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ORIGINAL ARTICLE

Where the Food Is: Diabetes in Pregnancy and Proximity to Healthy and Unhealthy Food Sources in the Bronx

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ABSTRACT
Objective: To assess the relationship between walkable access to healthy and unhealthy food sources and risk of diabetes in pregnancy.

Methods: Patient medical records were utilized to develop a cohort of obstetric patients who resided in Bronx, NY and initiated prenatal care in one calendar year. Locations of both healthy and unhealthy food sources (HFS and UFS, respectively) were derived from a combination of databases. Street network analysis was performed to identify stores within walking distance from each patient's geocoded residence. The odds of diabetes during pregnancy were obtained through logistic regression to determine the effect of walkable access to both HFS and UFS after adjusting for other patient-level covariables.

Results: A cohort of 4,833 records was created. For all patients, proximity to a UFS was not associated with increased risk of diabetes in pregnancy. For lower-income patients, as indicated by Medicaid coverage or uninsured status, those who lived further than 0.25 miles from a HFS showed increased odds of diabetes during pregnancy although this association was not statistically significant at the $\alpha = 0.05$ level (adjusted OR = 1.32, 95% CI 0.94-1.84). Patients with commercial insurance who lived farther than 0.25 miles from a HFS had statistically significant decreased odds of gestational diabetes (adjusted OR = 0.77, 95% CI 0.59-0.99).

Conclusions: Socioeconomic status appears to modify the effect of walkable street distance on the risk of diabetes during pregnancy in an urban environment.

INTRODUCTION

Diabetes mellitus is a condition in which the body responds abnormally to glucose. Diabetes is extremely prevalent in the Western world, even among young women, so pregnancy with pre-existing diabetes also is common (Menke, Casagrande, Geiss, & Cowie, 2015). However, even women without diabetes may develop the condition during pregnancy, which is then termed gestational diabetes. Gestational diabetes develops because of various physiologic but diabetogenic endocrine factors that accompany pregnancy, primarily including the placental secretion of growth hormone, corticotropin-releasing hormone, human placental lactogen, and progesterone (Committee on Practice Bulletins—Obstetrics, 2018).

Both pregestational and gestational diabetes are associated with obesity and high carbohydrate diets (Louie et al., 2011; Zhang, Liu, Solomon, & Hu, 2006). For all women who are at risk for diabetes before or during gestation, standard of care centers on counselling about healthy food intake and diet modification to avoid complications (Hu & Solomon, 2001). The goals of appropriate nutritional intake achieve normoglycemia, prevent ketosis, provide adequate weight gain, and contribute to fetal well-being (Committee on Practice Bulletins—Obstetrics, 2018; Luoto et al., 2011).

However, dietary modification is a health behavior that has barriers to compliance. Evidence strongly suggests that the local food environment is associated with individual dietary behavior and ability to adhere to a low-carbohydrate diet (Morland, Diez Roux, & Wing, 2006; Morland, Wing, Diez Roux, & Poole, 2002). Many studies have used spatial analysis techniques to demonstrate a relationship between the geographic access to healthy food sources (HFS) and unhealthy food sources (UFS), and nutrition-related conditions, such as obesity, hypercholesterolemia, and diabetes (Gibson, 2011; Janevic, Borrell, Savitz, Herring, & Rundle, 2010; Laraia, 2004; Morland et al., 2006; Rundle et al., 2009).

Though there have been developments in exploring how city environments affect access to healthy food, few studies have the ability to directly assess health outcomes (Walker, Keane, & Burke, 2010). Those studies with access to patient outcome data have focused largely on obesity and related diseases, including diabetes, but few studies of this type have included pregnant women (Lake & Townshend, 2006). Given that pregnancy is a unique time in human physiology, when even short-term changes to nutritional access and choices can deeply affect maternal, neonatal, and eventually pediatric outcomes, utilizing geocoding tools in this setting would be valuable. Therefore, this study was designed to evaluate the association between walkable access to either healthy or unhealthy food sources and diabetes in pregnancy in a large urban center.

MATERIALS AND METHODS

Patient Data Collection

This study was reviewed and granted approval by the Montefiore Medical Center/Albert Einstein College of Medicine Institutional Review Board. A retrospective cohort of all patients who presented for prenatal care during the year 2010 at one large academic medical center in Bronx, NY was created from the interactive software program Clinical Looking Glass (CLG™). In addition, ASObGyn and EPF Web, two electronic medical record systems, provided the demographic characteristics and prenatal course of patients as well as other relevant maternal and neonatal inpatient and outpatient characteristics.

