATION AND HEALTH PROMOTION

ABSTRACT

Given the growing obesity epidemic in the U.S., modifying current obesogenic food environment, and identifying and promoting an obesity-modifying dietary approach that fits in the food environment context are urgent. Emerging evidence indicates that Mediterranean diet (MD) could be a beneficial dietary pattern to protect against overweight/obesity. However, as a relatively new dietary pattern in the U.S., how the unique food environment influences MD adherence, and whether consuming a MD can mediate the relationship between food environment and obesity among the population remain unknown.

This dissertation, applying Geographic Information System (GIS) and path analytical methods using data from the REasons for Geographic and Racial Differences in Stroke (REGARDS) study and government surveillance databases, aimed to extend our understanding of the interplay between community food environment, MD adherence, and obesity among U.S. adults by answering the following research questions: (1) is community food environment related to obesity; (2) is community food environment related to MD adherence; and (3) does consuming a MD mediate the relationship between community food environment and obesity.

For the first paper, spatial mapping/modeling were used to examine the relationship between food environment and obesity. The results showed that greater access to healthy food outlets was related to lower BMI, and the relationship varied across regions. For the second paper, the same spatial analytical methods were used to examine the relationship between food environment and MD adherence. However, no significant relationship was found. For the third paper, path analysis was used to test if consuming a MD mediates the relationship between food environment and obesity. The results showed that MD adherence mediated the relationship between food environment and obesity among a subpopulation whose annual household income < $75K.

Overall, the findings from this dissertation extend our current understanding of the complex interrelationship between food environment and individuals' diet pattern and obesity outcome. It further provides strong evidence of the needs for local population- and geographically-tailored interventions and policies to achieve efficacious obesity prevention among the U.S. adult population. Future research is needed to inform policy decisions and intervention development to stop the obesity epidemic in the U.S.

Keywords: Mediterranean diet, obesity, community food environment, Geographical Information System, path analysis

DEDICATION

This dissertation is lovingly dedicated to my family for their constant encouragement, dedication, inspiration, and understanding that made the completion of this dissertation possible. Most of all, I want to thank my husband, Daniel Weissglass, for his unconditional love and support, his commitment to our family, and the many sacrifices he has made for me. Thank you, Daniel, for being my excellent husband, chef, driver, nurse, personal manager, wedding planner, housekeeper, think tank, audience, and psychological/philosophical counselor. I will always remember your delicious homemade pancakes, banana bread, and Cajun boiled peanuts, and those inspiring conversations and debates we had in the botanical garden. I could not, and would not, have accomplished all this without you.

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I also dedicate this dissertation to my deceased grandparents: Fengxian Zhou, Xinyou Shao, Gong Zhang, and Zetian Chen. I hope that you will be proud of your granddaughter’s accomplishment and rest in peace.

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LIST OF ABBREVIATIONS

BMI	Body Mass Index
GIS	Geographic Information System
GWR	Geographically Weighted Regression
MD	Mediterranean diet
mRFEI	Modified Retail Food Environment Index
OLS	Ordinary Least Squares
REGARDS	REasons for Geographic And Racial Differences in Stroke
RUCA	Rural-Urban Commuting Area codes

INTRODUCTION

Obesity is one of the most significant public health crises in the U.S., with over seven out of ten adults (72.1%) estimated to be either overweight or obese, and one in three (32.6%) estimated to be obese in 2014.[1] The prevalence of obesity has tripled and the overweight rate has doubled in the past three decades.[2] Excess weight associates with many adverse health consequences, notably increasing the risks of cardiovascular diseases, type 2 diabetes, and certain cancers.[3] The combined obesity-related medical costs was $147 billion in 2008 U.S. dollars, with an estimated increase of $48–66 billion/year by 2030.[3,4] Moreover, there are significant disparities in obesity as a function of race, age, gender, socioeconomic status (SES) and geographical region.[4-7] In general, individuals who are non-Hispanic black, middle age (40-59 years old), women, low-income, low education level, who live in rural areas and/or in the South region of the country are more likely to be overweight/obese.[4-6,8]

Traditionally, it has been believed that obesity and its related health issues and disparities were caused by individual attributes, such as dietary intake, inactive lifestyle, genetics, emotional factors, and age.[9] Many traditional intervention and prevention efforts to reduce overweight/obesity have focused on individual behavior changes, which have yielded limited effect on population outcomes.[10] Theories, such as Stokols' Social Ecologic Model for Health Promotion, suggest that apart from personal attributes, people's behaviors and health outcomes are also influenced by the physical and social environment.[11,12] In the past two decades, emerging research has been devoted to understanding the contribution of the so-called "obesogenic" community food environment to the obesity epidemic and its disparities among the population, especially the geographical disparities. Community food environment (also termed community nutrition environment), defined as the distribution of food sources, involving the number, type, location, and accessibility of food outlets, is usually measured by food outlets density (using buffer distance) or proximity to the nearest outlets.[13-15] It is hypothesized that the food environment drives people's dietary behavior and intake, which in turn, influences dietary-related health outcomes, like obesity. It is also assumed that diet is the key mechanism linking the food environment exposure and obesity outcome. Therefore, improving the food environment, and identifying and promoting an obesity-modifying dietary approach that fits in the unique U.S. food environment appears crucial to remediating obesity in the U.S. population.

The Mediterranean Diet (MD) dietary pattern has been increasingly considered as a healthy dietary pattern that promises to protect against obesity and its related health problems, and has been recommended as a healthy diet pattern for Americans by U.S. Department of Agriculture and the U.S. Department of Health and Human Services in the Dietary Guidelines for Americans 2015-2020.[16] The traditional Mediterranean Diet (MD), a dietary pattern typical of Crete, Greece, and southern Italy in the early 1960s was first described by Keys et al. in the Seven Country study.[17-19] The primary features of MD include: (1) a high consumption of plant-based foods, such as fruit, vegetables, legumes, nuts and seeds, and wholegrain cereals; (2) a high consumption of monounsaturated fatty acids, primarily from olive oil, (3) a moderate consumption of fresh fish and seafood, (4) a moderate consumption of dairy products, poultry and eggs, (5) low frequency and consumption of red meat, and (6) a frequent but moderate intake of wine (especially red), often with meals.[20-23]

Evidence from European countries, especially from Mediterranean countries, has suggested a significant and inverse association between adherence to a MD and overweight/obesity among the adult population.[20,24-26] Recently, increasing epidemiological and experimental studies have investigated the effect of the MD on obesity in the U.S. population. Overall, these findings are aligned with the findings from other countries that MD can be a potential protective dietary approach to prevent and treat overweight/obesity.[27-42] However, to date, little has been known about the interplay between the food environment, consumption of a MD, and obesity among the U.S. population. For instance, to what extent does community food environment contribute to obesity? How does the unique food environment influence the practice of consuming a MD? Can consuming a MD mediate the contribution of the food environment to the obesity-related health outcomes among the U.S. population?

In the past two decades, the Geographic Information System (GIS) techniques, combining computer-mapping capabilities with additional geographical databases and data analysis tools, have been increasingly applied in the public health arena.[43,44] These provide opportunities to assess the spatial distribution and patterns of health outcomes, and to link individuals' experiences and health with the features of their local environment. For instance, spatial mapping and analytical techniques have been used to provide sophisticated measures of the availability and accessibility of healthy foods, explore the spatial clustering of obesity rates, and examine the regional variations of the relationship between local food environment and fruit and vegetable intake.[45-47] The application of GIS techniques can potentially provide opportunities to identify at-risk populations and places, promote a more robust understanding of how local environment and contexts interact with individual characteristics to produce variations in health outcomes (e.g., obesity), and improve decision-making capabilities for public health efforts. Yet, to the author's knowledge, no study has used GIS techniques to examine the geospatial relationships between the food environment exposure, adherence to a MD, and obesity outcomes in the U.S. adult population.

This dissertation, using data from the REasons for Geographic and Racial Differences in Stroke (REGARDS) study cohort and incorporating food environment data obtained from government surveillance databases, sought to address the questions described above in three respective papers. In the first paper, the aim is to examine the relationship between community food environment and obesity among U.S. adults. Specifically, the spatial distribution pattern of obesity was depicted using Hot Spot analysis, and the spatial relationship between the community food environment and obesity was analyzed and mapped using global Ordinary Least Squares (OLS) linear regression and local geographically weighted regression (GWR) methods. The second paper, using the same spatial analytic techniques outlined above as well as logistic regression methods, described the spatial distribution pattern of adherence to a MD, examined the relationship between community food environment and adherence to a MD, as well as investigated predictive factors for MD adherence among U.S. adults. Finally, the third paper employed path analytic method to examine the hypotheses that in addition to a direct effect, community food environment has an indirect effect on obesity through consuming a MD among the whole study sample as well as among sociodemographic subgroups.

Given the growing obesity epidemic and the pervasive obesogenic environment in the U.S., understanding the complex of the interrelationship between food environment and individuals' diet and obesity, and identifying and promoting an obesity-modifying dietary approach that fits in the unique food environment context are urgent to combat this health crisis. This dissertation will contribute to literature and future obesity-preventing programs and policies in several important ways. First, this study disentangles the complex interrelationships between food environment, dietary pattern and obesity, and provide a better understanding of the mechanism underlying the relationship between the 'obesogenic' food environment and obesity-related health outcomes. Second, this study provides the opportunity to investigate the value of dietary guidance promoting the MD dietary pattern in the U.S. If the proposed hypotheses were found true, the study will provide strong research evidence to promote the practice of eating a MD in the U.S. population, to remediate obesity. Finally, the findings of this study will help policy makers and public health programs to identify at-risk populations and regions (e.g., those with lower MD adherence and/or higher BMI), provide guidance in allocating limited public health resources more efficiently, and developing geographically- and population-tailored policies and interventions to combat obesity.

ASSOCIATION OF COMMUNITY FOOD ENVIRONMENT AND OBESITY AMONG U.S. ADULTS

by

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ABSTRACT

Background: An increasing number of studies have investigated the contribution of community food environment to the obesity epidemic. However, the findings are inconsistent. Methodological explanations for the inconsistent findings include: (1) using individual store or restaurant exposure as food environment indictor, which might not represent individuals' overall food access experiences, and (2) not accounting for non-stationarity assumption, that is that the relationship between food environment and obesity may vary across geographical regions. This study uses a composite measure, the modified Retail Food Environment Index (mRFEI) as the community food environment indicator, and applies spatial analytical techniques to examine the relationship between community food environment and obesity and its variation across the U.S.

Methods: Data from adults aged ≥ 45 years who participated in the REasons for Geographic and Racial Differences in Stroke (REGARDS) study, and completed baseline assessment from January 2003 - October 2007 were used for the analysis. Hot Spot analysis was used to assess the spatial distribution pattern of obesity. The relationship between community food environment and obesity and its variation across the U.S. were examined using global Ordinary Least Squares (OLS) regression and local geographically weighted regression (GWR).

Results: Clusters of higher BMI were more likely to locate in socioeconomically disadvantaged, rural, minority neighborhoods with a smaller population size, while lower BMI clusters were more likely to appear in relatively more affluent, urban neighborhoods with a higher percentage of non-Hispanic white residences. There was a significant, inverse relationship between community food environment and obesity (β= -.0210;

$P<.0001$). Specifically, greater access to healthy food outlets was related to lower BMI. Moreover, the magnitude and direction of this relationship varied significantly across regions.

Conclusion: Results suggest that greater attention should be given to non-stationary relationship between the community food environment and obesity in future investigations. The findings also underscore the need for geographically-tailored public health interventions and policies to address unique local food environment issues to achieve maximum effects on obesity prevention.

INTRODUCTION

Obesity is a major public health problem in the United States owing to its rapidly increased prevalence, substantial mortality and morbidity, and increased health care costs. The prevalence of obesity has tripled and the overweight rate has doubled in the past three decades.[1,2] The excess weight associates with or causes many adverse health consequences, notably cardiovascular disease, type 2 diabetes, and certain cancers.[3] The combined obesity-related medical costs was $147 billion in 2008 U.S. dollars, with an estimation of an increase by $48–66 billion/year by 2030.[3,4]

Moreover, the prevalence of obesity is not evenly distributed across the United States, but instead tends to be geographically patterned.[5-8] A report from the Centers for Disease Control and Prevention (CDC; 2015) has suggested that the South was particularly notable for high prevalence of obesity (31.2%), while other regions, such as the Midwest (30.7%), the Northeast (26.4%), and the West (25.2%) had relatively low prevalence.[4] A recent study among participants from the 2005-2008 National Health and Nutrition Examination Survey (NHANES) found that obesity was markedly higher among adults from rural areas of the U.S. than those from urban areas.[7] Another study conducted by CDC further indicated there were significant county-level geographical differences in obesity prevalence cross the country.[6]

Meanwhile, there has been an emerging research interest in the contribution of the so-called "obesogenic" community food environment to the obesity epidemic and its related disparities among the U.S. population. Community food environment (also termed community nutrition environment), according to Glanz et al, is defined as the distribution of food sources, involving the number, type, location, and accessibility of food outlets, with stores and restaurants being the most common.[9] Given the nature of food accessibility (i.e., the location of food outlets and ease of getting to that location), the community food environment is predominantly measured by food outlet density (using buffer distance) or proximity to the nearest outlets.[10,11]

However, previous studies examining the relations between community food environment and obesity among the U.S. population have produced inconsistent results.[10,12,13] For instance, Feng et al (2010), Gamba et al (2014), and Cobb et al (2015) reviewed over 60 studies that examined the association of food environment and obesity among U.S. adults.[10,12,13] Some of the studies found that access to healthful food outlets (e.g. supermarkets) inversely associated to obesity, while a few studies found positive associations.[10,14-19] Similarly, some studies found that access to unhealthful food outlets (e.g. convenience store, grocery store and fast food restaurant) were positively associated with obesity among adults; however, others found null or even, negative associations.[10,16,20-25]

One major methodological issue, which may help explain the inconsistent findings, is that the majority of the previous studies used access to individual store or restaurant types (e.g., supermarkets, or fast food restaurants) to measure the community food environment, which might not provide a complete picture of an individual's food environment.[10] To solve this problem, the use of food environment measures that combine multiple food outlets types, which may provide an overall measure of the healthfulness of the food environment, was suggested. For instance, as reported in Cobb et al review study, several studies have used overall food access index (e.g., index designed to capture the ratio of unhealthy to healthy food outlets) as community food environment measures to examine its relationship with obesity. The findings from these studies were more likely to be consistent, significant and in expected direction comparing to those using individual food outlet types as food environment indicators.[10,26,27]

Another methodological issue that may help to explain the inconsistent findings is not accounting for non-stationarity in previous investigations. The majority of the previous studies investigated the relationship between community food environment and obesity used global regression to model the association, which relies on the assumption of a stationary relationship; that is, parameter estimates describe what is assumed to be an invariant relationship across space. However, the empirical evidence from previous studies conducted in difference local regions have suggested that the relationship between food environment and obesity may vary across the regions. For instance, a study investigating this relationship in California area showed that there was no relationship between food outlets within walking distance and obesity, while another study examined the relationship in New Jersey area, and the results showed that densities of fast-food establishments and storefronts were positively associated with obesity.[28,29] Therefore, this study will examine the relationship between food environment and obesity at national-level, and incorporate the non-stationarity assumption to investigate the variation of this relationship across regions.

This present study, using geospatial mapping and modeling techniques, sought to describe the spatial distribution pattern of obesity, and examine the relationship between community food environment and obesity, and its variation across the U.S. The modified Retail Food Environment Index (mRFEI), a composite index developed by the Centers for Disease Control and Prevention (CDC) to represent the overall access to healthful food outlets at census tract level, will be used as community food environment indicator. It is hypothesized that mRFEI significantly associates with BMI, and the magnitude and direction of the relationship vary across the study areas. Results may provide evidence of the need of geographically-tailored public health policies and interventions to address food environment issues unique to regional areas to achieve efficacious obesity prevention.

METHODS

Data Source and Study Participants

Data for individuals were drawn from the REasons for Geographic And Racial Differences in Stroke (REGARDS) study. The REGARDS study is a national population-based longitudinal cohort study of 30,183 black and white community-dwelling residents aged 45 years and older. The overall goal of REGARDS is to better understand the contributors to the substantial racial and geographic disparities in stroke.[30] Individuals were recruited from commercially available nationwide list of residents purchased through Genesys Inc. using a combination of mail and telephone contact during 2003-2007. After the baseline assessment, participants were followed via telephone at 6-month intervals. Participants' residency address was geocoded using SAS/GIS batch geocoding. Additional methodological details have been published previously.[30,31]

For the purpose of the present study, baseline cross-sectional data collected during January 2003 and October 2007 was used. Individuals who did not have Mediterranean Diet score (n=8927), body weight (n=215), or geocoded address (n=11) were excluded from the analysis. Furthermore, participants whose geocoded address could not match with 2000 census tract (n=2), did not have matched food environment data (mRFEI) (n=78), and whose BMI were significant outliers (n=53) were also excluded. Data from a total of 20,897 individuals were used in the analysis (**Figure 1**).

Community food environment data were retrieved from the Children's Food Environment State Indicator Report (2011) developed by the Division of Nutrition, Physical Activity and Obesity of the Centers for Disease Control and Prevention CDC, available to the public (http://www.cdc.gov/obesity/downloads/2_16_mrfei_data_table.xls).[32] Community sociodemographic feature data were drawn from publicly available Food Environment Atlas (2011) developed by the U.S. Department of Agriculture Economic Research Service (https://www.ers.usda.gov/data-products/food-environment-atlas/data-access-and-documentation-downloads/), as well as from Census of Population and Housing (2000) from U.S. Census Bureau website (https://www.census.gov/prod/www/decennial.html). The census cartographic boundary shapefiles (2000) for GIS mapping were also downloaded from the U.S. Census Bureau, which is publicly available from their geography website (https://www.census.gov/geo/maps-data/data/tiger-cart-boundary.html).

Data retrieved from the different sources were linked and pooled by using variables in common (e.g., the Federal Information Processing Standard (FIPS), and participants' IDs). Permission and approval were obtained from the REGARDS study executive committee and the University of Alabama at Birmingham Institutional Review Board, respectively, to conduct this cross-sectional study.

Variables

Community food environment: Modified Retail Food Environment Index (mRFEI) , obtained from the Children's Food Environment State Indicator Report, 2011, developed by the Division of Nutrition, Physical Activity and Obesity of CDC, was used as community food environment indicator.[32] The mRFEI represented the percentage of food retailers that were designated 'healthy' out of the total number of food retailers considered 'healthy' or 'less healthy' in a census tract. The mRFEI ranges from 0 to 100, with higher mRFEI scores indicating greater access to healthy food retailers in census tracts.[32] Healthy food retailers include supermarkets, larger grocery stores, supercenters, and produce stores within census tracts or ½ mile from the tract boundary. All data on supermarkets, supercenters, and produce stores were obtained from the InfoUSA business database, 2009. Less healthy food retailers include fast food restaurants, small grocery stores, and convenience stores within census tracts or ½ mile from the tract boundary. Convenience store data were obtained from the Homeland Security Information program database, 2008. Small grocery store data were obtained from the InfoUSA business database, 2009; and fast food restaurant data were obtained from the NavTeq database, 2009.

Obesity: Body Mass Index (BMI) (kg/m^2) was used to estimate body weight in this study. BMI was calculated using height and weight measured during REGARDS study home visit at baseline. Height was obtained utilizing an 8-foot metal tape measure without shoes. Weight was measured using a standard 300-lb calibrated digital scale.[30] In logistic regression, BMI was treated categorically in the analysis. The BMI was categorized and coded as 0 = not obese ($BMI<30\ kg/m^2$) and 1 = obese ($BMI\geq30\ kg/m^2$). The BMI was also categorized and coded as 0 = not overweight/obese ($BMI<25\ kg/m^2$) and 1 = overweight/obese ($BMI\geq25\ kg/m^2$).

Covariates

Sociodemographics: The following variables were included: age (years; continuous), gender (male vs. female), race (White vs. Black), health insurance (yes vs. no), marital status (single, married, divorced, widowed, or other), education (less than high school, high school graduate, some college, or college graduate and above), annual household income (<20K, 20-34K, 35-74K, ≥75K, or refused), employment (employment for wage, self-employed, unemployed for ≥ 1 year, unemployed for < 1 year, home maker, students, retired, unable to work, or refused), and time lived in current address (years; continuous).

Lifestyle: These factors included exercise (none, 1-3 times/week, or ≥ 4 times/week), watch TV/video (none, 1-6 hrs/week, 1 hr/day, 2 hrs/day, 3 hrs/day, or ≥ 4 hrs/day), alcohol use [none, moderate (women: 0-7 drinks/week; men: 0-14 drinks/week), or heavy (women: >7 drinks/week; men: >14 drinks/week)], and smoking (none, past, or current). To measure smoking status, the participants were asked two questions that (1) if they had smoked at least 100 cigarettes in their lifetime, and (2) if they smoked cigarettes now, even occasionally. Participants who answered 'yes' to both questions were considered as 'current smokers', while those answering 'yes' to the first question and 'no' to the second question were coded as 'former smokers', and those answering 'no' to both were classified as 'never smokers'.