Each patient's address at first obstetric appointment was converted to longitude and latitude coordinates through a geocoding tool built into the Clinical Looking Glass software. Cases of diabetes in pregnancy were identified through a keyword search in our prenatal records for the words "diabetes," "GDM," "glucose intolerance," "abnormal glucose tolerance," or "insulin resistance" as a diagnosis code for encounters within the current pregnancy. Each patient with a diagnosis code positive for diabetes had a chart reviewed by a clinician. A patient was considered to have diabetes in pregnancy if a one-hour oral glucose challenge test was positive or if she had any medications for diabetes initiated or continued during pregnancy.
The data set was limited in its ability to distinguish between pregestational and gestational diabetes, reflecting the limitations of clinical reality. Many women who are diagnosed with diabetes in pregnancy will have an unclear diagnosis of pregestational versus gestational diabetes. Since many women enter pregnancy without access to recent health care or screening, the duration of the diabetes is often uncertain.

Healthy and Unhealthy Food Source Data Collection

To develop a complete food source dataset for the Bronx, we defined healthy food sources as supermarkets and fruit and vegetable markets, similar to methods in other published literature (Morland et al., 2002). We defined unhealthy food sources as "fast food restaurants, snack and nonalcoholic beverage bars, bakeries, and candy and nut stores" (Morland et al., 2002; Rundle et al., 2009). For all food sources, we utilized their respective North American Industry Classification System or North American Industry Classification System code (Table 1). We then employed two commercial databases, Dun & Bradstreet and ReferenceUSA™, to locate latitude and longitude coordinates for all healthy food sources in the Bronx during our study period. Dun & Bradstreet is a commercial company that offers information on businesses throughout the world through a database that gathers and verifies data using a patented process ("Learn More About Our Company," 2018). ReferenceUSA is a library-oriented company providing business and consumer data about businesses throughout the United States for researchers.("About Us | About | ReferenceUSA," 2018). All supermarkets, as defined by North American Industry Classification System codes, were further refined by name recognition to include only chain supermarkets, as previously described (Morland et al., 2006, 2002). These stores were subsequently cross-validated using the store locator function provided by the respective chain websites.

All food sources were then verified by the Google Maps street-view application or by store phone numbers provided by the databases. Stores that failed to be verified by either method were excluded from the dataset and were assumed to no longer exist (Figure 1). Our final healthy food sources dataset included 142 supermarkets and 99 fruit and vegetable markets for a total of 241 HFS and 993 UFS in the Bronx.

Network Distance Calculation

Network analysis was performed to determine the closest healthy and unhealthy food sources to each patient in our cohort. According to previous studies, walkable access to a food sources was defined as living 0.25 miles or less from that source (Laraia, 2004; Tester, Yen, & Laraia, 2010; Thornton, Pearce, Macdonald, Lamb, & Ellaway, 2012).

Using ArcGIS™ v10.0 software, the latitude and longitude coordinates were plotted and exported into two separate layers for both patient residences and food sources (Figure 2). A street network dataset was obtained from the New York City Department of City Planning LION Road Network and clipped to only include road segments in the Bronx. These different data sources were integrated though a geodatabase for analyses and mapping, as in Figure 3.

The Network Analyst tool in ArcGIS™ v10.0 was then applied for calculating walking distance. Network analysis was performed to determine the closest healthy and unhealthy food sources to each patient in our cohort.

With this information, network analysis allowed for identifying walking paths to the nearest unhealthy food source (Figure 4) and to the nearest healthy food source (Figure 5) in the Bronx.

Statistical Analysis

The effect of distance and other covariables was quantified through logistic regression (Hosmer & Lemeshow, 2000) using SAS™ 9.2 (SAS Institute Inc. 2012) to obtain the odds of a pregnant woman having gestational diabetes for any level of a categorical covariable, relative to a reference level, after adjusting for the effect of other covariables in the model. Odds ratios were calculated along with their Wald 95% confidence limits.

Model fit was summarized by the percent concordance (Hanley & McNeil, 1982), which increases proportionally to the model's ability to discriminate between diabetic and non-diabetic patients. The Hosmer-Lemeshow statistic was also obtained, which assesses model fit by comparing observed with predicted cases. This is a chi-square test whereby larger p-values (>0.05) indicate a more appropriate model. Model specification was evaluated by the deviance statistic to assess over- or under-dispersion and by residual spatial autocorrelation through the Moran's I statistic (Lin & Zhang, 2007) to assess spatial independence of model residuals. Both the raw and adjusted odds ratios were obtained, in which adjustment refers to adjusting for all other covariables in the logistic regression model. Each covariable was inspected in the logistic regression model, in contrast with raw odds ratio calculations.

RESULTS

The cohort included 4,833 women. Of those, 490 were positive for diabetes during their pregnancy. Table 2 presents the distribution of patients across select variables with respect to diabetes status.

Table 3 presents the odds of diabetes in pregnancy relative to the stated reference value for select covariables conditional on insurance status. Odds ratios are presented as both unadjusted and adjusted for all other covariables listed in the table.

All adjusted models correctly discriminated between diabetes status for over 66% of the patients. Deviance statistics closely approximated their expected values, the degrees of freedom, indicating that over- or under-dispersion was not a problem. Spatial autocorrelation of the model deviance residuals was insignificant (*p*-value approximately 0.5), indicating there was no need for adding an effect to adjust for residual spatial autocorrelation.