Community features: Six factors were included: (1) percentage of county residents that was non-Hispanic white (2008), (2) percentage of county residents that was non-Hispanic black (2008), (3) county median household income (2008), (4) county poverty rate - the percentage of county residents with a household income below the poverty threshold (2008), (5) census-tract population size (2000), and (6) Rural-Urban Commuting Area Code (RUCA)(2000). RUCA code was used to indicate rural/urban resident status of the participants, which contains two levels.[33] Whole numbers (1-10) delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows. These 10 codes are further subdivided based on secondary commuting flows, providing flexibility in combining levels to meet varying definitional needs and preferences.[33] In the analysis, RUCA codes were categorized and coded as 1=urban, 2=large rural city/town, 3=small rural town, and 4=isolated small rural town, according to Categorization A by the University of Washington Rural Health Research Center.[34] (see **Appendix** for more details).

Data Analysis

Statistical analysis: The statistical analysis was implemented using SAS version 9.4 for Windows (SAS Institute, Inc, Cary, NC). Descriptive analyses of sociodemographic and lifestyle characteristics of the participants and community features were conducted using PROC UNIVARIATE and PROC FREQ procedures. Means and standard deviations (for continuous variables) and percentages (for categorical variables) were calculated. These characteristics were compared among the BMI clustering groups (higher BMI clusters, lower BMI clusters, and non-clustering group) using PROC FREQ, PROC ANOVA, and PROC NPAR1WAY procedures as appropriate. Supplementary analysis to examine individual and community factors that predict obesity was conducted employing multiple logistic regression (stepwise) models. A significance level of 0.3 is required to allow a variable into the model, and a significance level of 0.35 is required for a variable to stay in the model.[35] Odds ratios (ORs) and 95% confidence interval (CI) were used to estimate associations with obesity. The statistical significance, alpha, level was set at 0.05, two-tailed. Missing data were handled using listwise deletion.

GIS spatial analysis: The spatial mapping and modeling were implemented using ArcGIS 10.4 (ESRI Inc., Redlands, CA). The census cartographic boundary shapefiles and data of interest were imported and integrated in ArcMap to create digital map layers and prepare for analysis. First, Hot Spot analysis (Getis-Ord Gi*) was conducted to identify the spatial clusters of high values (hot spots) and low values (cold spots) of mRFEI and BMI across the study space. INVERSE_DISTANCE was used as conceptualization of spatial relationship and EUCLUDEAN_DISTANCE was chosen for distance method. False Discovery Rate (FDR) Correction was applied to account for both multiple testing and spatial dependence. Significance of local clustering was based on a P-value < 0.05. Hot spot analysis is a statistically based method to identify locations of statistically significant spatial high- and low-value clusters of a phenomenon of interest (e.g., individual's BMI) by evaluating each feature (e.g., individual) within the context of neighboring features and against all features in the dataset.[36] To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbors is compared proportionally to the sum of all features. When the observed local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance, a statistically significant z score results and a hot/cold spot is detected.[37] For statistically significant positive z scores, the larger the z-score is, the more intense the clustering of high values (hot spot). For statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of low values (cold spot).[37] Hot Spot technique has been employed in investigating numerous public health issues, such as patterns of sexually transmitted diseases in Mexico and community-level overweight and obesity in Canada.[38,39]

Second, ordinary least squares (OLS) linear regression with spatial diagnostics (Moran's I) was conducted to examine the global correlations between mRFEI and BMI.

Coefficient, standard errors, p-value and R^2 were reported. The performance of the model was evaluated by corrected Akaike Information Criterion (AICc) and spatial autocorrelation (Moran's I) on regression residual. Spatial autocorrelation test, Moran's I, examined spatial randomness of the regression standard residual (Eq. 1).[40,41]

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

Where n is the total number of individuals in the study, i and j represent different individuals, y_i is the measured regression residual in individual i and $\bar{y}$ is its mean. w_{ij} is the spatial weight between individual i and j.[40,41] The inverse of the distance between i and j was applied to specify the spatial relationship between them. EUCLUDEAN_DISTANCE was chosen for distance method. The Moran's I index values ranged from -1 (negative autocorrelation) to +1 (positive autocorrelation). Significance of the spatial autocorrelation was based on a p-value < 0.05. When p-value indicates statistical significance, a positive Moran's I index value indicates tendency toward clustering (e.g., adjacent individuals tend to have similar values) while a negative Moran's I index value indicates tendency toward dispersion (e.g., nearby indiviudals tend to have dissimilar values). A non-significant Moran's I on the OLS model regression residual indicates that the model is well-specified; that is, the model includes key predictors for the dependent variable (e.g., BMI in this study).[40,42]

Third, local geographically weighted regression (GWR) was conducted in order to account for the possible variations of the relationship between mRFEI and BMI across the study areas. GWR is a local form of linear regression used to model spatially varying relationships. A separate equation and local parameter for each individual in the analysis was generated using a 'local' subset of the data falling within the bandwidth of the target individual.[43,44] An adaptive kernel type with AICc estimated bandwidth was used to calibrate the model in order to account for spatial structure. The performance of the model was evaluated by R^2, AICc and Moran's I. R^2 is a measure of goodness of fit. Its value varies from 0.0 to 1.0, with higher values being preferable. The AICc was used to evaluate the model performance and compare difference regression models. If the AICc of the GWR model is more than 3 lower than that of the OLS model, it signifies the benefits of moving from a global model (OLS) to a local regression model (GWR). Spatial autocorrelation test (Moran's I) was conducted to examine spatial randomness of the regression residual, and a non- significant Moran's I indicated the model was properly specified. A raster surface, based on the regression coefficient of mRFEI from the GWR model, was created to visually present the regional variation of the relationship between mRFEI and BMI across the study areas.

RESULTS

Descriptive Analysis

Participant characteristics and their community features are summarized in **Table 1**. A total of 20,897 participants from REGARDS study were included in the analysis. As shown, participants were, on average, aged 65, with about half retired and having an income >35K. Slightly more than a half were female. About two-thirds of the participants were white, married, and reported greater than high school education. Almost all of the participants had health insurance. In addition, the majority were non-current smokers and non-alcohol users, exercised ≥ 1 time/week, and watched TV/Video ≥ 1 hour/day. Nearly 80% were residing in urban areas, living for an average of 29 years at their current residency. On average, the participants were living in neighborhoods comprised of 60% non-Hispanic whites, 27% non-Hispanic blacks, with a median household income of $48,182, poverty rate of 16%, a mean census-tract population of 5082, and a mean mRFEI of 10.92. Of the sample, the mean BMI was 28.96 kg/m^2, with about 38% classified as overweight and 36% as obese.

Figure 2 depicts the study areas and distribution of participants geographically. The participants were from 48 contiguous states and Washington, D.C., with the majority (64.42%) residing in South Carolina, North Carolina, Georgia, California, Louisiana, Alabama, Tennessee, Mississippi, and Ohio (see **Appendix** for more details**).** A mean of 1.89 participants (SD=1.95; range=1-38) were scattered throughout 11071 census tracts, with a mean mRFEI of 11.00 (SD=10.66), and a mean population of 4831 (SD=2337.48) in each tract.

Hot Spot Analysis

Figure 3 depicts the results of local clustering analysis of mRFEI. The clusters of participants with higher mRFEI are denoted in black, whereas grey represents clusters of participants with lower mRFEI. Overall, higher mRFEI clusters were primarily observed in West (e.g., California, Oregon, Washington, Utah, Arizona, and New Mexico), West North Central (e.g., North Dakota, South Dakota, Minnesota, Kansas, and Iowa), East North Central (e.g., northern area of Wisconsin and Michigan), Middle Atlantic (e.g., western area of Pennsylvania), South Atlantic (e.g., North and South Carolinas), and East South Central (e.g., merging areas of Alabama, Georgia, and Florida) regions of the country. Lower mRFEI clusters were primarily observed in South (e.g., eastern area of Texas, central area of Oklahoma, Mississippi, southeastern area of Louisiana, central area of Alabama, west area of Tennessee, and northern area of Georgia), East North Central (e.g., Lake Michigan coastal areas of Illinois and Indiana, eastern area of Michigan, and Ohio) and Northeast (e.g., eastern area of Pennsylvania, Washington D.C., New Jersey, New York City, Massachusetts, and Connecticut) regions. The higher mRFEI clusters had significantly higher mRFEI than that in the lower mRFEI clusters (12.69 (SD=11.09) vs. 9.10 (SD=8.68); $p<.0001$). Moreover, urban areas had significant lower mRFEI compared to rural areas (10.28 (SD=9.74) vs. 13.09 (SD=11.32); $p<.0001$).

Figure 4 displays the result of Hot Spot clustering analysis of BMI across the study areas. The clusters of participants with higher BMI are denoted in black, whereas grey represents clusters of participants with lower BMI. There were clusters of higher BMI in eastern area of Virginia (e.g., Hampton, Richmond, Petersburg county areas), northern area of Ohio (e.g., Cuyahoga, Lorain, Erie, and Locus county areas), eastern area of Michigan (e.g., Wayne, Oakland, Macomb, and Washtenaw county areas), northern area of Indiana (e.g., Howard and Tippecanoe county areas), southwestern areas of Georgia, northwestern corner area of Florida (e.g., Gadsden and Leon county areas), and southern area of Louisiana (e.g., Lafayette, St. Landry, Acadia, and Baton Rouge county areas). There were clusters of lower BMI in northwestern area of Washington (e.g., King county area), central northern area of Colorado (e.g., Denver, Jefferson, Arapahoe, and Douglas county areas), central and eastern areas of Tennessee (e.g., Davidson, Williamson, Hamilton, Bradley, and Knox county areas), western area of North Carolina (e.g., Buncombe, Haywood, Henderson, and Macon county areas), New Jersey (e.g., Essex county area), southern area of New York (e.g., New York City), Connecticut (e.g., New haven and Hartford county areas), and Massachusetts (e.g., Hampden, Middlesex and Suffolk county areas). The higher BMI clusters had significantly higher BMI than that in the low BMI clusters (29.81 (SD=6.35) vs. 27.91 (SD=5.38); $p<.0001$).

Comparing participant characteristics and community features among BMI spatial clusters, it showed that participants in the higher BMI clusters were more likely to be younger age, black, not retired, not married, without health insurance, current smokers, non-alcohol user, not have a college degree, have an annual household income of < $35K, exercise < 4 times/week, watch TV/video ≥4 hrs/day, and reside longer in their current dwelling, comparing to the participants in lower BMI clusters or non-clustering areas. Moreover, higher BMI clusters were more likely to appear in neighborhoods with a higher percentage of non-Hispanic black residents, a lower median household income, a higher poverty rate, and a smaller population size (**Table 2**). Oppositely, participants in lower BMI clusters were more likely to be older age, white, retired, with health insurance, moderate alcohol user, have a college degree and above, have an annual household income of ≥ \$35K, exercise ≥ 4 times/week, watch TV/video < 4 hrs/day, and reside fewer years in their current dwelling, comparing to the participants in higher BMI clusters or non-clustering areas. Moreover, lower BMI clusters were more likely to appear in neighborhoods in urban areas, with a higher percentage of non-Hispanic white residents, a lower percentage of non-Hispanic black residents, a higher median household income, and a lower poverty rate (**Table 2**).

Global and Local Regression Analysis

Table 3 summarizes the results of global and local regressions of the relationship between mRFEI and BMI among the REGARDS participants. The global OLS regression showed that mRFEI was significantly and negatively associated with BMI; that is, when mRFEI value increased, participants' BMI reduced (β= -.0210; $P<.0001$). Spatial autocorrelation on regression residuals was detected ($P<.0001$). The relationship between mRFEI and BMI was not statistically significant after adjusting for sociodemographic, lifestyle, and community feature covariates (refer to **Appendix** for more details). Local GWR, using 992 neighbors to calibrate each local regression equation yielded optimal results. Compared with global regression analysis, local modeling was associated with both a lower AICc (almost 74 points less) and a suppression of spatial autocorrelation in standardized residuals ($P=.3427$). A decrease of AICc more than 3 points indicated a real improvement in model performance by moving from global OLS regression to local regression. The non-significant result of spatial autocorrelation on standardized residuals indicated the GWR model was a properly specified model. Furthermore, **Figure 5** depicts the spatial variations in the magnitude and direction of the relationship between mRFEI and BMI across the study areas. Darker indicates stronger, inverse relation between mRFEI and BMI, whereas brighter indicates stronger, positive relations. Overall, greater access to healthy food outlets was strongly related to lower BMI in, for instance, northern area of California, central area of Texas, Montgomery area of Mississippi, Avoyelles area of Louisiana, Northern area of Alabama, northwestern and southeastern areas of Georgia, Laurens and Lancaster county areas of South Carolina, Franklin, Vance, and Forsyth county areas of North Carolina, merging areas of southeastern corner of West Virginia and Virginia. Greater access to healthful food outlets was significantly associated with higher BMI in, for instance, merging area of Pennsylvania, Maryland, Washington DC, Delaware, and Virginia, merging areas of Indiana, Ohio and Kentucky, northeastern area of Arkansas, southeastern coastal area of North Carolina, central area of Georgia, northeastern areas of Texas, and center area of Nevada.

Supplementary analysis

Stepwise logistic regression was conducted to identify individual and community factors that predict obesity. The variables that remained in the final model after the stepwise method are presented in **Table 4**. Being younger, black, female, non-heavy drinker, non-current smoker, not having a college degree, having an annual household income of < $75K, exercising < 4 times/week, watching TV/video ≥ 4 hrs/day were each associated with higher odds of being obese. Similarly, being younger, black, male, non-heavy drinker, non-current smoker, not having a college degree, having an annual household income of \$20-74K, exercising < 4 times/week, watching TV/video ≥ 4 hrs/day were each associated with higher odds of being overweight/obese.

DISCUSSION

The present study, based on data from REGARDS study and government surveillance sources, used spatial mapping and modeling methods to describe the spatial distribution and pattern of obesity, and examine the relationship between community food environment and obesity and its variation across the U.S.

Overall, the prevalence of obesity among the study population (74% overweight with 36% obese) confirmed the severity of the obesity issue in the U.S.[2] The results of local clustering analysis showed that clusters of participants with higher BMI were more likely to locate in socioeconomically disadvantaged, minority neighborhoods with smaller population sizes (e.g., in Deep South and East North Central regions of the country), and lower BMI clusters were more likely to appear in relatively more affluent, urban areas (e.g., northeast coastal areas). This finding supported previous reports on the uneven geographical distribution of obesity prevalence in the U.S.[7,8,45-49] For instance, Le et al's study reported the obesity prevalence were higher in the South and North Central regions, comparing to other regions in the U.S.[49] Befort et al study, based on the 2005-2008 National Health and Nutrition Examination Survey (NHANES) observed that the obesity prevalence was lower among urban adults compared to rural adults, even controlling for demographic, diet and physical activates.[7] Singleton et al's study examining the racial disparities in obesity prevalence among the U.S. population at county-level found that the adult obesity prevalence were higher in counties with higher percent of black residents, and lower median household income.[46] The results also support the finding from a recent national-wide study that higher obesity prevalence was related to smaller population size communities.[8] The configuration of the BMI clusters did not follow the political boundaries (e.g., state or county boundaries), which suggests that collaborations aiming at building regional/local networks might provide better resource alignment and more effective initiatives.

It is assumed that the participants in a given BMI cluster may share similar features that have contributed to the clustering. We further explored local individual factors, such as sociodemographic and lifestyle behavioral characteristics to explain the clustering of BMI across the study areas. We found that individuals, who are younger age, black, not retired, not married, without health insurance, non-alcohol user, current smokers, have less education and less income, live a more sedentary lifestyle, and reside longer in their current dwelling were more likely to live in the higher BMI clustering areas. In the supplementary analysis, using logistic regression to identify the predictive factors of obesity, we found the similar individual features were related to higher odds of being obese. These results are generally in line with the findings from previous reports.[8,48,50-52]

To answer the research question of this study, global and local regressions were conducted to examine the relationship between community food environment and obesity among the participants and its variation across the study areas. The finding from the global regression showed that greater access to healthy food outlets were significantly related to lower BMI, which supports the findings of previous research. For instance, Morland et al’s study examining the association between access to food outlets and obesity among adults in southern region of the U.S. found that areas with more supermarkets had lower obesity prevalence while areas with more small grocery stores or fast food restaurants had higher prevalence.[53] Similarly, a nation-wide study examining the effects of retail food environment on obesity at county-level indicated that greater access to fast-food restaurants related to higher adult obesity prevalence.[46] Future studies should explore potential threshold and saturation effects of healthful food outlet exposure on obesity, which will provide valuable guidance for future city planning or community zoning policies in food environment development and planning to yield optimal effects in reducing obesity.

Local GWR regression of the relation between community food environment and obesity showed a significant improvement in regression modeling performance (a significant lower AICc and a suppression of spatial autocorrelation in standardized residuals), compared to the global regression model. The result of the local regression supported our hypothesis and aligned with the findings from previous study examining the relationship between food environment and obesity. For instance, Chi et al's study examining the relationship between food environment and obesity at nationwide county level also found that areas with higher ratios of convenience-to-grocery stores was positively associated with obesity risk, and the association significantly varied across the U.S. counties.[54]

This local regression finding also provided a potential explanation for the inconsistent findings from previous studies. For instance, in this study, we found relatively stronger and inverse relations between access to healthy food outlets and obesity in Northern California, while the relations in the southern areas of California were weaker and some were positive. This echoes the inconsistent findings from previous studies conducted in California. A study conducted among 97,678 participants in California found no strong evidence that food outlets near home were related to BMI, while another study conducted in Northern California area found that more healthful food environments were associated with lower obesity rates.[29,55]

The significant magnitude and direction variation of the relationship between community food environment and obesity also pointed out that global policies or interventions (e.g., simply providing greater access to healthy food outlets, such as supermarket, across the country) may be not suitable and effective across the different regions. It emphasized the need for developing geographically tailored programs and policies to promote local food environment in order to prevent obesity; in another word, local programs/policies may vary their efforts on modifying food environment in response to the variation of the food environment-obesity relationship across regions. For example, in regions that greater access to healthy food outlets is strongly related to lower BMI, the local programs may make strong efforts to improve local healthy food access, while fewer efforts/resources may be invested in those regions that healthy food outlets access is not strongly related to obesity outcome.

There are several strengths of this study. First, incorporating the non-stationarity assumption provides the opportunity to account the spatial heterogeneity in the investigation, explore the nature of the relationship between community food environment and obesity across the U.S., and advances our current understanding of the complexity of the relationship. Second, unlike the majority of previous studies using a single type of retail food stores as food environment indicator, the use of a composite measure (e.g. modified retail food environment index) allows us to capture the complexity of food environment by incorporating data on the density of both healthful and unhealthful food stores. Moreover, the use of standard measures like mRFEI makes it easier to compare the findings across different studies. Third, keeping the spatial analysis at individual level in this study helps avoid the potential bias introduced by areal unit aggregation, which are typically arbitrary and modifiable, especially when it is uncertain about the actual geographic areas that exert contextual influences on the relationship between food environment and obesity (e.g., are census tracts, counties, or other spatial units most appropriate?). Fourth, the BMI used in this study was calculated based on the height and weight measured at baseline with a standardized protocol, which prevents the potential bias introduced by using self-reported data.[49] Lastly, using a large and geographically diverse sample from the REGARDS study allows us to yield precise estimates.

Several limitations of the present study also should be noted. First, the cross-sectional design of this study precluded drawing causal relation between community food environment and obesity. Future experimental and longitudinal studies are needed to extend the findings of current study. Second, the external validity of this study is limited, because of the sampling procedure used in the REGARDS study. For example, the participants were recruited through Genesys Inc. using mail and telephone contacts, which may preclude certain populations, especially in rural areas.[56] The study population also overrepresented residents in the South regions.[57,58] Moreover, the study sample only included mid- and older-age non-Hispanic white and black residents, which limited the capability to extend the findings to other age and racial/ethnic populations. Third, we considered a multilevel analysis. However, our analysis was limited at individual level. Because the study sample was not nationally representative of obesity at any level (e.g., census tract, county). The participants in the study are located in 11071 census tracts and

1708 counties, rendering a mean of 2 participants per tract and 12 participants per county. Moreover, the participants were oversampled from the South states.

CONCLUSION

This study found that there was a significant and inverse relation between community food environment and obesity among U.S. adults. More importantly, this relationship varied significantly across the country. The findings from this study further emphasized the importance of accounting for spatial variations in future investigations on this topic, and suggested the needs of geographically tailored public health policies and interventions to address issues unique to regional areas in order to achieve efficacious obesity prevention. In addition, the findings showed that the nature configurations of the clustering of obesity did not follow the political boundaries, which suggests that collaborations aiming at building regional/local networks might provide better resource alignment and more effective initiatives. Future studies should explore the potential threshold and saturation effects of healthful food outlets exposure on obesity, which will provide valuable guidance for future food environment development and planning. Moreover, future studies examining the mechanisms underlying the relationship between the community food environment exposure and obesity outcome are warranted.