For all patients, UFS environment was not associated with increased risk of diabetes during pregnancy (adjusted OR= 1.00, 95% CI 0.999-1.000). However, for patients with low socioeconomic status, as indicated by Medicaid coverage or uninsured status, those who lived greater than 0.25 miles from an HFS had a trend toward increased prevalence of diabetes during pregnancy when compared to those who lived closer (adjusted OR= 1.318, CI 0.943 – 1.843), though this association did not reach statistical significance . Patients with commercial insurance revealed the opposite effect, showing a decrease in diabetes during pregnancy if they lived >0.25 miles from a HFS (adjusted OR 0.77, CI 0.59-0.99).

DISCUSSION

In this large cohort from an urban area, living more than 0.25 miles from a HFS was associated with a trend toward increased risk of diabetes during pregnancy in women with public insurance or without insurance. Although the association demonstrated only marginal statistical significance, these findings support that residing close to a healthy food source may help offset other risk factors associated with lower income.

For women with private insurance, which can serve as a proxy for higher socioeconomic status, the opposite effect was observed with an association between increased distance from an HFS and lower diabetes odds during pregnancy. These findings warrant further study as it is plausible that variables we did not have access to may affect the data and our results. In particular, for those patients with higher socioeconomic status and private insurance, we did not have access to data regarding public or private transportation. Whether or not patients owned or had access to a vehicle or used mass transportation as their primary means of travel could plausibly impact these results. For patients with higher socioeconomic status, it is plausible that once the threshold for automobile ownership has been reached, distance to HFS and UFS becomes a less relevant barrier to healthy food choices. The inverse correlation in this population may also reflect that higher-income patients live in less dense and less urban areas of the Bronx, with lower levels of poverty but also greater distance to most destinations.

Within the fields of nutrition and geocoding, many studies have attempted to correlate societal and geographic factors with medical outcomes, but few have focused on pregnancy. Although Geographic Information Science continues to rapidly evolve, few studies have used this level of network analysis to assess relationships with clinical outcomes, and those that have done so faced difficulties in developing a cohesive food database.

The strength of this study is the use of geocoding techniques and their subsequent correlation with patient-level clinical and demographic data. In addition, the construction of our healthy and unhealthy food sources database utilized a novel and stringent approach by querying two commercial databases by North American Industry Classification System codes, and then further refining our dataset using Internet and telephone verification.

One area that would benefit from further study would be to measure the mobility of our cohort throughout their gestational period. We assumed the address self-reported at the first prenatal visit was the primary residence of each patient during pregnancy, which may not be true in a lower income population with high rates of transience. Another limitation of that study is that we did not have access to private or public transportation data for our patient cohort, as our database did not include vehicle ownership or public transportation. These factors may affect the mobility of our population, and could serve as a direction for future research.

A further direction to consider would be to include seasonal and mobile food sources, such as famers' markets or fruit and vegetable stands. Although these sources tend to be short-lived, and thus probably have a less marked effect on long-term nutrition, these resources would be an important addition to a more comprehensive model of healthy food sources in the future.

Finally, our database was created in a way that limited our ability to distinguish between pregestational diabetes and diabetes that develops in pregnancy within our cohort. This issue has been noted in other studies, as in a major study reporting on the prevalence of diabetes among delivery hospitalizations in the United States (Correa, Bardenheier, Elixhauser, Geiss, & Gregg, 2015). In conceptual thinking, pregestational and gestational diabetes are considered different disease states, but in clinical reality they are more often experienced as aspects of one disease. Thus, although pregestational diabetes is often considered a chronic disease state and gestational diabetes considered a short-term condition, in actual patient care these diagnoses are not unrelated and can be difficult to distinguish.

The links between these two forms of glucose intolerance are well-characterized, and include their shared pathophysiology and a complex list of factors such as obesity and sedentary lifestyles. Perhaps more importantly, grouping these diseases together reflects the delay in diagnosis that is often seen in underserved communities. Many women without access to stable medical screening will be diagnosed with diabetes during their pregnancy, but many of these women truly have pregestational diabetes. In some studies, up to 70% of women with a gestational diabetes diagnosis actually have pregestational diabetes which was not diagnosed earlier because of lack of care in their non-pregnant life (Committee on Practice Bulletins—Obstetrics, 2018; Kim, Newton, & Knopp, 2002). Thus, it is reasonable and useful in this clinical context to look at this disease as two aspects of glucose intolerance diagnosed in pregnancy rather than as two distinct diseases.

Based on our findings, additional research is needed to see if the observed effect can be strengthened in other populations and different residential environments. Future directions for this research should include more rigorous tracking of patient's residence, real-time verification of healthy food sources, inclusion of public transportation access points, and data about personal vehicle access.

This study is an important step in continuing our understanding of diabetes during pregnancy as not only a nutritionally-mediated condition, but an environmentally and behaviorally mediated one. In the future, a better understanding of the larger contexts of diabetes during pregnancy and other diseases will inform research and policy to better facilitate positive patient behaviors and achieve better outcomes.