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FIGURES AND TABLES

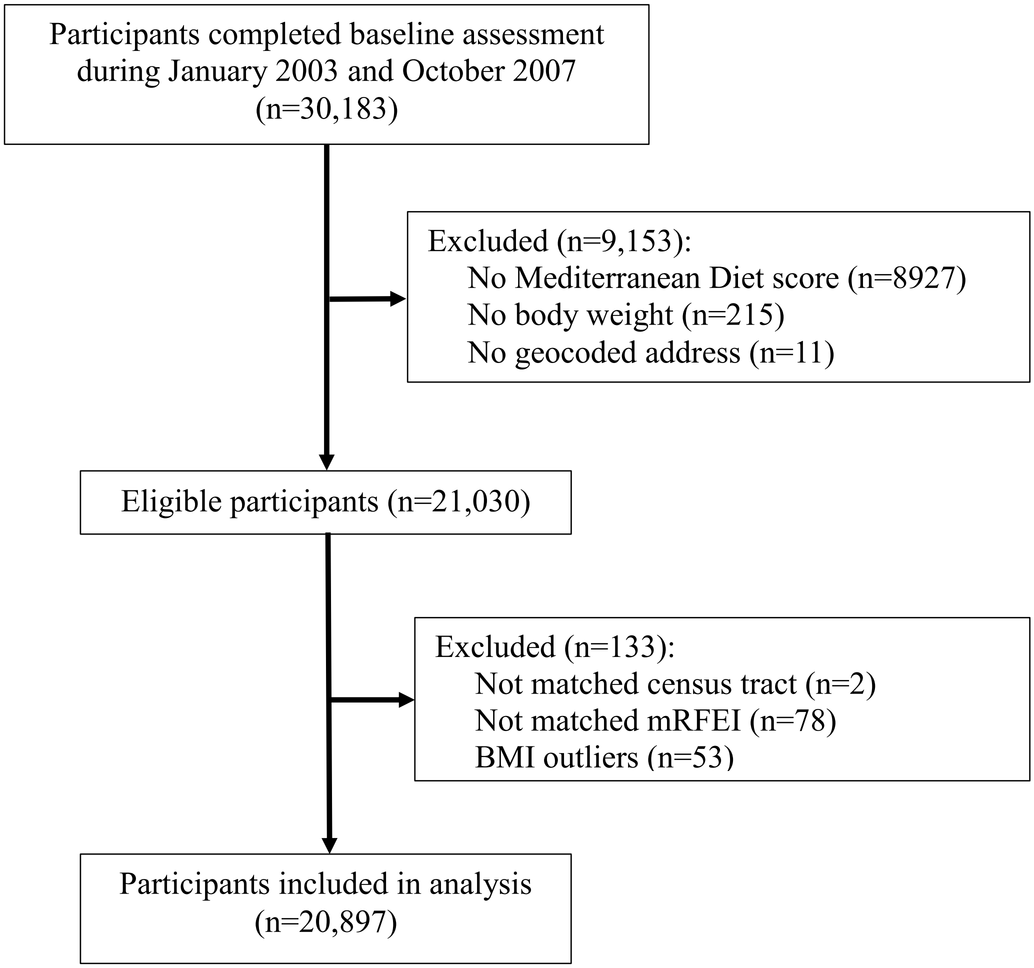


Figure 1. STROBE flow-chart of participants in analysis

Note: STROBE = Strengthening the Reporting of Observational Studies in Epidemiology, REGARDS = the REasons for Geographic And Racial Differences in Stroke study, mRFEI = modified Retail Food Environment Index, BMI=Body Mass Index. To calculate BMI outliers (<3.1882 kg/m^2 OR >53.7947kg/m^2), Q1 – 3*(Q3-Q1) was used as lower outer fence, and Q3 + 3*(Q3-Q1) was used as Higher outer fence (Q1 = the lower quartile, and Q3 = the upper quartile).

Table 1. Summary of individual and community characteristics of the REasons for Geographic and Racial Differences in Stroke (REGARDS) study participants (n=20897)

Characteristics	REGARDS participants
Sociodemographics	
Age, year, Mean(SD)	64.88 (9.26)
Male, % (n)	44.22 (9,241)
White, % (n)	66.71 (13,941)
Education, % (n)	
Less than high school	9.58 (2,002)
High school graduate	25.52 (5,331)
Some college	27.32 (5,707)
College graduate and above	37.57 (7,849)
Relationship, % (n)	
Single	5.11 (1,068)
Married	61.74 (12,901)
Divorced	13.89 (2,902)
Widowed	17.41 (3,638)
Other	1.86 (388)
Annual household income, % (n)	
<20K	15.63 (3,266)
20-34K	24.09 (5,034)
35-74K	31.39 (6,559)
≥75K	17.18 (3,590)
Refused	11.71 (2,448)
Employment, % (n)	
Employed for wages	27.09 (3,565)
Self-employed	9.00 (1,184)
Unemployed for ≥ 1 year	1.47 (194)
Unemployed for < 1 year	1.48 (195)
Homemaker	6.08 (800)
Student	.19 (25)
Retired	47.72 (6,279)
Unable to work	6.95 (914)
Refused	.02 (3)
Health Insured, % (n)	93.95 (19,620)
Time lived in current address, year, Mean(SD)	28.63 (20.62)
mRFEI, Mean(SD)	10.92 (10.19)
BMI, kg/m^2**,** Mean(SD)	28.96 (5.90)
Overweight (25 kg/m^2 ≤ BMI < 30 kg/m^2), % (n)	37.91 (7,923)
Obese (BMI ≥ 30 kg/m^2), % (n)	36.17 (7,558)
Life style	
Exercise, % (n)	
None	32.50 (6,701)
1 to 3 times/week	36.91 (7,609)
≥ 4 times/week	30.59 (6,307)
Watch TV/Video, % (n)	

None	.76 (156)
1-6 hrs/wk	12.69 (2,616)
1 hr/day	6.80 (1,401)
2 hr/day	22.55 (4,648)
3 hr/day	27.16 (5,599)
≥ 4 hr/day	30.05 (6,195)
Smoking [a], % (n)	
Never	45.23 (9,417)
Past	41.12 (8,562)
Current	13.65 (2,842)
Alcohol use [b], % (n)	
None	59.64 (12,463)
Moderate	35.93 (7,508)
Heavy	4.43 (926)
Community features	
Percentage of Non-Hispanic White [c], Mean(SD)	59.53 (18.95)
Percentage of Non-Hispanic Black [c], Mean(SD)	26.62 (18.34)
Median Household income [c], $, Mean(SD)	48182.49 (11932.72)
Poverty rate [c], Mean(SD)	15.92 (5.41)
Tract population [d], Mean (SD)	5081.58 (2387.90)
RUCA code [d], % (n)	
Urban	76.99 (16,089)
Large rural	12.61 (2,635)
Small rural	6.98 (1,459)
Isolated small rural	3.42 (714)

Note: SD=Standard Deviation; mRFEI=modified retail food environment index; BMI=body mass index;

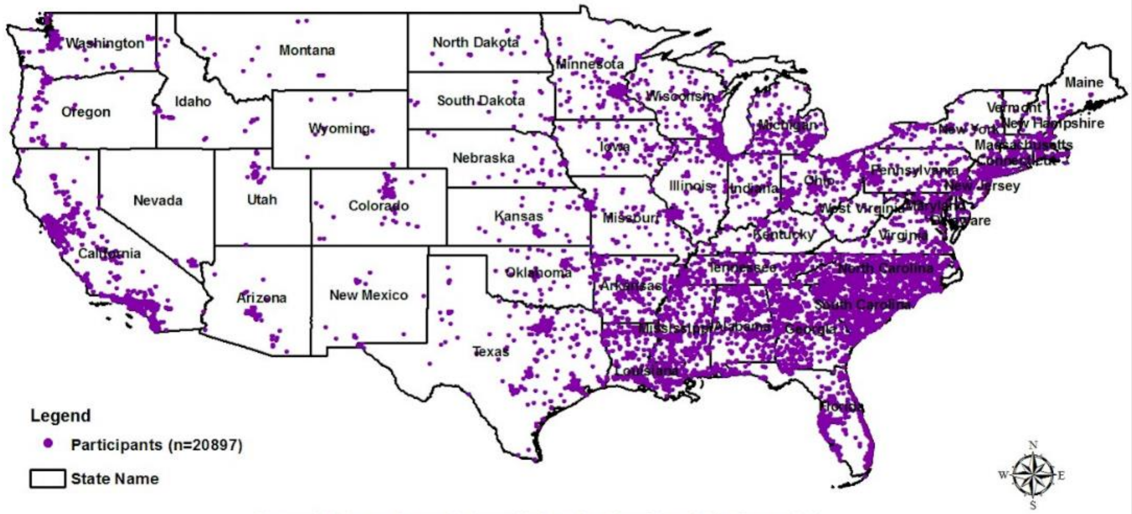
[a]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

[b]: Moderate alcohol use is defined as 0-7 drinks/week for women and 0-14 drinks/week for men; Heavy alcohol use is defined as having >7 drinks/week for women and >14 drinks/week for men.

[c]: County-level data

[d]: Census-tract-level data. Refer to Appendix for more details of RUCA code categories

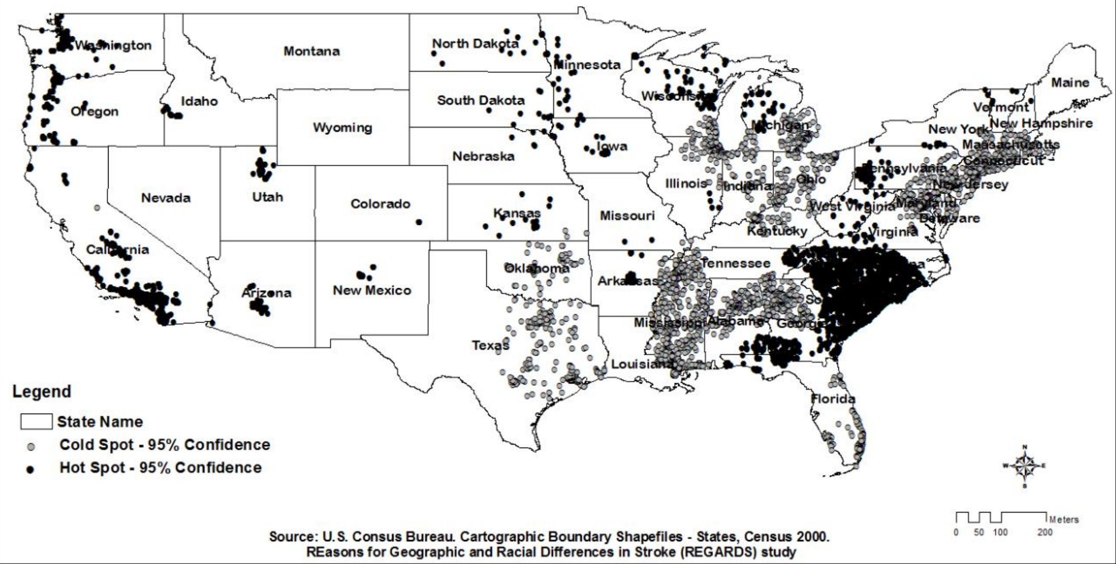
Figure 2. the REasons for Geographic And Racial Differences in Stroke (REGARDS) Study Areas and Partcipants Locations in the U.S.



Source: U.S. Census Bureau Cartographic Boundary Shapefiles - States, Census 2000.
REasons for Geographic And Racial Differences in Stroke (REGARDS) study.

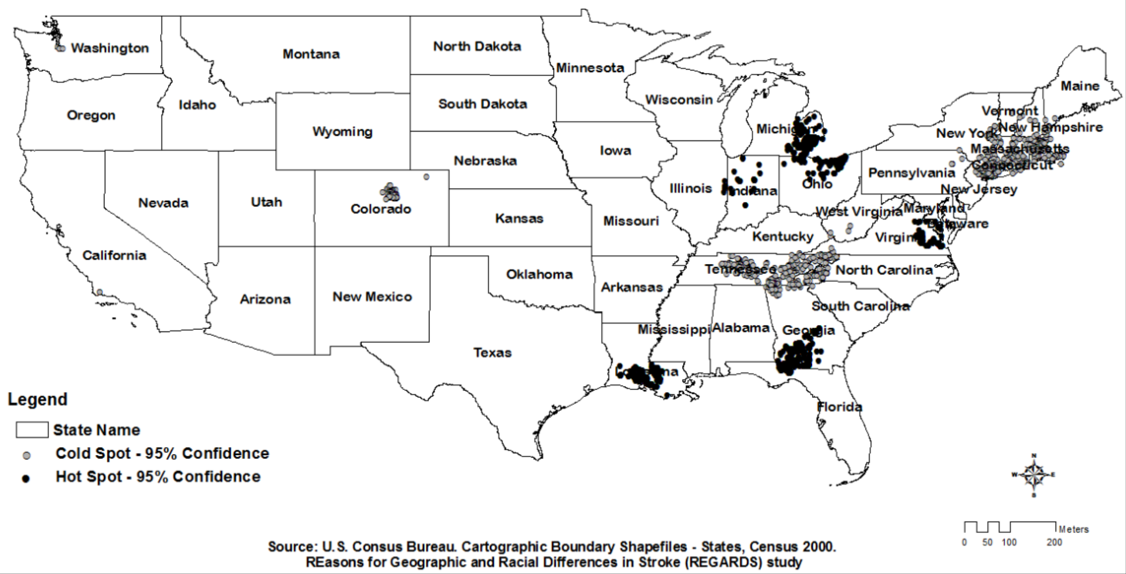
Note: The participants in this study were from 48 contiguous states and Washington, D.C., with the majority (64.42%) residing in South Carolina, North Carolina, Georgia, California, Louisiana, Alabama, Tennessee, Mississippi, and Ohio.

Figure 3. Hot Spot Analysis (Getis-Ord Gi*) for Community Food Environment (mRFEI) among the REGARDS Study Participants (n=20897)



Note: mRFEI = modified Retail Food Environment Index; REGARDS = Reasons for Geographic and Racial Differences in Stroke. Black (hot spot) indicates the clusters of participants with significantly higher mRFEI, comparing to the overall study area. Higher mRFEI clusters were primarily located in West, West North Central, East North Central, Middle Atlantic, South Atlantic, and East South Central regions of the U.S. Grey (cold spot) indicates the clusters of participants with significantly lower mRFEI, comparing to the overall study areas. Lower mRFEI clusters were primarily located in South, East North Central, and Northeast regions of the U.S. The significance of local clustering was based on a p-value < 0.05.

Figure 4. Hot Spot Analysis (Getis-Ord Gi*) for BMI among the REGARDS Study Participants (n=20897)



Note: BMI = Body Mass Index; REGARDS = Reasons for Geographic and Racial Differences in Stroke. Black (hot spot) indicates the clusters of participants with significantly higher BMI, comparing to all the participants across the study areas. Higher BMI clusters were located in, for instance, eastern area of Virginia, northern area of Ohio, eastern area of Michigan, northern area of Indiana, southwestern areas of Georgia, northwestern corner area of Florida, and southern area of Louisiana. Grey (cold spot) indicates the clusters of participants with significantly lower BMI, comparing to all the participants across the study areas. Lower BMI clusters were primarily located in northwestern area of Washington, central northern area of Colorado, central and eastern areas of Tennessee, western area of North Carolina, New Jersey, southern area of New York, Connecticut, and Massachusetts. The significance of local clustering was based on a p-value < 0.05.

Table 2. Comparing individual and community characteristics among different BMI clusters

Variables	Clusters: Lower BMI (n=1,187)	Higher BMI (n=1,630)	Non-clustering (n=18,080)	p-value
Sociodemographics				
Age, year, Mean(SD)	65.59 (8.81)	64.09 (9.01)	64.90 (9.31)	<.0001
Male, % (n)	46.08 (547)	44.66 (728)	44.06 (7,966)	0.3703
White, % (n)	74.22 (881)	51.96 (847)	67.55 (12,213)	<.0001
Education, % (n)				<.0001
Less than high school	6.57 (78)	11.72 (191)	9.59 (1,733)	
High school graduate	22.33 (265)	31.25 (509)	25.21 (4,557)	
Some college	25.44 (302)	27.56 (449)	27.42 (4,956)	
College graduate and above	45.66 (542)	29.47 (480)	37.77 (6,827)	
Relationship, % (n)				<.0001
Single	6.40 (76)	6.56 (107)	4.89 (885)	
Married	61.33 (728)	56.63 (923)	62.22 (11,250)	
Divorced	14.32 (170)	16.81 (274)	13.60 (2,458)	
Widowed	15.75 (187)	17.73 (289)	17.49 (3,162)	
Other	2.19 (26)	2.27 (37)	1.80 (325)	
Income, % (n)				<.0001
<20K	11.46 (136)	19.94 (325)	15.51 (2,805)	
20-34K	24.01 (285)	26.01 (424)	23.92 (4,325)	
35-74K	34.12 (405)	27.79 (453)	31.53 (5,701)	
≥75K	18.96 (225)	14.85 (242)	17.27 (3,123)	
Refused	11.46 (136)	11.41 (186)	11.76 (2,126)	
Employment, % (n)				0.0763
Employed for wages	24.68 (156)	30.44 (274)	26.96 (3,135)	
Self-employed	9.81 (62)	8.11 (73)	9.02 (1,049)	
Unemployed for ≥ 1 year	1.58 (10)	1.67 (15)	1.45 (169)	
Unemployed for < 1 year	1.58 (10)	1.67 (15)	1.46 (170)	
Homemaker	5.54 (35)	5.22 (47)	6.18 (718)	
Student	0.63 (4)	0.33 (3)	0.15 (18)	
Retired	51.42 (325)	45.44 (409)	47.69 (5,545)	
Unable to work	4.75 (30)	7.11 (64)	7.05 (820)	
Refused	0.00 (0)	0.00 (0)	0.03 (3)	
Health insured, % (n)	96.21 (1141)	92.51 (1506)	93.93 (16,973)	0.0002
Time in current address, year, Mean(SD)	26.30 (20.06)	32.91 (20.66)	28.40 (20.60)	<.0001
mRFEI, Mean(SD)	10.30 (9.54)	10.32 (9.73)	11.02 (10.27)	0.0027
BMI, Mean(SD)	27.91 (5.38)	29.81 (6.35)	28.96 (5.88)	<.0001
Obese, % (n)	28.98 (344)	40.98 (668)	36.21 (6,546)	<.0001
Overweight/Obese	68.41 (812)	77.30 (1,260)	74.16 (13,409)	<.0001
Life style				

Exercise, % (n)				0.0296
None	30.32 (356)	34.33 (551)	32.48 (5,794)	
1 to 3 times/week	37.73 (443)	38.26 (614)	36.73 (6,552)	
≥4 times/week	31.94 (375)	27.41 (440)	30.79 (5,492)	
Watch TV/Video, % (n)				<.0001
None	1.02 (12)	0.63 (10)	0.75 (134)	
1-6 hrs/wk	14.66 (173)	12.34 (197)	12.59 (2,246)	
1 hr/day	6.61 (78)	6.39 (102)	6.84 (1,221)	
2 hr/day	26.61 (314)	19.97 (319)	22.51 (4,015)	
3 hr/day	26.95 (318)	26.11 (417)	27.27 (4,864)	
4+ hr/day	24.15 (285)	34.56 (552)	30.04 (5,358)	
Smoking,[a] % (n)				0.0004
Never	45.23 (536)	41.06 (666)	45.60 (8,215)	
Past	40.42 (479)	42.23 (685)	41.07 (7,398)	
Current	14.35 (170)	16.71 (271)	13.33 (2,401)	
Alcohol use,[b] % (n)				0.0030
None	55.10 (654)	60.86 (992)	59.83 (10,817)	
Moderate	41.11 (488)	35.09 (572)	35.66 (6,448)	
Heavy	3.79 (45)	4.05 (66)	4.51 (815)	
Community features				
Percent of Non-Hispanic White [c], Mean(SD)	70.78 (21.23)	59.84 (15.12)	58.76 (18.87)	<.0001
Percent of Non-Hispanic Black [c], Mean(SD)	11.84 (10.06)	32.88 (15.43)	27.03 (18.51)	<.0001
Median Household income [c], $, Mean(SD)	54722.68 (14947.37)	44277.76 (9198.25)	48105.15 (11751.90)	<.0001
Poverty rate [c], Mean(SD)	13.40 (4.74)	18.22 (5.16)	15.88 (5.39)	<.0001
Tract population [d], Mean (SD)	5077.94 (2596.33)	4143.63 (1687.93)	5166.38 (2409.38)	<.0001
RUCA code[d], % (n)				<.0001
Urban	87.53 (1,039)	81.17 (1,323)	75.92 (13,727)	
Large rural	6.74 (80)	12.70 (207)	12.99 (2,348)	
Small rural	3.12 (37)	4.85 (79)	7.43 (1,343)	
Isolated small rural	2.61 (31)	1.29 (21)	3.66 (662)	

Note: SD=Standard Deviation; mRFEI=modified retail food environment index; BMI=body mass index;

[a]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

[b]: Moderate alcohol use is defined as 0-7 drinks/week for women and 0-14 drinks/week for men; Heavy alcohol use is defined as having >7 drinks/week for women and >14 drinks/week for men.

[c]: County-level data.

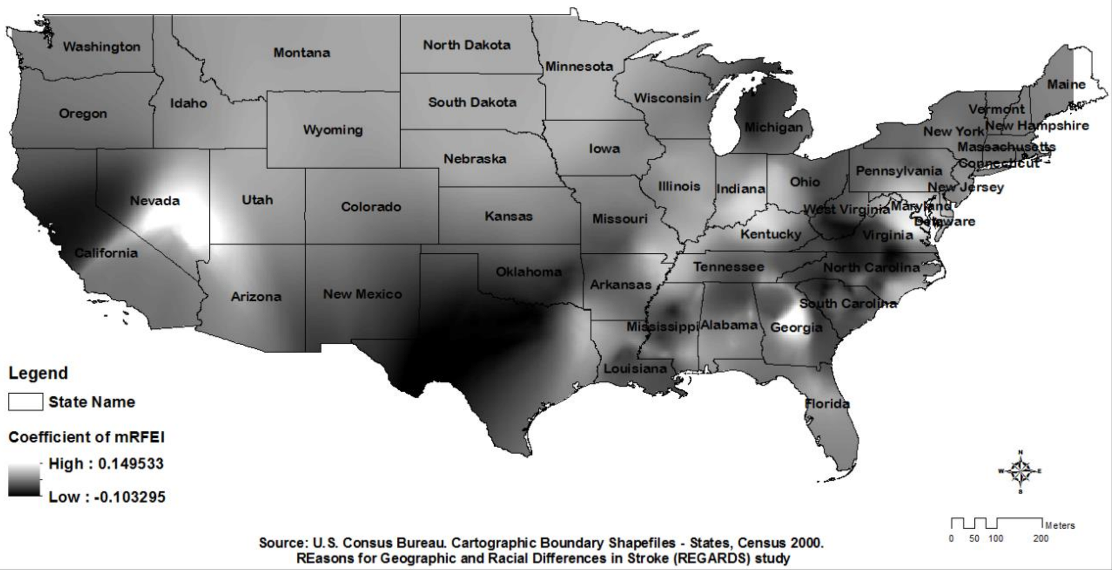
[d]: Census-tract-level data. Refer to Appendix for more details of RUCA code categories

Table 3. Summary of global OLS regression and local GWR of the relationship between mRFEI and BMI among the REGARDS study participants (n=20897)

Model	Coefficient[b]	SE	P-Value	R^2	AICc	Moran's I
OLS	-0.0210	0.0040	0.0000	0.0013	133492.56	0.0041*
GWR[a]	.	.	.	0.0156	133418.92	-0.0031

Note: OLS=Ordinary Least Squares; GWR=Geographically Weighted Regression; mRFEI=modified retail food environment index; BMI=body mass index; SE=Standardized Error; R^2: explained variation; AICc= corrected Akaike Information Criterion; *If the AICc values for two models differ by >3, the model with the lower AICc is held to be better.* Moran'I: examining the spatial autocorrelation of regression residuals to test if the model is well-specified; non-significant Moran's I indicates a well-specified model. [a]: GWR in ArcGIS did not report coefficient, standardized error, and P-value for the whole model; [b]: the coefficient of mRFEI; *p<.05

Figure 5. Spatial Variations in the Coefficient of mRFEI for the Relationship between mRFEI and BMI among the REGARDS Study Participants (n=20897)



Note: A raster surface map, based on the regression coefficient of mRFEI from the geographically weighted regression (GWR) model, presented the spatial variations of the relationship between mRFEI and BMI across the study areas. mRFEI = modified Retail Food Environment Index; BMI = Body Mass Index; REGARDS = Reasons for Geographic and Racial Differences in Stroke. Brighter color indicates there are stronger and positive relationships between mRFEI and BMI in these areas (e.g., central areas of Nevada and Georgia), while darker color indicates there are stronger and inverse relationships between mRFEI and BMI in these areas (e.g., North California, Texas).

Table 4. Stepwise logistic regressions for predictive factors for obesity (Obese OR Overweight/Obese) among the REGARDS participants [a]

Variables	OR (95% CI)	
	Obese [b]	**Overweight/obese [c]**
Age	0.97 (0.96- 0.97)*	0.97 (0.97- 0.98)*
Race/White	0.55 (0.54- 0.60)*	0.48 (0.43-0.53)*
Gender/Male	0.89 (0.82- 0.98)*	1.54 (1.40- 1.70)*
Income		
<20K	1.36 (1.16- 1.59)*	1.07 (0.90-1.27)
20-34K	1.33 (1.15- 1.53)*	1.22 (1.05-1.41)*
35-74K	1.25 (1.09- 1.43)*	1.16 (1.01- 1.34)*
≥75K	1.11 (0.95- 1.30)	1.04 (0.89- 1.22)
Refused	1 (Ref)	1 (Ref)
Education		
Less than high school	1.38 (1.17- 1.63)*	1.28 (1.06- 1.54)*
High school graduate	1.17 (1.05- 1.31)*	1.26 (1.12- 1.42)*
Some college	1.26 (1.14- 1.39)*	1.27 (1.14- 1.42)*
College graduate and above	1 (Ref)	1 (Ref)
Exercise		
None	1.74 (1.57- 1.93)*	1.62 (1.45- 1.8)*
1 to 3 times/week	1.26 (1.14- 1.39)*	1.41 (1.27- 1.56)*
≥4 times/week	1 (Ref)	1 (Ref)
Watch TV/video		
None	0.49 (0.31- 0.78)*	0.42 (0.28- 0.63)*
1-6 hrs/wk	0.57 (0.50- 0.65)*	0.55 (0.48- 0.63)*
1 hr/day	0.50 (0.42- 0.60)*	0.56 (0.47- 0.67)*
2 hr/day	0.67 (0.59- 0.75)*	0.79 (0.70- 0.89)*
3 hr/day	0.89 (0.80- 0.98)*	1.03 (0.91- 1.16)
≥ 4 hr/day	1 (Ref)	1 (Ref)
Smoking [d]		
Never	1.86 (1.63- 2.11)*	2.02 (1.78- 2.31)*
Past	2.07 (1.82- 2.36)*	2.51 (2.20- 2.88)*
Current	1 (Ref)	1 (Ref)
Alcohol use [e]		
None	2.04 (1.63- 2.57)*	1.65 (1.35- 2.02)*
Moderate	1.57 (1.25- 1.98)*	1.38 (1.13- 1.69)*
Heavy	1 (Ref)	1 (Ref)

Note: OR=odds ratio; CI=confident interval;

[a]: table only included significant variables in the final model;

[b]: Obese is defined as BMI≥ 30kg/m^2;

[c]: Overweight/Obese is defined as BMI≥ 25 kg.m^2;

[d]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

[e]: Moderate alcohol use is defined as 0-7 drinks/week for women and 0-14 drinks/week for men; Heavy alcohol use is defined as having >7 drinks/week for women and >14 drinks/week for men.
*P<.05

ASSOCIATION OF COMMUNITY FOOD ENVIRONMENT AND ADHERENCE TO A MEDITERRANEAN DIET AMONG U.S. ADULTS

by

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Format adapted for dissertation

ABSTRACT

Background: Emerging evidence has suggested the health benefits of Mediterranean diet (MD) against obesity. It is hypothesized that the food environment can exert significant influence on individuals' dietary intakes and behaviors. However, given MD as a relatively new dietary pattern in the U.S., it remains unclear how the unique U.S. food environment influences the adoption of a MD among the population. The aims of this present paper is to describe the spatial distribution of adherence to a MD, examine the relation between community food environment and adherence to a MD, as well as explore predictive factors for adherence to a MD among the U.S. adult population.

Methods: Data from adults aged ≥ 45 years who participated in the REasons for Geographic and Racial Differences in Stroke (REGARDS) study and completed baseline assessment during January 2003 and October 2007 were used for the analysis. Modified retail food environment index (mRFEI) was used as community food environment indicator. Hot Spot analysis was used to describe the spatial pattern of MD adherence. The relationship between community food environment and obesity was examined using Ordinary Least Squares (OLS) regression and geographically weighted regression (GWR). Stepwise logistic regression was used to explore predictors of high MD adherence.

Results: Clusters of higher MD adherence were more likely to be in more socioeconomically advantaged, urban neighborhoods with lower percentages of both non-Hispanic white and black residents, whereas lower MD adherence clusters were more likely to appear in socioeconomically disadvantaged, rural, minority neighborhoods with smaller population sizes. There was no significant relationship between access to healthy

food outlets and MD adherence found. Being older, black, not a current smoker, having a college degree and above, and annual household income ≥ $75K, exercising ≥ 4 times/week, and watching TV/video < 4 hrs/day were each associated with higher odds of high MD adherence.

Conclusion: This study found there was no strong relationship between community food environment and MD adherence among the U.S. adult population. However, the significant improvement in local regression model emphasized the importance of accounting for spatial non-stationarity of the relationship in future investigations on this topic. The identification of higher/lower MD adherence clustering and predictors of MD adherence provide information for future MD promoting interventions and policies to target at-risk populations and places.

INTRODUCTION

Traditional Mediterranean diet (MD) is a dietary pattern typical of Crete, Greece, and Southern Italy in the early 1960s, whose potential health benefits was first described by Keys et al in the Seven Country study.[1] Since then, increasing research evidence from different countries and populations has indicated that eating a MD reduces disease risks (e.g., cardiovascular disease, dementia, and certain cancers), and perhaps, promotes long-term health.[2]

Given the obesity epidemic in the U.S., and the well-established health benefits of MD from European countries, there has been increasing research exploring the potential protective role of eating a traditional MD against obesity and its associated co-morbidities among the U.S. population.[3] As the author's systematic review of 28 studies that examined the association between adherence to a MD and overweight/obesity among U.S. cohorts, the overall findings from previous studies indicate the promising potential of eating a MD as a protective dietary approach to prevent and treat overweight/obesity among U.S. adults.[4-32]

Meanwhile, the obesity crisis in the U.S. also triggered a burst of policy interest and interventions to improve the diet quality in an effort to reduce or prevent obesity. One of the major efforts has been improving the built food environment.[33] It is hypothesized that people's dietary quality and intake can be improved by improving access to healthful food outlets (e.g., supermarkets and large grocery stores) and reducing exposure to unhealthful food outlets (e.g., fast food restaurants and convenience stores). The overall body of research among the U.S. cohorts, as reviewed by Larson et al. and Giskes et al., supports the hypothesis that access to healthful food options positively associates with the consumption of healthier foods.[34-37] For instance, studies found that people having better access to supermarkets and large chain grocery stores and limited access to convenience stores tended to have healthier dietary intake (e.g. more fruit and vegetable intake).[37-42] However, results from studies that examine the association of access to various types of restaurants and dietary intake are inconsistent. Greater access to fast-food restaurants, in general, tends to be associated with less healthful diet intake; however, access to full service restaurants shows either no relationship or positive relationship with healthy dietary intake.[38,43,44] Furthermore, studies also indicate that residents' dietary intakes in the rural, low-income, and minority neighborhoods are more likely to be affected by limited access to supermarket, chain grocery stores and healthful food products.[38] For instance, a national study found that the presence of each additional supermarket was related to increase in meeting guidelines for fruit and vegetable intake of 32% for blacks and 11% for whites.[45]

One of the limitations of previous studies is that the majority used specific foods/food groups (i.e. fruit and vegetable intake, fast food consumption), specific nutrients, and/or overall diet quality indices as dietary intake indicators.[38,46] Although the Academy of Nutrition and Dietetics has recommended that the overall pattern of food that a person eats is more important than focusing on single foods or individual nutrients, few studies have examined the relations between community food access and specific dietary patterns.[47]

Moreover, despite the fact that the U.S. Department of Agriculture recommended MD as a healthy dietary pattern in its 2015-2020 edition of the *Dietary Guidelines for Americans*, only one study, to the author's knowledge, has examined how community food access related to consumption of MD among the U.S. population. Hardin-Fanning‘s study conducted among 43 female rural Appalachian residents reported that limited access to healthy foods was a barrier to adopting and adhering to an MD, especially among those women who had limited incomes and lived in remote areas.[48] More and larger-scale studies are needed to explore the influence of food environment on the practice of eating a MD.

The present study uses geospatial mapping and modeling as well as logistic regression to describe the spatial distribution of adherence to a MD, examine the relationship between community food environment and MD adherence, as well as investigate predictive factors for MD adherence among U.S. adults. It is hypothesized that greater access to healthful food outlets in the community significantly associates with higher MD adherence, and the magnitudes and direction of this relationship vary across the U.S. The results may extend our understanding of how the community food environment influences the consumption of MD, and provide information to for future MD promoting programs/policies.

METHODS

Data Source and Study Participants

Data of individuals from the REasons for Geographic And Racial Differences in Stroke (REGARDS) study were used in this study. REGARDS is a national population-based longitudinal cohort study of 30,183 non-Hispanic black and white community-dwelling residents aged 45 years and older to investigate racial and geographic disparities in stroke.[49] Individuals were recruited from commercially available nationwide list of residents purchased through Genesys Inc. using a combination of mail and telephone contact during 2003-2007. After the baseline assessment, participants are followed via telephone at 6-month intervals. Participants' residency address was geocoded using SAS/GIS batch geocoding. Additional methodological details have been published previously.[49,50] In this study, baseline cross-sectional data collected during January 2003 and October 2007 were used. The same inclusion/exclusion criteria as described in previous publication were used in this study, leaving a total of 20,897 individuals in the analysis (refer to **Figure 1** in paper "Association of Community Food Environment and Obesity among U.S. Adults" for more details).

The publicly available community food environment data were retrieved from the Children's Food Environment State Indicator Report (2011) developed by the Division of Nutrition, Physical Activity and Obesity of the Centers for Disease Control and Prevention (CDC) (http://www.cdc.gov/obesity/downloads/2_16_mrfei_data_table.xls).[51] Community sociodemographic feature data were drawn from the Food Environment Atlas (2011) developed by the U.S. Department of Agriculture Economic Research Service (https://www.ers.usda.gov/data-products/food-environment-atlas/data-access-and-documentation-downloads/), as well as from Census of Population and Housing (2000), available from U.S. Census Bureau website (https://www.census.gov/prod/www/decennial.html). The publicly available census cartographic boundary shapefiles (2000) for GIS mapping were also downloaded from the U.S. Census Bureaus' geography website (https://www.census.gov/geo/maps-data/data/tiger-cart-boundary.html).

Data retrieved from these sources were linked and pooled by using variables in common (e.g. the Federal Information Processing Standard (FIPS), and participants' IDs). Permission and approval was obtained from the REGARDS study executive committee and UAB's Institutional Review Board, respectively, to conduct this cross-sectional study.

Variables

Community food environment: Modified Retail Food Environment Index (mRFEI), developed by CDC the Division of Nutrition, Physical Activity and Obesity, was used as community food environment indicator.[52] The mRFEI represented the percentage of food retailers that were designated 'healthy' out of the total number of food retailers considered 'healthy' or 'less healthy' in a census tract. The mRFEI value ranges from 0 to 100, with higher mRFEI scores indicating greater access to healthy food retailers in a census tract.[51] Healthy food retailers include supermarkets, larger grocery stores, supercenters, and produce stores within census tracts or ½ mile from the tract boundary. All data on supermarkets, supercenters, and produce stores were obtained from the InfoUSA business database, 2009. Less healthy food retailers include fast food restaurants, small grocery stores, and convenience stores within census tracts or ½ mile from the tract boundary. Convenience store data were obtained from the Homeland Security Information program database, 2008. Small grocery store data were obtained from the InfoUSA business database, 2009; and fast food restaurant data were obtained from the NavTeq database, 2009.[51]

Mediterranean Diet adherence: The MD score drawn from the REGARDS study was used to indicate the dietary pattern adherence. The food intake data were collected using the self-administered Block 98 Food Frequency Questionnaire (FFQ) at REGARDS study baseline assessment. The full-length of Block 98 FFQ, including 110 food items, was developed by National Cancer Institute under the direction of Gladys Block.[53,54] The measure was validated in multi-cultural populations.[55,56] The calculation of MD score was followed Trichopoulou et al.'s method.[57] The intake of each nine food category (dairy, meat, fruit, vegetables, legumes, cereals, fish, fat, and alcohol) was computed, and a value of 0 or 1 was assigned to each of nine food components with the use of sex-specific medians as the cutoffs. For beneficial components (fruit, vegetables, legumes, cereals, and fish), persons whose consumption was below the median were assigned a value of 0, and persons whose consumption was at or above the median was assigned a value of 1. For meat, fat, and dairy consumption, a value of 1 was assigned to persons whose intake was less than the median. Regarding alcohol consumption, persons with moderate alcohol intake were assigned a value of 1, otherwise a value of 0 was assigned. Then, the MD adherence score scale was generated by summing up the scores of the nine food categories. The scale ranged from 0 to 9, with a higher score indicating a higher adherence to MD.[57] The MD adherence score was treated as both continuous and binary variables in the analysis. The binary score was created by assigning a value of 0 or 1 to each participant to indicate low or high MD adherence with the use of median 4 among the participants in analysis as the cutoff. Participants with MD score ≤ 4 were considered to have low MD adherence, and participants with MD score >4 were considered to have high MD adherence.

Covariates

Sociodemographics: The following variables were included: age (years; continuous), gender (male vs. female), race (non-Hispanic white vs. non-Hispanic black), health insurance (yes vs. no), marital status (single, married, divorced, widowed, or other), education (less than high school, high school graduate, some college, or college graduate and above), annual household income (<20K, 20-34K, 35-74K, ≥75K, or refused), employment (employment for wage, self-employed, unemployed for ≥ 1 year, unemployed for < 1 year, home maker, students, retired, unable to work, or refused), and time lived in current address (years; continuous).

Lifestyle: These factors included exercise (none, 1-3times/week, or ≥ 4 times/week), TV/video watching (none, 1-6 hrs/week, 1 hr/day, 2 hrs/day, 3 hrs/day, or ≥ 4 hrs/day), and smoking (none, past, or current). To measure smoking status, the participants were asked two questions. (1) Had they smoked at least 100 cigarettes in their lifetime, and (2) did they smoked cigarettes now, even occasionally? Participants who answered 'yes' to both questions were considered as 'current smokers', while those answering 'yes' to the first question and 'no' to the second question were coded as 'former smokers', and those answering 'no' to both were classified as 'never smokers'.

Community features: Six factors were included: (1) percent of county residents that was non-Hispanic white (2008), (2) percent of county residents that was non-Hispanic black (2008), (3) county median household income (2008), (4) county poverty rate - percent of county residents with household incomes below the poverty threshold (2008), (5) census-tract population size (2000), and (6) Rural-Urban Commuting Area Code (RUCA)(2000). RUCA code was used to indicate rural/urban resident status of the participants, which contains two levels.[58] Whole numbers (1-10) delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows. These 10 codes are further subdivided based on secondary commuting flows, providing flexibility in combining levels to meet varying definitional needs and preferences.[58] In the analysis, RUCA codes were categorized and coded as 1=urban, 2=large rural city/town, 3=small rural town, and 4=isolated small rural town, according to Categorization A by the University of Washington Rural Health Research Center.[59] (see **Appendix** for more details).

Data Analysis

Statistical analysis: The statistical analysis was implemented using SAS version 9.4 for Windows (SAS Institute, Inc, Cary, NC). Descriptive analyses of sociodemographic and lifestyle characteristics of the participants and community features were conducted using PROC UNIVARIATE and PROC FREQ procedures. Means and standard deviations (for continuous variables) and percentages (for categorical variables) were calculated. The characteristic differences were compared among the MD score clustering groups (higher MD score clusters, lower MD score clusters, and non-clustering group) using PROC

ANOVA, PROC NPAR1WAY, and PROC FREQ procedures as appropriate. Multiple logistic regression (stepwise) models were developed to examine factors that predict MD adherence among the study participants. A significance level of 0.3 was required to allow a variable into the model, and a significance level of 0.35 was required for a variable to stay in the model.[60] Odds ratios (ORs) and 95% confidence interval (CI) were used to estimate associations with MD adherence. The statistical significance, alpha, level was set at 0.05, two-tailed. Missing data were handled using listwise deletion.

GIS spatial analysis: The spatial mapping and modeling were implemented using ArcGIS 10.4 (ESRI Inc., Redlands, CA). The census cartographic boundary shapefiles and data of interest were imported and integrated in ArcMap to create digital map layers and prepare for analysis. First, Hot Spot anlaysis (Getis-Ord Gi*) was conducted to identify the spatial clusters of high values (hot spots) and low values (cold spots) of MD score across the study areas. Inverse distance was used as conceptualization of spatial relationship, and EUCLUDEAN_DISTANCE was chosen for distance method. False Discovery Rate (FDR) Correction was applied to account for both multiple testing and spatial dependence. Significance of local clustering was based on a p-value < 0.05.