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Author Contributions: All authors contributed to this work. The study was designed by all authors in concert. Mapping and geocoding analysis was done by Dr. Bottalico. Statistical analysis was performed by Dr. Johnson. The clinical review of charts was performed by Dr. Karkowsky with additional clinical contributions by Dr. Chazotte. All authors contributed to the background research, interpretation of results, writing of the manuscript, and subsequent editing. All the authors approve this paper to be published.

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FIGURES

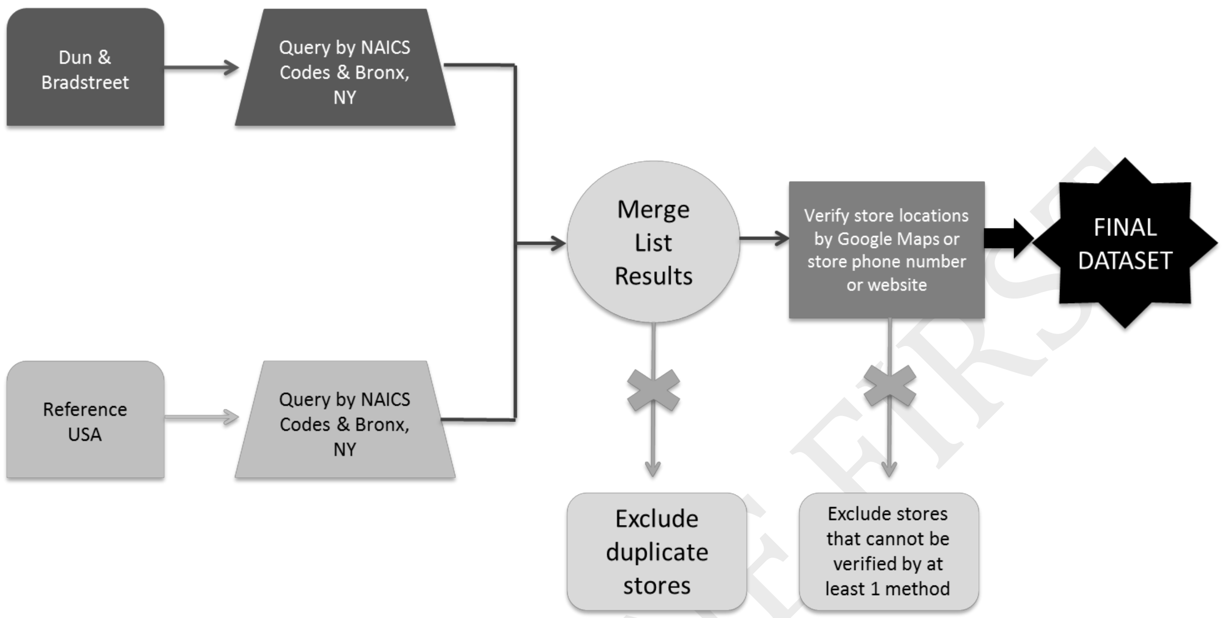

Figure 1: Verification of food source location.
Stores were identified in two commercial databases, Dun & Bradstreet and ReferenceUSA™, to locate longitude and latitude coordinates for all healthy food sources in Bronx, NY during our study period, and were then verified using the North American Industry Classification System (NAICS). Findings were further refined by name recognition to include only chain supermarkets, and then subsequently cross-validated using the store locator function provided by the respective chain websites. All food sources were then verified by Google Maps street-view application or by store phone number provided by the databases. Stores that failed to be verified by either method were excluded from the dataset and were assumed to no longer exist. Our final food sources dataset included 142 supermarkets and 99 fruit and vegetable markets for a total of 241 HFS; and 993 UFS in Bronx, NY.