Second, ordinary least squares (OLS) linear regression with spatial diagnostics (Moran's I) was conducted to examine the global correlations between mRFEI and MD score. Coefficient, standard errors, p-value, and R^2 were reported. The performance of the model was evaluated by corrected Akaike Information Criterion (AICc) and spatial autocorrelation on regression residual. Spatial autocorrelation test, Moran's I, examined spatial randomness of the regression standard residual. The inverse of the distance was applied as conceptualization of spatial relationship. EUCLUDEAN_DISTANCE was chosen for distance method. Significance of the spatial autocorrelation was based on a p-value < 0.05. A non-significant Moran's I indicated that the model performed well.

Third, local geographically weighted regression (GWR) was conducted in order to account for the possible spatial nonstationarity of the relation between mRFEI and MD scores across the study areas. An adaptive kernel type with AICc estimated bandwidth was used to calibrate the model in order to account for spatial structure. The performance of the model was evaluated by R^2, AICc and Moran's I. R^2 is a measure of goodness of fit. Its value varies from 0.0 to 1.0, with higher values being preferable. The AICc was used to evaluate the model performance and compare difference regression models. If the AICc of the GWR model is more than 3 lower than that of the OLS model, it signifies the benefits of moving from a global model (OLS) to a local regression model (GWR). Spatial autocorrelation test (Moran's I) was conducted to examine spatial randomness of the regression standard residual, and a non- significant Moran's I indicated the model was properly specified. A raster surface, based on the regression coefficient of mRFEI from the GWR model, was created to display the regional variation of the relationship between mRFEI and MD score across the study areas.

RESULTS

Descriptive Analysis

The major characteristics of the participants and their community are described in **Table 1**. A total of 20,897 participants from REGARDS study were in the analysis. Overall, the average age of the participants was 65 years old. About half of the participants were retired and having income ≥ $35K. Slightly more than half were female. Almost two-thirds of the participants were white, married, and had a high school diploma. Nearly all of the percipients had health insurance. The participants lived a relatively healthy lifestyle, majority of whom were non-current smokers (86%), exercised ≥ 1 time/week (67%), and watched TV/Video < 4 hour/day (70%). About four-fifths of the participants (77%) were residing in urban areas, with an average of 29 years living at their current address. On average, the participants were living in neighborhoods with 60% non-Hispanic white, 27% non-Hispanic black residents, median household income of $48,182, poverty rate of 16%, tract population of 5,082, and mRFEI of 10.92. The participants were from 11,071 census tracts throughout 48 contiguous states and Washington, D.C., with the majority from the South region (refer to **Figure 2** in paper "Association of Community Food Environment and Obesity among U.S. Adults" and **Appendix** for more details). Of the sample, the mean Mediterranean Diet score was 4.36 (SD=1.70), and 46.5% had high MD adherence.

Hot Spot Analysis

The result of local clustering analysis of MD adherence is depicted in **Figure 1**. The clusters of participants with higher MD score are displayed in black, and the clusters of participants with lower MD score are represented in grey. Overall, higher MD score clusters were primarily located in, for instance, western coastal areas of Californian (e.g. San Francisco and Los Angeles areas), southeastern areas of Tennessee, northern area of Georgia, southern areas of Florida, and southern areas of Northeast region of the country (e.g. Pennsylvania, New Jersey, New York City, Connecticut, and Massachusetts). Lower MD score clusters were primarily observed in South (e.g. Arkansas, Louisiana, northern area of Mississippi, north central area of Alabama, west area of Tennessee, southwestern area of Georgia, and eastern area of North Carolina), and East North Central (e.g. southern area of Michigan and northern area of Indiana) regions of the country. The higher MD score clusters had significantly higher MD score than that in the lower MD score clusters (4.73 vs. 4.18; $p<.0001$). Moreover, higher MD clusters were more likely to appear in urban neighborhoods with a higher median household income, a lower poverty rate, a lower mRFEI, and lower percentages of both non-Hispanic white and black residents. Lower MD clusters were more likely to be in rural communities with a higher percentage of non-Hispanic black, a lower median household income, a higher poverty rate, and a smaller population size (**Table 2**).

Further comparing participant characteristics among the different MD score clusters, it showed that participants in the higher MD clusters were more likely to be older age, black, not married, retired, health insured, and not a current smoker, have a college degree and above, an annual household income of ≥ $35K, exercise ≥ 1 time/week, and watch TV/video < 4 hrs/day. Oppositely, participants in the lower MD clusters were more likely to be younger age, not retired, not health insured, a current smoker, not have a college degree, have an annual household income of < $35K, reside more years in their current dwelling, exercise < 4 time/week, and watch TV/video ≥ 4 hrs/day (**Table 2**).

Global and Local Regression Analysis

The results of global and local regressions of the relationship between mRFEI and MD score among the REGARDS participants were displayed in **Table 3**. The global OLS regression showed that there was an inverse relationship between mRFEI and MD score; however, the relationship was not significant. Local GWR was conducted to examine the variation of the magnitude and direction of the relationship across the study areas. Compared with global regression model, local GWR modeling was associated with a lower AICc (almost 240 points less), which indicated a significant improvement in model performance. However, the significant result of Moran's I test examining the spatial autocorrelation on regression residuals indicated the GWR model was not well specified; that is, mRFEI did not well predict MD adherence across the study area. The variation of the magnitude and direction of the relationship between mRFEI and MD score across the study area is depicted in **Figure 2**. Brighter areas indicate stronger, positive relationship between mRFEI and MD score, whereas darker areas indicate stronger, inverse relationship between the two. Specifically, greater access to healthful food outlets was strongly related to higher MD score in, for instance, Utah, western area of Texas, eastern area of Oklahoma, southern areas of Wisconsin, northern area of Illinois, and north central area of North Carolina (bright area). Greater access to healthful food outlets was related to lower MD score in, for example, central area of Nevada, central and northwestern areas of Arizona, southern area of Illinois, merging areas of Nebraska, Iowa, Kansas and Missouri, north central area of Ohio, northern area of Mississippi, northeastern area of South Carolina, and southern area of Florida (darker areas).

Logistic Regression

Stepwise logistic regression was conducted to identify the predictors for MD adherence. The variables that remained in the final model after the stepwise method are presented in **Table 4**. Being older, black, not a current smoker, having a college degree and above, an annual household income of ≥ $75K, exercising ≥ 4 times/week, and watching TV/video < 4 hrs/day were each associated with higher odds of high MD adherence.

DISCUSSION

The overall aim of this study was to better understand the distribution of the Mediterranean dietary pattern consumption across the U.S., and how our current unique food environment relates to the MD adherence among the U.S. adult population. To accomplish this aim, using data from the REGARDS study and government surveillance sources, spatial mapping and modeling techniques were applied to describe the spatial distribution of MD adherence, and examine the relationship between community food environment and MD adherence. Moreover, a stepwise logistic regression method was used to identify predictive factors for MD adherence, in turn, to inform future policy and interventions to promote MD adherence among U.S. adults.

The mean MD score among this study population was 4.36 (SD=1.70), with 46.5% considered as high MD adherence (scored 5-9 on a scale of 0-9). MD adherence among the participants in this study is similar as the adherence conditions reported from previous studies. A study conducted among a sample of adults, aged 45–75 years, living in the Greater Boston area reported a mean MD score of 4.37 (SD=1.61).[61] Another study using data from elder participants (≥65 years) residing in northern Manhattan reported 45.1% of the participants had high MD adherence (scored 5-9).[62]

The results of local clustering analysis of MD adherence showed that clusters of participants with higher MD score was more likely to be located in more socioeconomically advantaged, urban neighborhoods with lower percentages of both non-Hispanic white and black residents (e.g. northeast and southwest coastal areas of the U.S.), whereas lower MD adherence clusters were more likely to appear in socioeconomically disadvantaged areas with a higher percentage of black residents and a smaller population size (e.g. South and East North Central regions). No study to date, to the author's knowledge, has reported the community sociodemographic features that relate to MD adherence among the U.S. population. Observations in European countries, especially Mediterranean countries, however, show contrary conditions; that is, as incomes and urbanization in the neighborhood increase, adherence to a MD tends to wane among the population as dietary pattern shifts towards consumption higher in animal products and energy density.[63] For instance, research evidence from these countries has found that residents living in urban areas were more likely to have lower adherence to a MD.[64-66] Replication among the U.S. populations is required to confirm the findings from this study.

The results of comparing individual features among the different clustering groups illustrated that participants residing in the higher MD score clusters had certain characteristics that significantly differed from those in the lower MD score clusters or non-clustering areas. Logistic regression to identify the predictive factors for high MD adherence further confirmed these findings. Being older, black, not current smoker, having higher education and income, and living a more active lifestyle were associated with higher odds of high MD adherence. These results generally align with findings from previous studies among the U.S. populations.[12,16,67] However, this study found that being black was related to higher MD adherence, while Koyama et al study reported that being white was more likely to be higher MD adherence.[12] Further examination found that compared to white participants, black participants in this study were more likely to be younger (63.6563 vs. 65.4862, $p<.0001$), women (65.9% vs. 50.7%, $p<.0001$), not married (45.5% vs. 69.8%, $p<.0001$), and living in urban communities (86.3% vs. 72.4%, p<.0001). Future studies exmining how race influences the MD adherence among the U.S. population are needed to examine the consistency of the findings from this study.

The global regression did not find strong evidence to support the hypothesis that greater access to healthy food outlets was related to higher MD adherence. There are several potential explanations for this non-significant finding. One may be that the participants in this study are mid- and older- age population whose food preference are likely to be well established, so that their food choices and consumption are less likely to be affected by the food environment. Future studies examining the relationship among different age populations are needed to test this hypothesis. Second, mRFEI may not accurately represent individuals' food environment experience. When generating mRFEI, the classification of retail food outlets were based on typical food offerings in the types of retailers, which may not represent the foods actually offered in each store. In fact, the same type of food stores can offer very different types of foods. For instance, one convenience store located in a minority and low-income community is more likely to provide unhealthy foods, while another convenience store located in a contrast area that is low poverty and predominantly white is more likely to sell fresh produce.[68] However, these two stores can be both simply categorized as unhealthy stores in mRFEI calculation. Future studies using different community food environment measures are needed.

Local GWR examining the relationship between community food environment and MD adherence showed a significant improvement in model performance compared to the global model. The result of local regression also provided a potential explanation for the non-significant finding from the global regression; that is, the local positive and negative relations may balance each other out, and neutralize the overall effect of food environment on MD adherence across the study areas. However, the significant result of the Moran's I examining the spatial autocorrelation on the GWR regression residual indicated that the local model was still not well-specified; in another word, the model still missed at least one key predictor of MD score. Future studies investigating local individual and contextual characteristics that relate to MD adherence and its geographical disparity are needed.

This study has several strengths. First, to the author's knowledge, this is the first study describes the spatial distribution pattern of MD adherence, and examine the relationship between community food environment and MD adherence among U.S. adults at national level. The recognition of concentrated higher and lower MD adherence regions provides an opportunity to explore the nature of MD adherence pattern, and extend our knowledge of the geographical disparity of MD adherence in the U.S. Moreover, the use of GIS techniques, especially local geographically weighted regression, allows the study to account for spatial non-stationarity and spatial heterogeneity in the analysis. The methods used here could be employed as diagnostics for future studies on this topic to examine local effects. Second, the use of composite measures of community food environment (e.g. mRFEI) rather than counts of various retail food outlets offers several advantages, including data reduction, capturing the complexity of the food environment, and allowing comparison across studies. Third, the analysis used a geographically diverse and large sample size of more than 20,000 from REGARDS study, enabling the ability to yield precise estimates.

There are some limitations in this study. First, mRFEI may not accurately capture the individual's true food environment experience, which may introduce bias to the study. Besides the classification issue mentioned above, the mRFEI was developed using secondary data from private companies.[51] Previous studies that validate commonly used secondary retail food outlets data indicated concerns regarding the accuracy of such data sources. For instance, a study comparing retail food outlets data from Dun & Bradstreet, Inc. and InfoUSA, Inc. and the South Carolina Department of Health and Environmental Control to field census food outlets in eight countries in South Carolina reported that field census identified about 26% more outlets than the three secondary data sources, the sensitivities were fair to moderate (55% - 68%), the positive predictive values (PPV) were moderate (78% -89%), and the geospatial accuracy was moderate with over 80% of outlets geocoded to the correct US census tract.[69] Another study conducted in Bronx, NY reported even worse conditions as sensitivity was only 39% and the PPV was 46% when comparing business names.[70] Moreover, the mRFEI did not include the consideration of food shopping habits (e.g., transportation, car ownership, grocery shopping on the way home from work) in the index calculation. For example, the mRFEI was a measurement indicating the access to healthy food outlets in a given census tract. According to findings from the USDA's National Household Food Acquisition and Purchase Survey, the average household primarily shops for groceries at a store 3.79 miles from home.[71] Therefore, food outlets far away from the individual's residence, even in the same census tract, may not affect their daily grocery shopping experience, especially for those who do not have car or access to public transportation.

Second, the MD score was calculated based on self-reported dietary intake data, which could introduce potential bias into the study. For instance, participants might misreport their dietary intake due to the inaccurate recalls, or a tendency towards social desirability resulting in individuals over-reporting healthy food intake, and underreporting unhealthy food intake. Moreover, the dietary intake data was only assessed once at baseline. Therefore, the stability of the dietary pattern among the participants is unknown. However, findings from Scarmeas et al longitudinal study among a similar older adult cohort in northern Manhattan showed that MD dietary pattern adherence was stable during a 7-8 year follow-up, supporting the relative stability of diet patterns among elder populations.[72] Third, caution is required when interpreting and generalizing the findings, due to the sampling of the parent study. The majority of the participants were residing in urban areas and the southern region of the country, so findings of this study may not well estimate the experience among residents in rural areas or other regions of the country. The participants in this study represent only two racial groups (non-Hispanic white and black) and mid- to old- age populations, so the findings might not represent the experience of younger generations and other racial groups.

CONCLUSION

In sum, this study found no evidence that community food environment exposure was related to MD adherence among the U.S. adult population. However, the significant improvement provided by the local regression model emphasizes the importance of accounting for spatial nonstationarity of the relation in future studies on this topic. Moreover, future investigations may use different community food environment indicators that better capture individuals' food environment experiences to examine the relationship. The results of the spatial pattern analysis and the identification of predictive factors for MD adherence can provide valuable information for future interventions and policies to identify at-risk populations and places. Future studies may examine other local individual and contextual factors, such as food-related culture, zoning policy, and public transportation, which could uncover useful information to better understand the geospatial cluttering of MD adherence, and help develop more geographically and population tailored interventions and policies.

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FIGURES AND TABLES

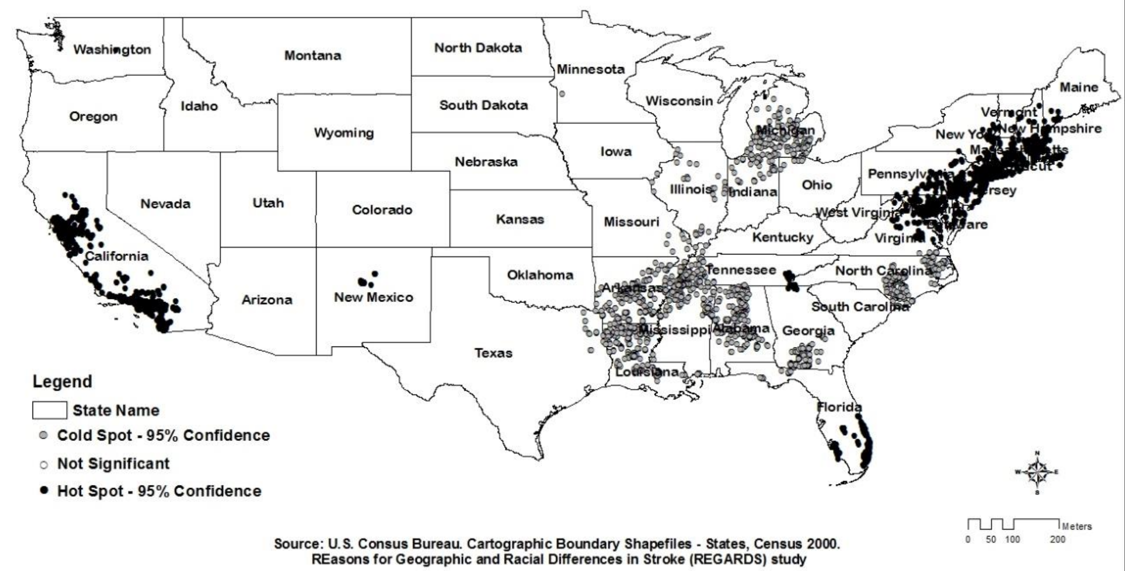
Table 1. Summary of individual and community characteristics of the REasons for Geographic and Racial Differences in Stroke (REGARDS) study participants (n=20897)

Characteristics	**REGARDS participants**
Sociodemographics	
Age, year, Mean(SD)	64.88 (9.26)
Male, % (n)	44.22 (n=9241)
White, % (n)	66.71 (n=13941)
Education, % (n)	
Less than high school	9.58 (2002)
High school graduate	25.52 (5331)
Some college	27.32 (5707)
College graduate and above	37.57 (7849)
Relationship, % (n)	
Single	5.11 (1068)
Married	61.74 (12901)
Divorced	13.89 (2902)
Widowed	17.41 (3638)
Other	1.86 (388)
Income, % (n)	
<20K	15.63 (3266)
20-34K	24.09 (5034)
35-74K	31.39 (6559)
>75K	17.18 (3590)
refused	11.71 (2448)
Employment, % (n)	
Employed for wages	27.09 (3565)
Self-employed	9.00 (1184)
Unemployed for ≥ 1 year	1.47 (194)
Unemployed for < 1 year	1.48 (195)
Homemaker	6.08 (800)
Student	.19 (25)
Retired	47.72 (6279)
Unable to work	6.95 (914)
Refused	.02 (3)
Health insured, % (n)	93.95 (19620)
Time lived in current address, year, Mean(SD)	28.63 (20.62)
mRFEI, Mean(SD)	10.92 (10.19)
Mean MD score, Mean(SD)	4.36 (1.70)
High MD adherence [a], % (n)	46.53 (9723)
Life style	
Exercise, % (n)	
None	32.50 (6701)
1 to 3 times/week	36.91 (7609)

≥4 times/week	30.59 (6307)
Watch TV/Video, % (n)	
None	.76 (156)
1-6 hrs/wk	12.69 (2616)
1 hr/day	6.80 (1401)
2 hr/day	22.55 (4648)
3 hr/day	27.16 (5599)
≥ 4 hr/day	30.05 (6195)
Smoking [b], % (n)	
Never	45.23 (9417)
Past	41.12 (8562)
Current	13.65 (2842)
Community features	
Percentage of Non-Hispanic White [c], Mean(SD)	59.53 (18.95)
Percentage of Non-Hispanic Black [c], Mean(SD)	26.62 (18.34)
Median Household income [c], $, Mean(SD)	48182.49 (11932.72)
Poverty rate [c], Mean(SD)	15.92 (5.41)
Tract population [d], Mean (SD)	5081.58 (2387.90)
RUCA code [d], % (n)	
Urban	76.99 (16089)
Large rural	12.61 (2635)
Small rural	6.98 (1459)
Isolated small rural	3.42 (714)

Note: SD=Standard Deviation;
[a]: using sex-specific medians 4s as cutoffs, high MD adherence is defined as MD score > 4 on a scale of 0 - 9.
[b]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.
[c]: County-level data;
[d]: Refer to Appendix for more details of RUCA code categories

Figure 1. Hot Spot Analysis (Getis-Ord Gi*) for Mediterranean Diet (MD) Score among the REGARDS Study Participants (n=20897)



Note: REGARDS = Reasons for Geographic and Racial Differences in Stroke. Black (hot spot) indicates the clusters of participants with significantly higher Mediterranean diet (MD) score, comparing to the overall study areas. Higher MD score clusters were primarily located in, for instance, western and northeastern coastal areas of the U.S. (e.g., Californian, Pennsylvania, New Jersey, New York City, Connecticut, and Massachusetts). Grey (cold spot) indicates the clusters of participants with significantly lower MD score, comparing to the overall study areas. Lower MD score clusters were primarily observed in South and East North Central regions of the U.S. (e.g., Arkansas, Louisiana, Alabama, Georgia, North Carolina, Michigan and northern area of Indiana). The significance of local clustering was based on a p-value < 0.05.

Table 2. Comparing individual and community characteristics among different Mediterranean Diet (MD) score clusters

Variables	Clusters			p-value
	Lower MD (n=3,339)	**Higher MD (n=3,444)**	**Non-clustering (n=14,114)**	
Sociodemographics				
Age, year, Mean(SD)	64.35 (9.17)	65.77 (9.58)	64.78 (9.19)	<.0001
Male, % (n)	43.28 (1,445)	44.28 (1,525)	44.43 (6,271)	0.4807
White, % (n)	65.38 (2,183)	58.59 (2,018)	69.01 (9,740)	<.0001
Education, % (n)				<.0001
Less than high school	11.50 (384)	5.92 (204)	10.02 (1,414)	
High school graduate	29.96 (1,000)	19.45 (670)	25.95 (3,661)	
Some college	26.36 (880)	26.77 (922)	27.68 (3,905)	
College graduate and above	32.17 (1,074)	47.85 (1,648)	36.34 (5,127)	
Relationship, % (n)				<.0001
Single	4.31 (144)	8.77 (302)	4.41 (622)	
Married	62.83 (2,098)	53.86 (1,855)	63.40 (8,948)	
Divorced	13.03 (435)	16.43 (566)	13.47 (1,901)	
Widowed	18.00 (601)	18.23 (628)	17.07 (2,409)	
Other	1.83 (61)	2.70 (93)	1.66 (234)	
Income, % (n)				<.0001
<20K	19.47 (650)	11.03 (380)	15.84 (2,236)	
20-34K	25.07 (837)	21.34 (735)	24.53 (3,462)	
35-74K	30.22 (1,009)	32.03 (1,103)	31.51 (4,447)	
>75K	13.96 (466)	24.25 (835)	16.22 (2,289)	
Refused	11.29 (377)	11.35 (391)	11.90 (1,680)	
Employment, % (n)				<.0001
Employed for wages	26.62 (578)	27.23 (608)	27.17 (2,379)	
Self-employed	7.60 (165)	10.66 (238)	8.92 (781)	
Unemployed for ≥ 1 year	1.29 (28)	1.93 (43)	1.40 (123)	
Unemployed for < 1 year	1.38 (30)	1.75 (39)	1.44 (126)	
Homemaker	7.28 (158)	3.36 (75)	6.48 (567)	
Student	0.14 (3)	0.40 (9)	0.15 (13)	
Retired	46.61 (1,012)	50.11 (1,119)	47.38 (4,148)	
Unable to work	9.07 (197)	4.52 (101)	7.04 (616)	
Refused	0.00 (0)	0.04 (1)	0.02 (2)	
Health insured, % (n)	92.38 (3,081)	95.96 (3,303)	93.83 (13,236)	<.0001
Time in current address, year, Mean(SD)	30.70 (20.56)	27.96 (19.75)	28.31 (20.81)	<.0001
mRFEI, Mean(SD)	11.00 (10.01)	10.45 (10.09)	11.02 (10.25)	0.0105
MD score, Mean(SD)	4.18 (1.66)	4.73 (1.75)	4.32 (1.68)	0.0005
Life style				

Exercise, % (n)				0.0272
None	34.80 (1,148)	31.95 (1,088)	32.09 (4,465)	
1 to 3 times/week	36.25 (1,196)	37.59 (1,280)	36.89 (5,133)	
≥4 times/week	28.95 (955)	30.46 (1,037)	31.01 (4,315)	
Watch TV/Video, % (n)				0.0319
None	0.58 (19)	1.03 (35)	0.73 (102)	
1-6 hrs/wk	12.15 (401)	13.23 (449)	12.69 (1,766)	
1 hr/day	6.24 (206)	6.89 (234)	6.90 (961)	
2 hr/day	21.52 (710)	23.16 (786)	22.64 (3,152)	
3 hr/day	26.97 (890)	26.99 (916)	27.25 (3,793)	
4+ hr/day	32.55 (1,074)	28.70 (974)	29.79 (4,147)	
Smoking,[a] % (n)				0.0008
Never	46.23 (1,537)	45.47 (1,561)	44.93 (6,319)	
Past	38.74 (1,288)	42.53 (1,460)	41.34 (5,814)	
Current	15.04 (500)	12.00 (412)	13.72 (1,930)	
Community features				
Percent of Non-Hispanic White [b], Mean(SD)	59.03 (15.59)	48.11 (20.86)	62.43 (18.11)	<.0001
Percent of Non-Hispanic Black [b], Mean(SD)	34.11 (16.16)	18.20 (18.08)	26.91 (18.05)	<.0001
Median Household income [b], $, Mean(SD)	42036.17 (7965.88)	61307.64 (14344.41)	46433.84 (9569.99)	<.0001
Poverty rate [b], Mean(SD)	18.26 (5.30)	12.60 (5.00)	16.17 (5.16)	<.0001
Tract population [c], Mean (SD)	4924.68 (2033.70)	4934.03 (2259.58)	5154.70 (2490.45)	<.0001
				<.0001
RUCA code,[c] % (n)	65.65 (2,192)	96.46 (3,322)	74.93 (10,575)	
Urban	14.97 (500)	1.97 (68)	14.65 (2,067)	
Large rural	15.18 (507)	0.73 (25)	6.57 (927)	
Small rural	4.19 (140)	0.84 (29)	3.86 (545)	
Isolated small rural				

Note: SD=Standard Deviation; mRFEI=modified retail food environment index; MD=Mediterranean diet;

[a]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

[b]: County-level data;

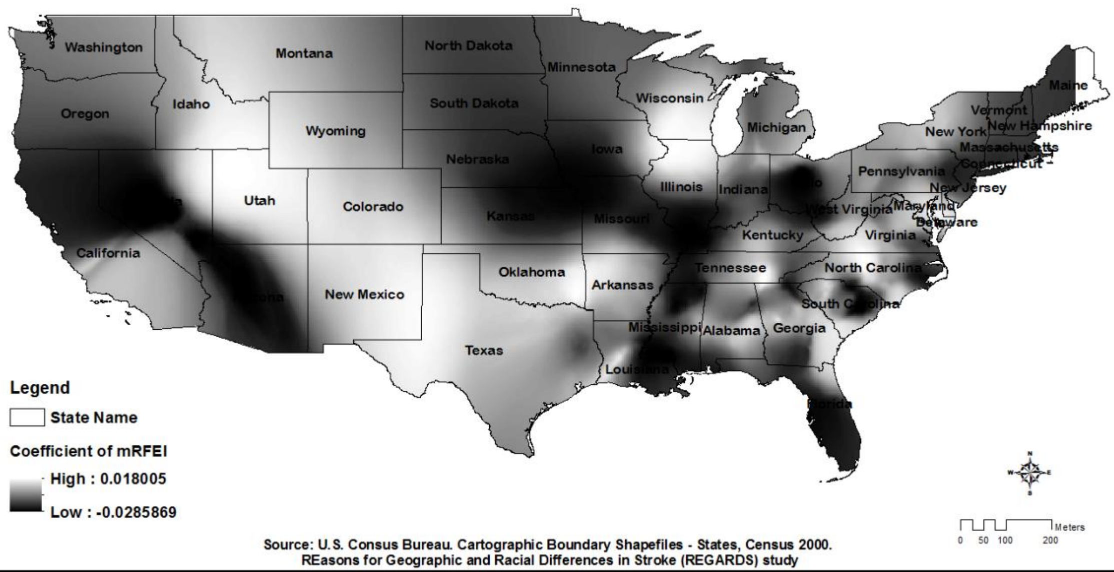
[c]: Census-tract-level data; Refer to Appendix for more details of RUCA code categories.

Table 3. Summary of global OLS regression and local GWR of the relationship between mRFEI and MD score among the REGARDS Participants (n=20897)

Model	Coefficient [b]	SE	P-Value	R^2	AICc	Moran's I
OLS	-0.0015	0.0012	0.2131	0.0001	81376.52	0.0116*
GWR[a]	.	.	.	0.0221	81137.73	0.0452*

Note: OLS=Ordinary Least Squares; GWR=Geographically Weighted Regression; mRFEI=modified retail food environment index; MD=Mediterranean diet; SE=Standardized Error; R^2: explained variation; AICc= corrected Akaike Information Criterion; ***If the AICc values for two models differ by >3, the model with the lower AICc is held to be better.*** Moran'I: examining the spatial autocorrelation of regression residuals to test if the model is well-specified; non-significant Moran's I indicates a well-specified model. [a]: GWR in ArcGIS did not report coefficient, standardized error, and P-value for the whole model; [b]: the coefficient of mRFEI; *p<.05

Figure 2. Spatial Variation in the Coefficient of mRFEI for the Relationship between mRFEI and MD score among the REGARDS Study Participants (n=20897)



Note: A raster surface map, based on the regression coefficient of mRFEI from the geographically weighted regression (GWR) model, presented the spatial variations of the relation between mRFEI and MD score across the study areas. mRFEI = modified Retail Food Environment Index; MD = Mediterranean diet; REGARDS = Reasons for Geographic and Racial Differences in Stroke. Brighter color indicates there are stronger and positive relationships between mRFEI and MD score in these areas (e.g., Utah, Texas, and eastern area of Oklahoma), while darker color indicates there are stronger and inverse relationships between mRFEI and MD score in these areas (e.g., Nevada, Arizona, and Florida).

Table 4. Stepwise logistic regression for predictive factors for high Mediterranean Diet adherence among the REGARDS participants [a]

Variables	OR (95% CI)
Age	1.02 (1.02- 1.03)*
Race/White	0.71 (0.65- 0.78)*
Income	
<20K	0.90 (0.77- 1.05)
20-34K	1.02 (0.90- 1.17)
35-74K	1.04 (0.92- 1.18)
>75K	1.31 (1.14- 1.52)*
Refused	1 (Ref)
Education	
Less than high school	0.57 (0.48 - 0.67)*
High school graduate	0.65 (0.59 - 0.73)*
Some college	0.77 (0.70 - 0.85)*
College graduate and above	1 (Ref)
Exercise	
None	0.60 (0.55 - 0.67)*
1 to 3 times/week	0.82 (0.75 - 0.90)*
≥4 times/week	1 (Ref)
Watch TV/video	
None	2.16 (1.44 - 3.25)*
1-6 hrs/wk	1.35 (1.19 - 1.54)*
1 hr/day	1.45 (1.24 - 1.71)*
2 hr/day	1.49 (1.34 - 1.67)*
3 hr/day	1.17 (1.06 - 1.30)*
≥4 hr/day	1 (Ref)
Smoking[b]	
Never	1.49 (1.32 - 1.68)*
Past	1.61 (1.42- 1.83)*
Current	1 (Ref)
Percent of non-Hispanic White	1.00 (0.99 – 1.00)*

Note: High Mediterranean Diet adherence defined as MD score >4; OR=Odds Ratio, CI=Confidence Interval;

[a]: table only included significant variables in the final model;

[b]: Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

*P<.05

IF ADHERENCE TO A MEDITERRANEAN DIET MEDIATES THE ASSOCIATION BETWEEN FOOD ENVIRONMENT AND OBESITY AMONG U.S. ADULTS?

by

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ABSTRACT

Background: Previous research suggests that community food environment, individual dietary patterns, and individual obesity patterns form an interrelated network. However, the literature rarely examines the network as a whole system. As a relatively new dietary pattern in the U.S., the role of consuming a Mediterranean Diet (MD) in combating obesity within the context of the prevailing community food environment in the U.S. remains unknown. This study's primary aim was to test the hypotheses that in addition to a direct effect, the community food environment is indirectly associated with obesity through the MD consumption among the U.S. adult population.

Methods: Data from adults aged ≥ 45 years who participated in the REasons for Geographic and Racial Differences in Stroke (REGARDS) study, and completed baseline assessment during January 2003 and October 2007 were used for the analysis. The modified retail food environment index (mRFEI) was used as the food environment measure. Direct pathway from food environment to obesity status and indirect pathway through MD consumption were quantified using path analysis among the whole sample population as well as among sociodemographic subpopulations.

Results: The findings showed that access to healthy food outlets and MD adherence had significant and inverse relationships with BMI among the participants. Adherence to a MD mediated the relationship between community food environment and obesity among a subpopulation who had an annual household income of < $75K. However, contrary to our hypothesis, the relationship showed that greater access to healthy food outlets was related to lower adherence to a MD and higher BMI among this segment of population.

Conclusion: Overall, the findings from this study suggest that greater healthy food access and higher Mediterranean diet adherence were related to lower obesity risk. Moreover, the finding suggested the needs for developing population-tailored interventions to modify food environment and promote consumption of MD, thus to achieve efficacious obesity prevention. Future studies, especially experimental studies, are needed.

INTRODUCTION

Obesity continues to be a significant public health issue in the U.S., which confers substantial mortality, morbidity, and increased health care costs.[1-4] Diet plays an important role in this obesity epidemic.[5,6] Many efforts have been made to identify healthy dietary approaches that can reduce obesity. The Mediterranean Diet (MD) dietary pattern has been increasingly considered as a healthy dietary pattern that promises to protect against obesity and its related health problems, and has been recommended as a healthy diet pattern for Americans by U.S. Department of Agriculture and the U.S. Department of Health and Human Services in the Dietary Guidelines for Americans 2015-2020.[7-40] Meanwhile, researchers and policy makers are increasingly interested in employing an ecological approach to better understand the factors that influence individuals' diet and obesity outcomes, allowing for the development of more effective interventions and policies to promote healthy diet and reduce obesity. One major factor of interest is the built community food environment.[41-43] Community food environment has been considered a key component of the obesogenic environment, and one that might constitute an important determinant of the obesity epidemic.

Previous research suggests that community food environment, individual dietary patterns, and individual obesity patterns form an interrelated network; however, the literature rarely examines the network as a whole system. Most existing research uses regression analysis, focusing on examining a single part of the pathway - either direct association for community food environment with dietary behavior/intake or with obesity-related parameters (e.g. BMI), or direct relation between diet and obesity.[6,44-53] The extent to which community food environment contributes to obesity through diet has not been well understood. Moreover, as a relatively new dietary pattern in the U.S., the role of consuming a MD in combating obesity within the context of the prevailing community food environment in the U.S. remains unknown. Using statistical approaches that allow more explicit consideration of complex interrelationship (e.g. path analysis) may provide new and important insights, and inform in the design of more efficient and effective interventions by identifying a mechanism through which interventions can have an effect.

This study, inspired by the social ecological model, uses path analysis to examine the relations between community food environment, consuming a MD, and obesity status among U.S. adults aged ≥ 45 years in the REasons for Geographic and Racial Differences in Stroke (REGARDS) study.[54,55] It is hypothesized that in addition to a direct relationship, the community food environment is indirectly associated with obesity through the consuming of a MD as depicted in **Figure. 1**.

METHODS

Data Source and Study Participants

Data for individuals were drawn from the REasons for Geographic And Racial Differences in Stroke (REGARDS) study. REGARDS is a national population-based longitudinal cohort study of 30,183 non-Hispanic black and white community-dwelling residents aged 45 years and older. The overall goal of REGARDS is to better understand the contributors to the substantial racial and geographic disparities in stroke.[56] Individuals were recruited from commercially available nationwide list of residents purchased through Genesys Inc. using a combination of mail and telephone contact during 2003-2007. Subsequent to a baseline assessment, participants are followed via telephone at 6-month intervals. Additional methodological details of REGARDS have been published previously.[56] For the purpose of the present study, baseline cross-sectional data collected during January 2003 and October 2007 were used. The same inclusion/exclusion criteria as those described in previous two papers were used in this study, leaving a total of 20,897 individuals in the analysis (refer to **Figure 1** in paper "Association of Community Food Environment and Obesity among U.S. Adults" for more details). Community food environment data were retrieved from the Children's Food Environment State Indicator Report (2011) developed by the Division of Nutrition, Physical Activity and Obesity of CDC, available to the public.[57]

Permission and approval was obtained from the REGARDS study executive committee and the UAB Institutional Review Board, respectively, to conduct this cross-sectional study.

Variables

Community food environment: The Modified Retail Food Environment Index (mRFEI) (continuous), developed by the Division of Nutrition, Physical Activity and Obesity of CDC, was retrieved from their website and used as community food environment indicator (http://www.cdc.gov/obesity/downloads/2_16_mrfei_data_table.xls).[58] The mRFEI represented the percentage of food retailers that were healthy out of the total number of food retailers considered healthy or less healthy in a census tract. Healthy food retailers include supermarkets, larger grocery stores, supercenters, and produce stores within census tracts or ½ mile from the tract boundary. All data on supermarkets, supercenters, and produce stores were obtained from the InfoUSA business database, 2009. Less healthy food retailers include fast food restaurants, small grocery stores, and convenience stores within census tracts or ½ mile from the tract boundary. Convenience store data were obtained from the Homeland Security Information program database, 2008. Small grocery store data were obtained from the InfoUSA business database, 2009; and fast food restaurant data were obtained from the NavTeq database, 2009. The mRFEI ranges from 0 to 100, with lower mRFEI scores indicating that census tracts contain many convenience stores and/ or fast food restaurants compared to the number of healthy food retailers. For example, an mRFEI score of 10 means that only 10 out of every 100 of these stores in the community are likely to offer healthy foods, while the other 90 stores were unlikely provide access to healthy foods. A zero score indicates that no healthy food retailers are located in the census tract.[57]

Mediterranean Diet adherence: The MD score drawn from the REGARDS study was used to indicate the dietary pattern adherence. The food intake data were collected using the self-administered Block 98 Food Frequency Questionnaire (FFQ) at REGARDS study baseline assessment. The full-length of Block 98 FFQ, including 110 food items, was developed by National Cancer Institute under the direction of Gladys Block.[59,60] The measure was validated in multi-cultural populations.[61,62] The calculation of MD score was followed Trichopoulou et al.'s method.[63] The intake of each nine food category (dairy, meat, fruit, vegetables, legumes, cereals, fish, fat, and alcohol) was computed, and a value of 0 or 1 was assigned to each of nine food components with the use of sex-specific medians as the cutoffs. For beneficial components (fruit, vegetables, legumes, cereals, and fish), persons whose consumption was below the median were assigned a value of 0, and persons whose consumption was at or above the median was assigned a value of 1. For meat, fat, and dairy consumption, a value of 1 was assigned to persons whose intake was less than the median. Regarding alcohol consumption, persons with moderate alcohol intake were assigned a value of 1, otherwise a value of 0 was assigned. Then, the MD adherence score scale was generated by summing up the scores of the nine food categories. The scale ranged from 0 to 9, with a higher score indicating a higher adherence to MD.[63]

Obesity: Body Mass Index (BMI) (kg/m^2) (continuous) was used to estimate body weight in this study. BMI was calculated using height and weight measured during the REGARDS study home visit at baseline. Height was obtained utilizing an 8-foot metal tape measure without shoes. Weight was measured using a standard 300-lb calibrated digital scale.[56]

Data Analysis

Data retrieved from the different sources were linked and pooled by using SPACIAL JOIN function in ArcGIS 10.4 (ESRI Inc., Redlands, CA). A spatial join involves matching rows from the variables in one dataset (Join Features) to the Target variables in another dataset (target Features) based on their relative spatial locations.[64] This procedure was used to join the REGARDS study dataset and census-tract food environment dataset. The statistical analysis was implemented using SAS version 9.4 for Windows (SAS Institute, Inc, Cary, NC). Descriptive analyses of sociodemographic and lifestyle characteristics of the participants were conducted using PROC UNIVARIATE and PROC FREQ procedures. Means and standard deviations (for continuous variables) and percentages (for categorical variables) were calculated.

Path analysis using PROC CALIS procedure was conducted to examine the relation between community food environment, MD adherence, and obesity. Path Analysis, developed by Sewall Wright, is an extension of multivariate linear regression based on a diagram that specifies the relationships between the variables.[65] Path analysis differs from multivariate regression by allowing a variable to be a covariate in one equation and an outcome in another equation, such as the MD adherence score in the hypothesis model. Multiple, related equations are solved simultaneously to determine parameter estimates. Moreover, path Analysis is the sub-model of Structural Equation Model (SEM), in which all variables (except error terms) are manifest, meaning observable. Whereas, SEM allows for both manifest and latent variables.[65] As shown in **Figure 1**, in this study, in addition to the direct effects of community food environment on obesity, indirect effect of community food environment on obesity through adherence to a MD was also examined. That is, it is hypothesized that adherence to a MD can partially explain the relationship between community food environment exposure and obesity outcome.

Moreover, the same path analyses were conducted among subgroups stratified by the sociodemographic factors that were possibly related to MD adherence as suggested in previous studies.[19,66,67] These factors included age (≤64yrs old, or >64yrs old), gender (female or male), race (white or black), education (≤ some college or college graduate and above), annual household income (< $75k or ≥ $75K), exercise (<4times/week or ≥4times/week), watch TV/video (< 4 hrs /day or ≥4 hrs /day), and smoking status (current smoker or not a current smoker). In addition, path analyses were conducted among subgroups stratified by their rural/urban residence status (urban, large rural, small rural, or isolated rural) (refer to Appendix for more details).[68]

Proper data transformations were made using Box-Cox power transformation to meet certain analysis assumptions (e.g. multivariate normality). Standardized path coefficients and p-values for paths and explained variation for endogenous variables (R^2) were reported. The alpha level denoting statistical significance was set at 0.05, two-tailed. Unlike regression models, a single path analysis model tests a theoretical model that is believed to be applicable to a general population. Thus, it does not control for factors that are considered confounders in regression analysis because it would result in an over-specification of the model.[69] To assess how well the data fit the models, the following statistics were calculated (with the threshold for a 'good' fit reported in brackets): Chi-square (χ^2<.05), Goodness of Fit Index (GFI >0.95), Root Mean Square Residual (RMR <0.05), and Standardized Root Mean Square Residual (SRMR <0.05).