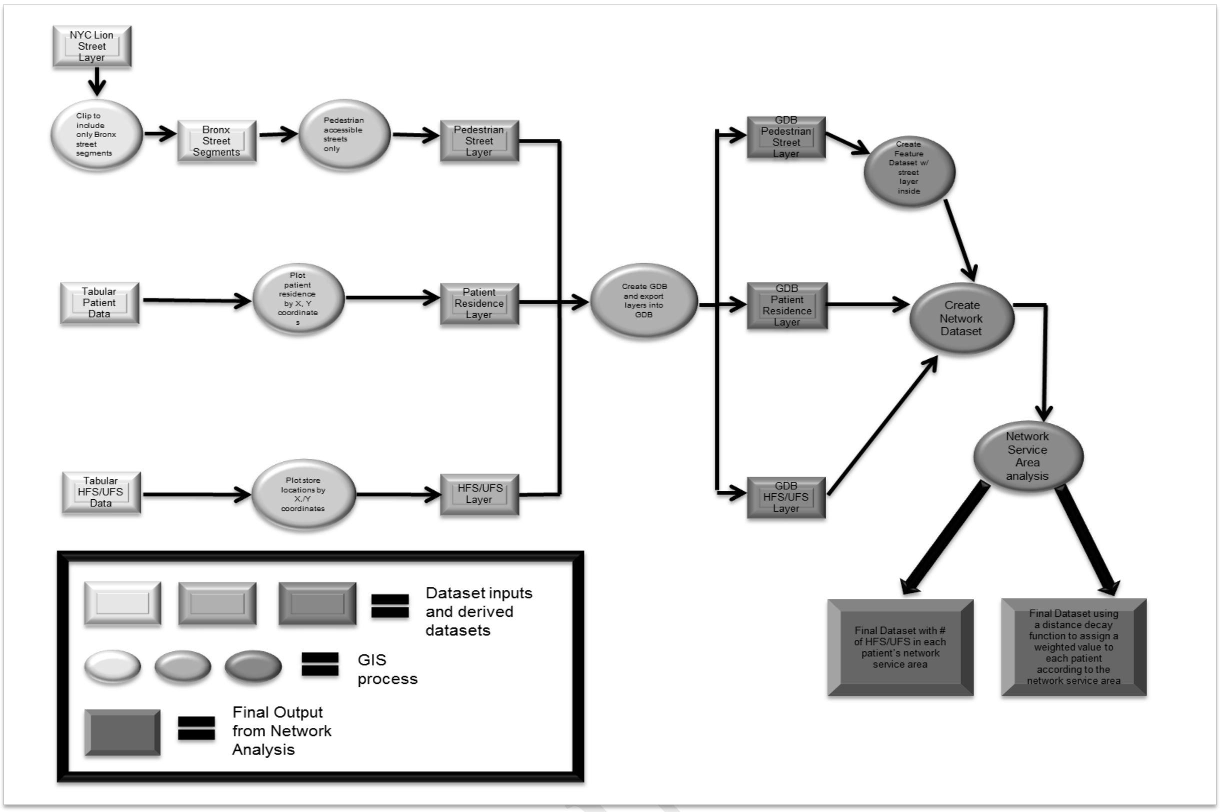

Figure 2. Network analysis to determine walkable access to healthy food sources.
Clear boxes signify dataset inputs and derived datasets; shaded boxes signify ArcGIS™ v10.0 software processes; heavily outlined box signifies final output from network analysis.