RESULTS

Descriptions of the characteristics of the participants are summarized in **Table 1**. A total of 20,897 participants from REGARDS study were included in the analysis (refer to **Figure 1** in paper "Association of Community Food Environment and Obesity among U.S. Adults" for more details). The study cohort was aged 65 on average (median=64.00), half of whom were retired. Only about one third of the participants had a college degree. Slightly more than half were female. About two-thirds were white, married. Nearly 80% had an annual household income of less than $75K. Almost all had health insurance. Majority of the participants were not a current smoker and not heavy alcohol user. Most exercised < 4 time/week, and watched TV/Video < 4 hour/day. About four fifths of the participants (77.0%) resided in urban areas, with length of tenure in their current address at an average of 29 years. The mean mRFEI of the participants was 10.92, the mean MD score was 4.36 (SD=1.70), and the mean BMI was 28.96 kg/m^2 (SD=5.90).

The results of the path analysis for the effects of community food environment on MD adherence and obesity outcome among the whole sample population is presented in **Figure 2**. Obesity outcome was measured by 1/sqrt (BMI) (continuous), transformed from the original BMI values as suggested by Box-Cox transformation. The model was a good fit, as indicated by the fit indices (χ^2= .0000, GFI=1.000, RMR=.0000, SRMR=.0000). The result showed that access to healthful food outlets (β=.04, p<.0001) and adherence to a MD (β=.08, p<.0001) had significant direct effects on 1/sqrt (BMI). Specifically, a greater access to healthful food outlets and higher MD adherence were associated with lower BMI. However, no significant indirect effect of access to healthful food outlets was found on BMI through adherence to MD. In total, all variables in the path analysis explained only about 1% of the variation in 1/sqrt (BMI).

The path analysis was also conducted among subgroups stratified by sociodemographic features to test the direct and indirect effects of community food environment on obesity. The study hypotheses were supported among a subgroup whose annual household income of less than $75K. Obesity outcome was measured by 1/sqrt (BMI), transformed from the original BMI values as suggested by Box-Cox transformation. The model was a good fit, as indicated by the fit indices (χ^2= .0000, GFI=1.000, RMR=.0000, SRMR=.0000). The result showed that besides the significant direct effects of access to healthful food outlets (β=.03, $p<.0001$) and adherence to a MD (β=.07, $p<.0001$) on 1/sqrt (BMI), access to healthful food outlets had a significant indirect effect on obesity through adherence to a MD among this subpopulation (β=.-02, p=.0391). In contrast to expectations, the relation showed that a greater access to food outlets was related to lower MD adherence, and higher BMI among this segment of population (**Figure 3**). **Table 2** summarizes the results from the path models of the whole sample and the subpopulation with income less than 75K in terms of the partitioned direct and indirect effects and the total effects of the three primary variables. Among other subgroups, no significant indirect effect of access to healthful food outlets on BMI through adherence to a MD were found (see **Appendix** for more details).

DISCUSSION

This study, based on the social ecological model, sought to examine the relative influence of community food environment on obesity, including a direct effect, and indirect effects through adherence to a Mediterranean diet (MD). The results of the path analysis among the whole sample showed that community food environment had an significant relationship with obesity. Specifically, access to healthy food outlets had a significant direct and inverse effect on BMI; that is, greater access to healthy food outlets (e.g. supermarkets) was related to lower BMI. Although the findings from previous studies on this topic were inconsistent, as recently reviewed by Feng et al, Gamba et al and Cobb et al, the result from this study supported the hypothesis of the significant contribution of community food environment to obesity among the U.S. populations.[42,70,71] The results also showed that MD adherence had a significant direct and inverse relation with BMI, which align with previous studies findings that MD has a protective effect against obesity.[11-39]

However, contrary to our hypothesis, we did not find evidence that adherence to a MD mediates the effect of community food environment exposure on obesity among the whole sample population. One potential explanation for this non-significant finding may be that individual and structural factors rather than individual dietary intake behavior (e.g. consuming a MD) may play an important role in the relation between food environment exposure and obesity. Such potential factors could be, for instance, food-related belief, preference, and culture, certain biological and sociopsychological factors (e.g. aging, self-efficacy, stress, and anxiety), and structural factors (e.g. car ownership, access to public transportation, and neighborhood walkability). [72-81]

Examining the hypotheses among the sociodemographic subgroups, we found that the hypotheses were true among a subgroup who had an annual household income < $75K. Besides significant direct, inverse effect, the community food environment exposure had a significant indirect effect on obesity through adherence to a MD among this subpopulation. Interestingly, this indirect effect was in an opposite direction we expected. The result showed that greater access to healthy food outlets was related to lower adherence to a MD and higher BMI among this segment of population. One potential explanation for this unexpected finding may be that this segment of population has such a strong preference for a typical 'Western diet' that even given better healthy food access they tend to continue to make suboptimal decisions. Previous studies have described that the dietary preference among the general U.S. population is the typical 'Western diet', a diet loosely defined as one high in saturated fat, red meats, empty carbohydrates-junk food- and low in fresh fruits and vegetables, whole grain, seafood, and poultry, the features of which are almost opposite of those of a MD dietary pattern.[40,82,83] In this study, greater access to healthy foods means a greater access to healthy food retailers like supermarkets, larger grocery stores, and supercenters. While these types of stores are typically considered to offer healthy foods, they also carry numerous of less healthy foods.[57] Given the preference for typical 'Western diet', it is no wonder that facing more food choices, individuals tends to maintain their preferred dietary pattern, consuming more typical 'western diet' foods and shifting away from the MD dietary pattern, which in turn, may increase body weight.[84,85] This finding among this segment of population suggests that future interventions to prevent obesity and promote MD consumption should not simply seek to increase the availability of healthy food outlets in the neighborhoods, but instead, increased efforts should be made understand how individuals respond to their food environment, and structure the food environment to make it easy for the population to shift their current dietary preference towards healthier patterns (e.g. MD dietary pattern). For instance, studies have shown that point-of-choice nutrition information can be provided in grocery store and restaurant settings to increase customers' awareness and simulate demands for healthier food products.[86] Other interventions, such as increasing the variety and convenient access to healthy foods and decreasing prices for healthy foods (e.g., fruits and vegetables) have also shown the potentials of encouraging healthy eating behaviors.[86] Future studies are needed to support the findings from current study, and test possible hypotheses.

This study has several strengths. First, the use of path analysis allows us to extend current understanding of the mechanism underlying the relationship between the obesogenic food environment and obesity-related health outcomes. To our knowledge, this is the first study using pathway-based modeling to examine the potential modifying role of adherence to a MD in the relationship between community food environment exposure and obesity outcome. The findings from this study provide research evidence to support that promoting access to healthy food outlets and the consumption of MD could be effective approaches to reduce obesity among the U.S. adult population. However, further studies are needed to confirm the findings from this study, and establish solid cause-and-effect relationship. Second, this study was based on a relatively large national sample from REGARDS study, which allows us to establish precise estimates. Moreover, the BMI was calculated based on height and weight measured during REGARDS study home visit at baseline with a standardized protocol. This prevents the potential bias introduced by using self-reported data as in previous studies.[24,87]

There are several limitations of this study. First, the cross-sectional design precludes establishing causal inference. Second, the external validity of the study may be limited by the oversampling of populations residing in urban areas and south region of the country. Moreover, the participants in the analysis were mid- to older-age non-Hispanic white and black adults, so that the findings of the study may not apply to other age and racial groups. Third, the MD adherence score was calculated based on self-reported dietary intake data assessed only one time at the REGARDS study baseline, which may introduce potential bias to the study due to the possibility of misreporting and the unknown stability of dietary pattern over time. Fourth, although the use of a composite measure, like mRFEI, to characterize the food environment have many strengths (e.g. capturing the complexity of food environment, reducing data amount), it may not accurately represent individuals' healthy food access experiences. Because the mRFEI calculation was based on the classification of types of food outlets instead of the actual in-store foods availability. Moreover, the mRFEI represents the overall density of the food outlets in a given census tract level, but not for each individual. Lastly, the use of data transformed from original BMI to meet certain analysis assumptions in the analysis, may make the estimates harder to interpret.

CONCLUSION

To our knowledge, this is the first national-wide study using pathway-based modeling to examine the relationships between food environment exposure, MD adherence and obesity outcome among the U.S. adult population. Overall, the findings indicated that community food environment and MD adherence had significant and inverse relationships with obesity. The finding also supported our hypothesis that adherence to a MD can mediate the relation between community food environment exposure and obesity, at least among a large subpopulation who have low- and median-income. Overall, the findings from this study suggest that increasing healthy food access and promoting consumption of Mediterranean diet could be effective approaches to combat the obesity crisis among the U.S. adult population. Moreover, the findings emphasize the importance of developing population-tailored interventions to effectively improve food environment and healthy eating behavior in future obesity-preventing programs. Investigations to further understand the mechanism underlying the relationship between the obesogenic food environment and obesity are warranted. Experimental and longitudinal studies to establish causal inference are needed to extend the findings from current study.

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FIGURES AND TABLES

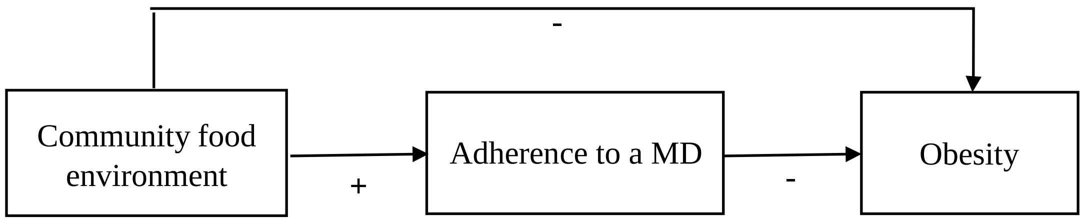

Figure 1. Path analytic hypotheses of community food environment on MD adherence and obesity. **Note:** The plus and minus signs below the arrows indicate the directions of the hypothesized associations. Minus (-) indicates inverse relation; plus (+) indicates positive relation; MD = Mediterranean diet.

Table 1. Summary of individual and community characteristics of the REasons for Geographic and Racial Differences in Stroke (REGARDS) study participants (n=20897)

Characteristics	REGARDS participants
Sociodemographics	
Age, year, Mean(SD)	64.88 (9.26)
Male, % (n)	44.22 (n=9241)
White, % (n)	66.71 (n=13941)
Education, % (n)	
Less than college graduate	62.43 (13040)
College graduate and above	37.57 (7849)
Relationship, % (n)	
Married	61.74 (12901)
Single/widowed/devoiced	38.26 (7996)
Income, % (n)	
≤75K	80.54 (14859)
>75K	19.46 (3590)
Employment, % (n)	
Employed for wages	27.09 (3565)
Self-employed	9.00 (1184)
Unemployed for ≥ 1 year	1.47 (194)
Unemployed for < 1 year	1.48 (195)
Homemaker	6.08 (800)
Student	.19 (25)
Retired	47.72 (6279)
Unable to work	6.95 (914)
Refused	.02 (3)
Health insured, % (n)	93.95 (19620)
Time lived in current address, year, Mean(SD)	28.63 (20.62)
mRFEI, Mean(SD)	10.92 (10.19)
MD score, Mean(SD)	4.36 (1.70)
BMI, kg/m^2, Mean(SD)	28.96 (5.90)
Life style	
Exercise, % (n)	
<4 times/week	69.41 (14310)
≥4 times/week	30.59 (6307)
Watch TV/Video, % (n)	
< 4 hr/day	69.95 (14420)
≥4 hr/day	30.05 (6195)
Smoking,[a] % (n)	
Non-current	86.35 (17979)
Current	13.65 (2842)
Alcohol use,[b] % (n)	
Non-heavy	95.57 (19971)
Heavy	4.43 (926)
RUCA codes,[c] % (n)	
Urban	76.99 (16,089)

Large rural	12.61 (2,635)
Small rural	6.98 (1,459)
Isolated small rural	3.42 (714)

Note: SD=Standard Deviation; mRFEI=modified retail food environment index; BMI=body mass index; MD=Mediterranean diet; RUCA=Rural-Urban Commuting Area;

[a]: Non-current smokers include never and past smokers; Never smoker is defined as an adult who has smoked < 100 cigarettes per lifetime and not smoking at the time of interview; Past smoker is defined as an adult who has smoked at least 100 cigarettes in his or her lifetime but who had quit smoking at the time of interview; Current smoker is defined an adults who has smoked 100 cigarettes in his or her lifetime and who currently smokes cigarettes.

[b]: Non-heavy alcohol users include never and moderate alcohol user; Moderate alcohol use is defined as 0-7 drinks/week for women and 0-14 drinks/week for men; Heavy alcohol use is defined as having >7 drinks/week for women and >14 drinks/week for men.

[c]: Refer to Appendix for more details of RUCA code categories

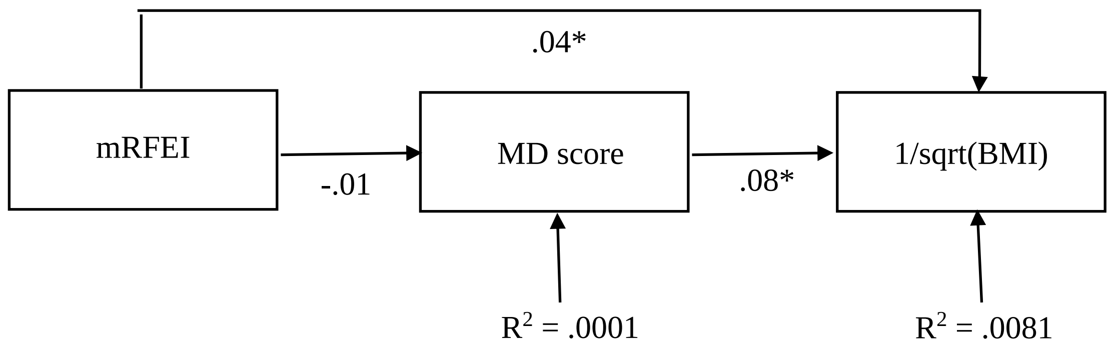

Figure 2. Path analytic model of the effects of community food environment on MD adherence and obesity among the REGADRS study participants (n=20897). **Note:** mRFEI=modified retail food environment index, MD score= Mediterranean diet score, BMI=body mass index; Box-Cox transformation was used to transform original BMI to meet the multivariate normality assumption. Values shown are standardized path coefficients (β), explained variations (R^2); *indicated statistical significance at $p<.05$.

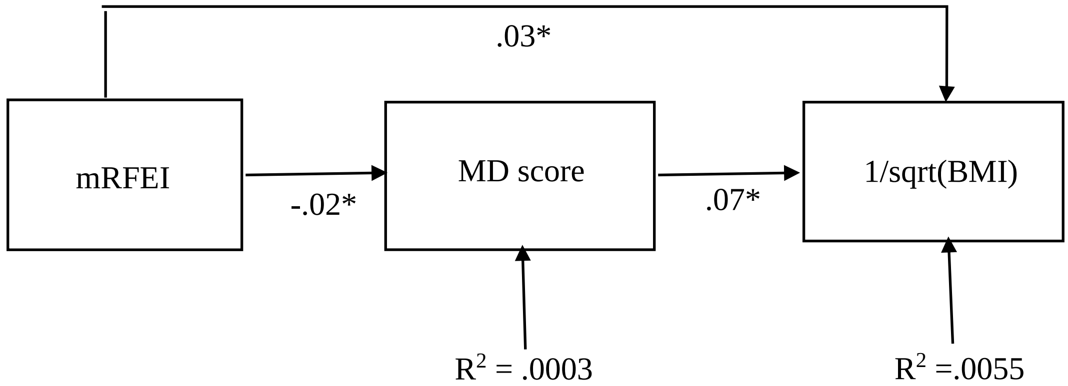

Figure 3. Path analytic model of the effects of community food environment on MD adherence and obesity among a subgroup of REGADRS study participants whose annual household incomes were less than $75K (n=14859). **Note:** mRFEI=modified retail food environment index, MD score= Mediterranean diet score, BMI=body mass index; Box-Cox transformation was used to transform original BMI to meet the multivariate normality assumption. Values shown are standardized path coefficients (β), explained variations (R^2); *indicated statistical significance at p<.05.

Table 2. Partitioning the effects of community food environment on MD adherence and obesity from the path models, expressed as standardized path coefficients among the REGARDS study participants (n=20897) and the subgroup who had an annual household income less than $75K (n=14859)

Variables	**Standardized Path Coefficients**		
	Direct effect	**Indirect effect**	**Total effect**
Model 1[a]			
mRFEI	0.0376*	-0.0007	0.0369*
MD score	0.0819*	.	0.0819*
Model 2[a]			
mRFEI	0.0321*	-0.0012*	0.0309*
MD score	0.0675*	.	0.0675*

Note: Model 1: path analysis conducted among the whole REGARDS study population; Model 2: path analysis conducted among the subgroup who had an annual household income of less than $75K.

[a]: in both of the models, obesity outcomes were measured as 1/sqrt(BMI), which were transformed from original BMI data as suggested by Box-Cox transformation test.

*p<.05

CONCLUSIONS

Obesity continues to be one of the most significant public health challenges in the U.S. In response to geographical disparities in obesity prevalence among the population and the moderate effects of previous individual-based interventions, researchers and policy makers have increasingly realized the ecological perspective of the issue that individual's lifestyle behaviors and health outcomes are not only determined by the individual but also by the environment they interact with. Community food environments have been identified as key components of the obesogenic environment, which might constitute an important determinant of the obesity epidemic. It is hypothesized that the food environment may influence an individual's diet behavior and in turn, affect individual's obesity outcome. Moreover, it is also assumed that diet is the key mechanism linking the food environment exposure and obesity outcome. Therefore, it is important to identify a dietary pattern that can fit in the unique food environment and combat obesity. Mediterranean diet (MD) has been suggested as a diet that can exert protective effects against obesity and its related health conditions among the U.S. population.

This dissertation, using spatial analysis and path analytic methods with data from the REGARDS study and government surveillance sources, sought to examine the relationships between community food environment, MD adherence and obesity among U.S. adults. Overall, the combined results of this dissertation appear to support the hypotheses that community food environment is associated with obesity, and that consuming a MD can mediate the relationship between community food environment and obesity (in particular, among a subgroup population who has annual household income < $75K). However, the findings did not support the hypothesis that community food environment is significantly related to adherence to a MD among U.S. adults.

In the first paper, the findings supported the hypothesis that access to healthy food outlets had a significant and inverse relationship with BMI (β= -.0210; $P<.0001$). More importantly, the magnitude and direction of this relationship varied significantly across regions. The findings also showed there were significant local clusters of higher/lower BMI across the study areas. Higher BMI clusters were more likely to be located in socioeconomically disadvantaged, minority neighborhoods with a smaller population size, while lower BMI clusters were more likely to appear in relatively more affluent, urban neighborhoods with a higher percentage of white residences. Replication of these estimates among different national-wide populations should be conducted to confirm the findings.

In the second paper, the global regression found an inverse relationship between access to healthy food outlets and MD adherence among the study population, although the relationship was not significant. The local spatial regression showed the spatial heterogeneity of the relationship between access to healthy food outlets and MD adherence across the regions, which provided a plausible explanation for the non-significant finding from the global regression. The findings from this study also showed clusters of higher MD adherence were more likely to appear in more socioeconomically advantaged, urban neighborhoods with lower percentages of non-Hispanic white and black, whereas lower MD adherence clusters were more likely to appear in socioeconomically disadvantaged, rural areas with a higher percentage of black residents.

Furthermore, the findings showed that being older, non-Hispanic black, not a current smoker, having a college degree and above, an annual household income of more than \$75K, exercising ≥ 4 times/week, and watching TV/video < 4 hrs/day were each associated with higher odds of high MD adherence.

In the third paper, the findings showed that access to healthy food outlets and adherence to a MD had a significant, inverse direct relationship with BMI among the participants. Although there was a non-significant finding among the overall population, the results among a segment of population who had an annual household income of less than \$75K showed strong evidence to support the hypothesis that adherence to a MD can mediate the relationship between community food environment and obesity in this group. However, contrary to our hypothesis, the relationship showed that greater access to healthy food outlets was related to lower adherence to a MD and higher BMI among this segment of population. Replication of these estimates is required to examine the consistency of these findings.

FUTURE DIRECTIONS

The findings of this dissertation highlight the variations of the relationships among the community food environment, MD adherence, and obesity across the U.S., and emphasize the importance of accounting for spatial non-stationarity in future investigations on this topic. It suggests that GIS spatial mapping and modeling techniques, especially geographically weighted regression, could be useful tools to explore the nature of the issues across the regions, and extend our understanding of how contextual and individual factors shape individuals' responses to their local food environments.