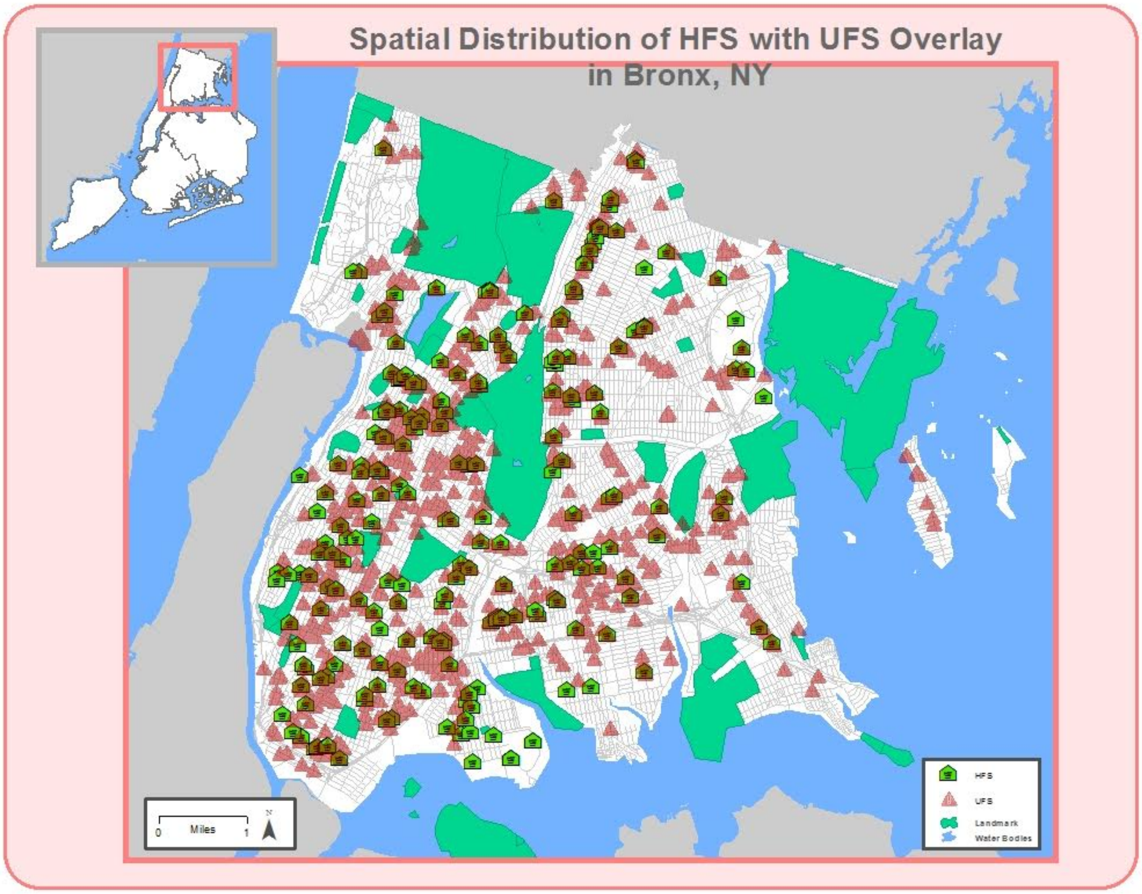

Figure 3: Map of healthy and unhealthy food sources in the Bronx.
Using ArcGIS™ v10.0 software, the longitude and latitude (x/y) coordinates were plotted and exported into two separate layers for both HFS and UFS. These coordinates were plotted onto a street network dataset obtained from the New York City Department of City Planning LION Road Network and clipped to only include road segments in Bronx, NY. Our final mapped food sources dataset included 142 supermarkets and 99 fruit and vegetable markets for a total of 241 HFS and 993 UFS in Bronx, NY.

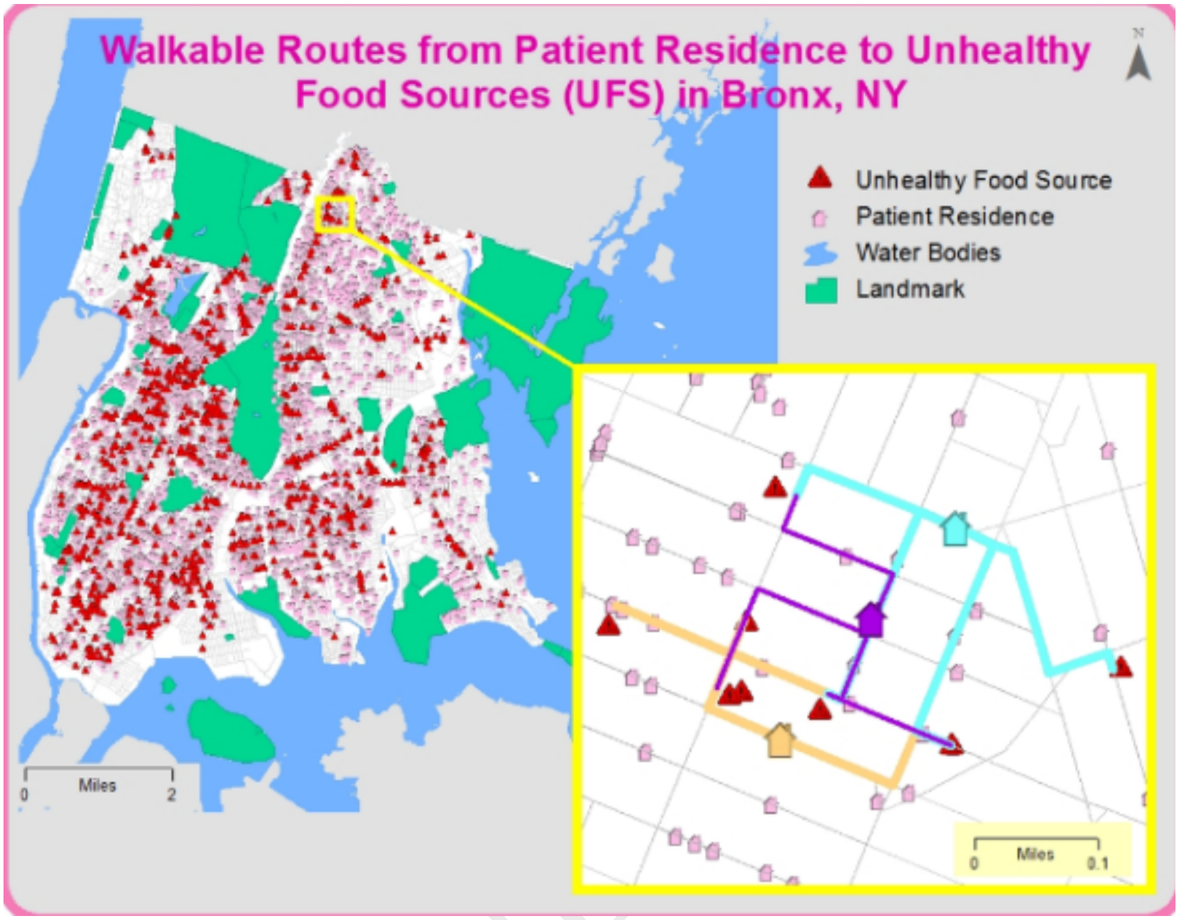

Figure 4: Map of walkable routes to unhealthy food sources in the Bronx.
A street network dataset was obtained from New York City Department of City Planning LION Road Network and clipped to only include road segments in Bronx, NY. These different data sources were integrated with the final database of HFS and UFS as above. The Network Analyst tool was activated in ArcGIS™ v10.0 and set to model turns in street segments, and network analysis was performed to determine the closest healthy and unhealthy food sources to each patient in our cohort. With this information, network analysis allowed for the creation of maps showing walking path to nearest healthy food sources in Bronx, NY. This map includes all 4833 subjects and 993 UFS in Bronx, NY.