The findings of this dissertation also suggest that future studies should use path analytic method to study the complex interrelationship between food environment and individuals' dietary behavior and its related health outcomes. Path analysis allows us to test theoretical pathway models and conduct simultaneous regression modeling via systems of equations, which is a step towards uncovering the mechanism(s) underlying associations between the food environment exposure and obesity, and in identifying potentially modifiable features to improve health outcomes.

Moreover, future research studies should focus on several aspects to increase our understanding. For instance, first, in this study, we used a cross-sectional design to examine the concurrent relationships between food environment, MD adherence and obesity. Future studies using experimental and longitudinal designs are suggested to establish causality. Second, this study primarily focused on testing the influence of environment on individuals' diet and obesity outcome. Future studies should also consider the path in the other direction that individuals can have influence on their environments, which will require researchers to incorporate individual variations (e.g., health awareness) in future investigations. Third, future studies should explore potential threshold and saturation effects of healthful food outlet exposure on obesity, which will provide valuable guidance for developing anti-obesity food environment in future. Forth, given the significant findings of the regional clusters of MD adherence and obesity in this study, future studies examining the local contextual and individual features that relate to clustering across the regions are warranted to inform future interventions of modifiable factors to improve healthy eating and reduce obesity.

The findings from the current studies also provide some insights for future obesity-preventing intervention programs and policies. First, the findings of the significant geographical clusters of MD adherence and obesity in certain communities and among certain characteristic individuals provide opportunities for future interventions to identify at-risk populations and communities, and allocate limited public health resources more effectively to satisfy local unique needs in order to achieve maximum effects on promoting MD adherence and reducing obesity. Moreover, the findings showed that the configurations of the local clustering did not follow the state or county boundaries, which suggests that collaborations aiming at building regional/local networks might provide better resource alignment and more effective initiatives to combat obesity and promote healthy eating.

Second, the findings from this dissertation suggest that global strategies or policies may be not sufficient to combat obesity in this country. Instead, public health professionals should develop geographically- and populations-tailored interventions to modify food environment and promote consumption of MD, thus to achieve efficacious obesity prevention. For example, local programs may vary their efforts on modifying food environment in response to the variation of the food environment-obesity relationship across regions. In regions that access to healthy food outlets is a strong predictor for obesity outcome, the local programs may make strong efforts to improve local food access, while fewer efforts may be needed in regions that healthy food outlets access is not strongly related to obesity outcome. Moreover, according to the finding from the path analysis, simply increasing the availability of healthy food outlets (e.g. supermarkets) in the neighborhood may be not sufficient to promote MD adherence, in turn, to remediate obesity among the population with an annual household income of less than $75K. Instead, more efforts (e.g., structuring the consumption food environment) may be needed to make it easy for the population to shift their current dietary preference towards healthier patterns (e.g. MD dietary pattern). Interventional strategies, such as providing point-of-choice nutrition information, increasing the variety and convenient access to healthy foods, and decreasing prices for healthy foods (e.g., fruits and vegetables) may be employed in grocery store and restaurant settings, to increase customers' awareness and simulate demands for healthier food products.[48]

In sum, the findings from this dissertation extend our current understanding of the complex interrelationship between food environment and individuals' diet and obesity, provide research evidence to promote MD adherence, and emphasize the needs for local population- and geographically-tailored interventions and policies to achieve efficacious obesity prevention in the U.S. adult population. Future research is needed to better understand the nature of the relationships between food environment, dietary parrtern, and obesity to inform policy decisions and intervention development to stop the obesity epidemic in the U.S.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL

THE UNIVERSITY OF ALABAMA AT BIRMINGHAM

Institutional Review Board for Human Use

Form 4: IRB Approval Form
Identification and Certification of Research
Projects Involving Human Subjects

UAB's Institutional Review Boards for Human Use (IRBs) have an approved Federalwide Assurance with the Office for Human Research Protections (OHRP). The Assurance number is FWA00005960 and it expires on November 8, 2021. The UAB IRBs are also in compliance with 21 CFR Parts 50 and 56.

Principal Investigator:	CHEN, MEIFANG
Co-Investigator(s):	CREGER, THOMAS N JUDD, SUZANNE E.
Protocol Number:	**X160331009**
Protocol Title:	*Associations for Food Environment, Mediterranean Diet and Obesity in United States: A Geographic Information System (GIS) Analysis*

The IRB reviewed and approved the above named project on 4/14/17. The review was conducted in accordance with UAB's Assurance of Compliance approved by the Department of Health and Human Services. This Project will be subject to Annual continuing review as provided in that Assurance.

This project received EXPEDITED review.

IRB Approval Date: 4-14-17

Date IRB Approval Issued: 4/14/17

IRB Approval No Longer Valid On: 4/14/18

Marilyn Doss
Expedited Reviewer
Member - Institutional Review Board
for Human Use (IRB)

Investigators please note:

The IRB approved consent form used in the study must contain the IRB approval date and expiration date.

IRB approval is given for one year unless otherwise noted. For projects subject to annual review research activities may not continue past the one year anniversary of the IRB approval date.

Any modifications in the study methodology, protocol and/or consent form must be submitted for review and approval to the IRB prior to implementation.

Adverse Events and/or unanticipated risks to subjects or others at UAB or other participating institutions must be reported promptly to the IRB.

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APPENDIX B

NUMBER OF THE REASONS FOR GROGRAPHIC AND RACIAL DIFFERNECES IN STROKE (REGARDS) STUDY PARTICIPANTS BY STATE

Appendix Table B. Number of the REasons for Geographic and Racial Differences in Stroke (REGARDS) study participants by state (n=20897)

State Name	N (%)
North Carolina	2,440 (11.68)
South Carolina	2,425 (11.60)
Georgia	2,123 (10.16)
California	1,516 (7.25)
Louisiana	1,417 (6.78)
Alabama	1,078 (5.16)
Tennessee	878 (4.20)
Mississippi	811 (3.88)
Ohio	776 (3.71)
Florida	720 (3.45)
Michigan	715 (3.42)
Arkansas	597 (2.86)
New York	557 (2.67)
Texas	533 (2.55)
Illinois	522 (2.50)
Pennsylvania	422 (2.02)
Maryland	408 (1.95)
Virginia	309 (1.48)
Missouri	302 (1.45)
Wisconsin	246 (1.18)
Indiana	243 (1.16)
Minnesota	181 (0.87)
Kentucky	170 (0.81)
New Jersey	155 (0.74)
Massachusetts	148 (0.71)
Oklahoma	135 (0.65)
District of Columbia	107 (0.51)
Iowa	106 (0.51)
Colorado	99 (0.47)
Washington	97 (0.46)
Connecticut	86 (0.41)
Oregon	84 (0.40)
Arizona	70 (0.33)
Kansas	65 (0.31)
Nebraska	53 (0.25)
Utah	43 (0.21)
Delaware	36 (0.17)
West Virginia	33 (0.16)
Idaho	28 (0.13)
Nevada	24 (0.11)
South Dakota	21 (0.10)
Maine	19 (0.09)
New Mexico	19 (0.09)

North Dakota	19 (0.09)
New Hampshire	15 (0.07)
Rhode Island	14 (0.07)
Montana	13 (0.06)
Wyoming	13 (0.06)
Vermont	6 (0.03)

APPENDIX C

RURAL-URBAN COMMUTING AREA CODES (RUCA)

Appendix Table C. Rural-Urban Commuting Area codes (RUCA), 2000*

Names	Primary and Secondary codes	
RUCA codes	1 Metropolitan area core: primary flow within an urbanized area (UA)	
	1	No additional code
	1.1	Secondary flow 30% to 50% to a larger UA
	2 Metropolitan area high commuting: primary flow 30% or more to a UA	
	2	No additional code
	2.1	Secondary flow 30% to 50% to a larger UA
	3 Metropolitan area low commuting: primary flow 5% to 30% to a UA	
	3	No additional code
	4 Micropolitan area core: primary flow within an Urban Cluster of 10,000 to 49,999 (large UC)	
	4	No additional code
	4.1	Secondary flow 30% to 50% to a UA
	4.2	Secondary flow 10% to 30% to a UA
	5 Micropolitan high commuting: primary flow 30% or more to a large UC	
	5	No additional code
	5.1	Secondary flow 30% to 50% to a UA
	5.2	Secondary flow 10% to 30% to a UA
	6 Micropolitan low commuting: primary flow 10% to 30% to a large UC	
	6	No additional code
	6.1	Secondary flow 10% to 30% to a UA
	7 Small town core: primary flow within an Urban Cluster of 2,500 to 9,999 (small UC)	
	7	No additional code
	7.1	Secondary flow 30% to 50% to a UA
	7.2	Secondary flow 30% to 50% to a large UC
	7.3	Secondary flow 10% to 30% to a UA
	7.4	Secondary flow 10% to 30% to a large UC
	8 Small town high commuting: primary flow 30% or more to a small UC	
	8	No additional code
	8.1	Secondary flow 30% to 50% to a UA
	8.2	Secondary flow 30% to 50% to a large UC
	8.3	Secondary flow 10% to 30% to a UA
	8.4	Secondary flow 10% to 30% to a large UC
	9 Small town low commuting: primary flow 10% to 30% to a small UC	
	9	No additional code
	9.1	Secondary flow 10% to 30% to a UA
	9.2	Secondary flow 10% to 30% to a large UC

	10 Rural areas: primary flow to a tract outside a UA or UC	
	10	No additional code
	10.1	Secondary flow 30% to 50% to a UA
	10.2	Secondary flow 30% to 50% to a large UC
	10.3	Secondary flow 30% to 50% to a small UC
	10.4	Secondary flow 10% to 30% to a UA
	10.5	Secondary flow 10% to 30% to a large UC
	10.6	Secondary flow 10% to 30% to a small UC
Categorization A of RUCA codes [a]	Urban: 1.0, 1.1, 2.0, 2.1, 3.0, 4.1, 5.1, 7.1, 8.1, and 10.1 Large rural: 4.0, 4.2, 5.0, 5.2, 6.0, and 6.1 Small rural:7.0, 7.2, 7.3, 7.4, 8.0, 8.2, 8.3, 8.4, 9.0, 9.1, and 9.2 Isolated rural: 10.0, 10.2, 10.3, 10.4, 10.5, and 10.6	

Note: * RUCA codes were developed by the United States Department of Agriculture Economic Research Service; [a]: categorization were according to Categorization A by the University of Washington Rural Health Research Center

APPENDIX D

SUMMARY OF GLOBAL ORDINARY LEAST SQUARES REGRESSION OF THE RELATIONSHIP BETWEEN MRFEI AND BMI, CONTROLLED BY SOCIODEMOGRAPHIC, LIFESTYLE AND COMMUNITY FEATURE COVARIATES AMONG THE REGARDS STUDY PARTICIPANTS (N=20897)

Appendix Table D. Summary of global OLS regression of the relationship between mRFEI and BMI, controlled by sociodemographic, lifestyle and community feature covariates among the REGARDS study participants (n=20897)

Variables	Coefficient	SE	P-Value
mRFEI	-0.0077	0.0052	0.1257
Sociodemographics			
Age	-0.1107	0.0067	0.0000*
Race	2.1546	0.1308	0.0000*
Gender	-0.2668	0.1158	0.0155*
Income	-0.2436	0.0472	0.0000*
Education	-0.2670	0.0590	0.0000*
Employment	0.0379	0.0220	0.0910
Relationship	0.0179	0.0630	0.7928
Health insurance	-0.1621	0.2197	0.5202
Time lived in current address	0.0007	0.0028	0.8126
Lifestyle			
Exercise	-0.8835	0.0677	0.0000*
Watch TV/Video	0.4899	0.0403	0.0000*
Smoking	-0.7412	0.0778	0.0000*
Alcohol use	-0.8738	0.0975	0.0000*
Community features			
Percentage of Non-Hispanic White [a]	-0.0004	0.0046	0.9323
Percentage of Non-Hispanic Black [a]	-0.0027	0.0045	0.5473
Median Household income [a]	-0.0000	0.0000	0.0583
Poverty rate [a]	-0.0247	0.0230	0.2758
Tract population [b]	0.0000	0.0000	0.4570
RUCA code [b]	0.1351	0.0768	0.0753

Note: OLS=Ordinary Least Squares; mRFEI=modified retail food environment index; BMI=body mass index; SE=Standardized Error.

[a]: county-level data; [b]: census tract-level data;

*p<.05

APPENDIX E

PARTITIONING THE EFFECTS OF COMMUNITY FOOD ENVIRONMENT ON MEDITERRANEAN DIET ADHERENCE AND OBEISTY OUTCOME FROM THE PATH MODELS FOR SUBGROUPS OF REGARDS STUDY PARTICIPANTS

Appendix Table E. Partitioning the effects of community food environment on MD adherence and obesity outcome from the path models, expressed as standardized beta coefficients among the subgroups of the REGARDS study participants

Variables	Standardized Beta Coefficients		
	Direct effect	**Indirect effect**	**Total effect**
Model 1[a]			
mRFEI	0.0376*	-0.0007	0.0369*
MD score	0.0819*	.	0.0819*
Model 2 [a]			
mRFEI	0.0321*	-0.0012*	0.0309*
MD score	0.0675*	.	0.0675*
Model 3 [a]			
mRFEI	0.0301	-0.0013	0.0288
MD score	0.1103*	.	0.1103*
Model 4 [b]			
mRFEI	0.0350*	-0.0009	0.0341*
MD score	0.0837*	.	0.0837*
Model 5 [a]			
mRFEI	0.0382*	-0.0006	0.0376*
MD score	0.0662*	.	0.0662*
Model 6 [a]			
mRFEI	0.0208*	-0.0017	0.0191*
MD score	0.1108*	.	0.1108*
Model 7 [c]			
mRFEI	0.0193	-0.0016	0.0177
MD score	-0.0596*	.	-0.0596*
Model 8 [a]			
mRFEI	0.0076		0.0067
MD score	0.0836*	-0.0008	0.0836*
Model 9 [b]			
mRFEI	0.0561*	-0.0007	0.0554*
MD score	0.0793*	.	0.0793*
Model 10 [b]			
mRFEI	0.0347*	-0.0006	0.0341*
MD score	0.0417*	.	0.0417*
Model 11 [a]			
mRFEI	0.0345*	-0.0015	0.0329*
MD score	0.1121*	.	0.1121*
Model 12 [a]			
mRFEI	0.0273*	-0.0008	0.0265*
MD score	0.0728*	.	0.0728*
Model 13 [a]			
mRFEI	0.0539*		0.0535*
MD score	0.0746*	-0.0004	0.0746*
Model 14 [a]			

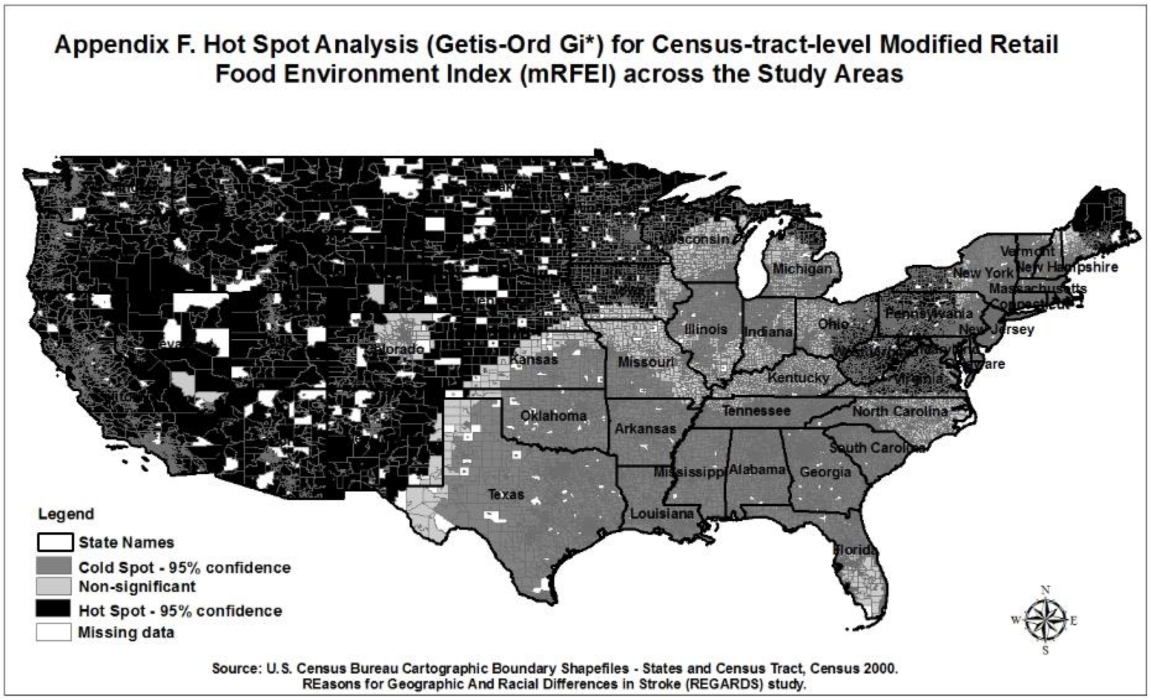
mRFEI	0.0376*	-0.0005	0.0372*
MD score	0.0866*	.	0.0866*
Model 15 [d]			
mRFEI	-0.0177	0.0013	-0.0164
MD score	-0.0311*	.	-0.0311*
Model 16 [a]			
mRFEI	0.0457*	-0.0011	0.0446*
MD score	0.1139*	.	0.1139*
Model 17 [e]			
mRFEI	-0.0080	-0.0005	-0.0084
MD score	0.0147	.	0.0147
Model 18 [a]			
mRFEI	0.0437*	-0.0002	0.0435*
MD score	0.0768*	.	0.0768*
Model 19 [a]			
mRFEI	0.0511*	0.0015	0.0526*
MD score	0.1250*	.	0.1250*
Model 20 [b]			
mRFEI	0.0221	-0.0001	0.0220
MD score	0.0404	.	0.0404
Model 21 [a]			
mRFEI	-0.0536	-0.0014	-0.0550
MD score	0.1195*	.	0.1195*

Note: mRFEI = modified retail food environment index; MD=Mediterranean diet;
Model 1: path analysis among the whole REGARDS study population (n=20897);
Model 2: path analysis among the subgroup who had an income of ≤ 75K (n=14859);
Model 3: path analysis among the subgroup who had an income of > 75K (n=3590);
Model 4: path analysis among the subgroup aged ≤64 years old (n=10553);
Model 5: path analysis among the subgroup aged >64 years old (n=10344);
Model 6: path analysis among the subgroup who were white (n=13941);
Model 7: path analysis among the subgroup who were black (n=6956);
Model 8: path analysis among the subgroup who were male (n=9241);
Model 9: path analysis among the subgroup who were female (n=11656);
Model 10: path analysis among the subgroup who had < a college degree (n=13040);
Model 11: path analysis among the subgroup who had ≥ a college degree (n=7849);
Model 12: path analysis among the subgroup who exercised < 4 times/week(n=14310);
Model 13: path analysis among the subgroup who exercised ≥ 4 times/week (n=6307);
Model 14: path analysis among the subgroup who watched TV/Video < 4 hrs/day (n=14420);
Model 15: path analysis among the subgroup who watched TV/Video ≥ 4 hrs/day (n=6195);
Model 16: path analysis among the subgroup who were non-current smoker (n=17979);
Model 17: path analysis among the subgroup who were current smoker (n=2842);
Model 18: path analysis among the subgroup who lived in urban areas (n=16089);
Model 19: path analysis among the subgroup who lived in large rural areas (n=2635);
Model 20: path analysis among the subgroup who lived in small rural areas (n=1459);

Model 21: path analysis among the subgroup who lived in isolated rural areas (n=714);
[a]: Obesity outcomes were measured as 1/sqrt(BMI) in the model, which were transformed from original BMI data as suggested by Box-Cox transformation test;
[b]: Obesity outcomes were measured as sqrt(1/Sqrt(BMI))in the model;
[c]: Obesity outcomes were measured as log(BMI)in the model;
[d]: Obesity outcomes were measured as sqrt (log(BMI))in the model;
[e]: Obesity outcomes were measured as log (log (BMI))in the model;
*p<.05

APPENDIX F

HOT SPOT ANALYSIS (GETIS-ORD GI*) FOR CENSUS-TRACT-LEVEL MODIFIED RETAIL FOOD ENVIRONMENT INDEX (MRFEI) ACROSS THE STUDY AREAS



Note: mRFEI = modified Retail Food Environment Index; REGARDS = Reasons for Geographic and Racial Differences in Stroke. Black (hot spot) indicates the clusters of census tracts with significantly higher mRFEI, comparing to the overall study areas. Dark Grey (cold spot) indicates the clusters of census tracts with significantly lower mRFEI, comparing to the overall study areas. Lighter grey indicates no significant clustering. White indicates census tracts with missing data on mRFEI. The significance of local clustering was based on a p-value < 0.05.