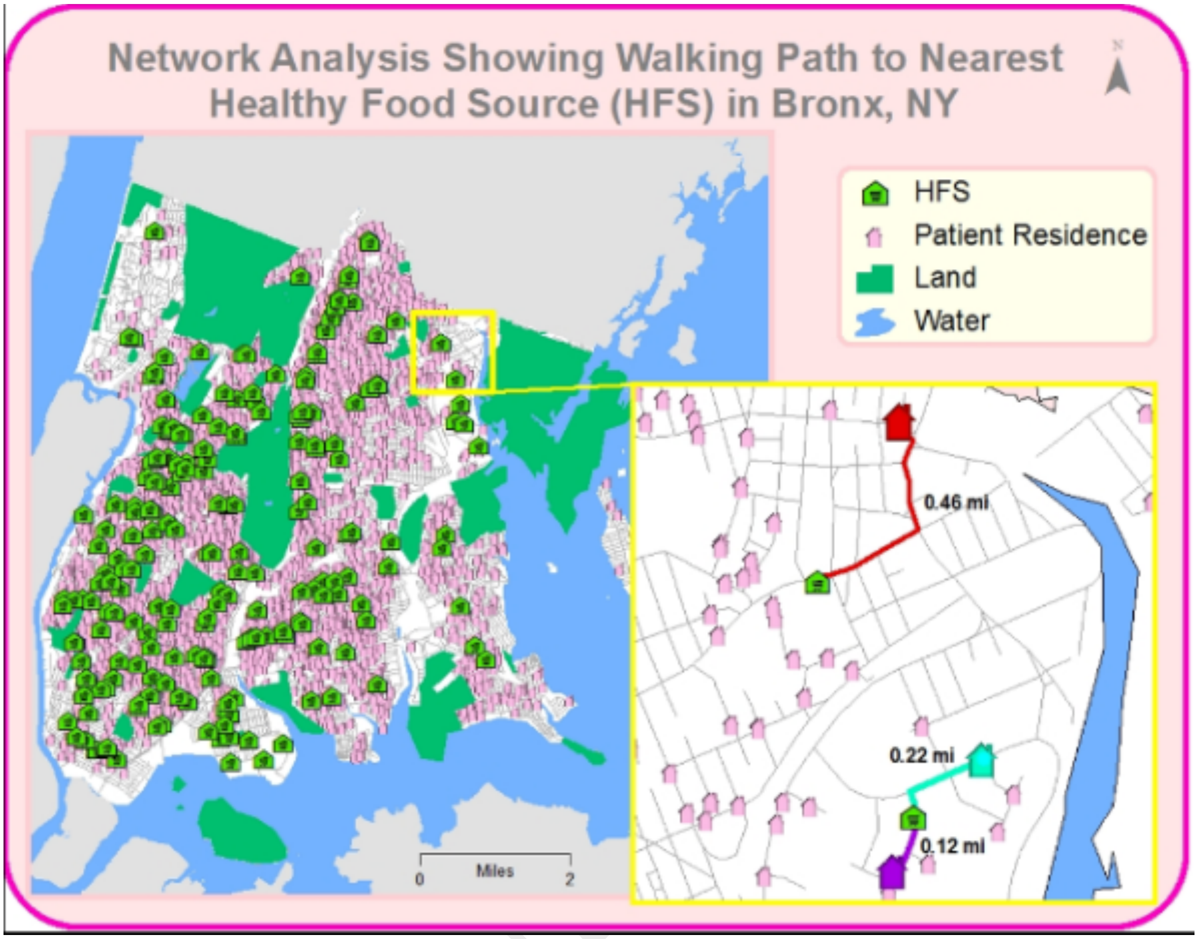

Figure 5: Network analysis showing walking path to nearest healthy food source in Bronx, NY. A street network dataset was obtained from New York City Department of City Planning LION Road Network and clipped to only include road segments in Bronx, NY. These different data sources were integrated with the final database of HFS and UFS as above. The Network Analyst tool was activated in ArcGIS™ v10.0 and set to model turns in street segments, and network analysis was performed to determine the closest healthy and unhealthy food sources to each patient in our cohort. With this information, network analysis allowed for the creation of maps showing walking path to the nearest healthy food source in Bronx, NY. This map includes all 4833 subjects and 241 HFS in Bronx, NY.

Table 1: Healthy Food Sources Definitions

Healthy Food Sources	North American Industry Classification System Code	Example
Supermarkets	445110	A&P, Stop & Shop, Pathmark, Foodtown, C Town
Fruit and vegetable markets	445230	Garden Market, Kim's Fruit Market, Modern Fruit, New Era Produce

Table 2: Distribution of patients across select variables, with respect to diabetes status. Presented as the full cohort and conditional on insurance status.

	Full Cohort		Medicaid / Uninsured		Commercial Insurance	
Covariables	diabetic	not diabetic	diabetic	not diabetic	diabetic	not diabetic
Patient's age (years)						
<20	68	1218	26	443	42	775
20-24	66	893	28	393	38	500
25-29	132	974	48	339	84	635
30-34	129	735	38	200	91	535
35-39	64	292	31	72	33	220
40+	31	106	5	30	26	76
missing age		125		39		86
first prenatal visit						
1st month	32	749	14	274	18	475
month 2-3	305	2062	91	588	214	1474
month 4-6	125	968	55	378	70	590
> month 6	50	542	23	269	27	273
race						
Asian	17	128	1	32	16	96
black	190	1505	64	570	126	935
multi-racial	201	1741	76	593	125	1148
other	70	624	33	221	37	403
white	34	323	9	93	25	230
gravidity						
1	74	742	24	278	50	464
2-3	159	1202	52	392	107	810
4-5	101	578	39	192	62	386
6+	68	321	19	104	49	217
missing gravidity		1588		592		996
insurance						
Medicaid or uninsured	183	1509				
commercial	329	2812				
distance to HFS						
> 0.25 miles	171	1485	68	485	103	1000
≤ 0.25 mile	341	2836	115	1024	226	1812

Table 3: Odds of Diabetes Mellitus, relative to the stated reference value for select covariables, conditional on insurance status. Adjusted odds ratios are adjusted for all other covariables listed in this table.

odds ratios (95% Wald confidence intervals)

Covariables	full cohort						Medicaid and uninsured						commercial insurance					
	unadjusted			adjusted			unadjusted			adjusted			unadjusted			adjusted		
	OR	LL95	UL95	OR	LL95	UL95	OR	LL95	UL95	OR	LL95	UL95	OR	LL95	UL95	OR	LL95	UL95
Patient's age (years)																		
< 20	0.41	0.30	0.56	0.46	0.34	0.62	0.42	0.25	0.68	0.44	0.27	0.73	0.41	0.28	0.60	0.47	0.32	0.69
20-24	0.55	0.40	0.74	0.55	0.40	0.75	0.50	0.31	0.82	0.49	0.30	0.81	0.58	0.39	0.86	0.61	0.41	0.91
25-29 (ref)																		
30-34	1.30	1.00	1.68	1.35	1.03	1.75	1.34	0.85	2.13	1.34	0.84	2.13	1.29	0.94	1.77	1.35	0.98	1.86
35-39	1.62	1.17	2.24	1.68	1.21	2.34	3.04	1.81	5.11	3.00	1.78	5.07	1.13	0.74	1.75	1.21	0.78	1.87
40+	2.16	1.39	3.35	2.21	1.42	3.45	1.18	0.44	3.18	1.24	0.46	3.39	2.59	1.57	4.27	2.64	1.59	4.38
first prenatal visit																		
1st month (ref)																		
month 2-3	3.46	2.38	5.03	2.95	2.01	4.34	3.03	1.69	5.41	2.48	1.37	4.50	3.83	2.34	6.27	3.25	1.95	5.43
month 4-6	3.02	2.03	4.51	2.69	1.78	4.06	2.85	1.55	5.22	2.25	1.21	4.20	3.13	1.84	5.33	2.95	1.70	5.12
> month 6	2.16	1.37	3.41	1.84	1.15	2.95	1.67	0.84	3.32	1.39	0.69	2.80	2.61	1.41	4.83	2.23	1.18	4.23
race																		
Asian																		
black	1.20	0.82	1.76	1.40	0.92	2.12	1.16	0.56	2.41	1.50	0.66	3.45	1.24	0.79	1.95	1.40	0.86	2.28
multiple	1.10	0.75	1.61	1.35	0.89	2.04	1.32	0.64	2.73	1.89	0.83	4.31	1.00	0.64	1.57	1.17	0.72	1.91
other	1.10	0.72	1.67	1.30	0.83	2.04	1.39	0.64	3.01	1.85	0.77	4.42	0.98	0.59	1.61	1.12	0.66	1.91
white (ref)																		
insurance																		
Medicaid or uninsured (relative to commercial)	1.01	0.82	1.26	1.21	0.96	1.52												
distance to HFS																		
> 0.25 mile (relative to ≤ 0.25 mile)	0.96	0.79	1.16	0.93	0.76	1.13	1.25	0.91	1.72	1.32	0.94	1.84	0.83	0.65	1.06	0.77	0.59	0.99
% concordance†				66.4						68.7						66.4		
HL p-value††				0.81						0.16						0.24		
Deviance / df†††				1.03						1.18						0.94		

* "ref" = reference value

† Percent concordance increases with increasing ability of the model to discriminate between anemic and non-anemic.

†† Hosmer-Lemeshow *p*-value: higher values, from 0 to 1, indicate better fit.

††† Deviance/degrees of freedom (df), where close to 1.0 indicates a properly specified model.