Published in final edited form as:

Appl Geogr. 2015 June ; 60: 197–203. doi:10.1016/j.apgeog.2014.10.006.

Multilevel built environment features and individual odds of overweight and obesity in Utah

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Abstract

Based on the data from the Behavioral Risk Factor Surveillance System (BRFSS) in 2007, 2009 and 2011 in Utah, this research uses multilevel modeling (MLM) to examine the associations between neighborhood built environments and individual odds of overweight and obesity after controlling for individual risk factors. The BRFSS data include information on 21,961 individuals geocoded to zip code areas. Individual variables include BMI (body mass index) and socio-demographic attributes such as age, gender, race, marital status, education attainment, employment status, and whether an individual smokes. Neighborhood built environment factors measured at both zip code and county levels include street connectivity, walk score, distance to parks, and food environment. Two additional neighborhood variables, namely the poverty rate and urbanicity, are also included as control variables. MLM results show that at the zip code level, poverty rate and distance to parks are significant and negative covariates of the odds of overweight and obesity; and at the county level, food environment is the sole significant factor with stronger fast food presence linked to higher odds of overweight and obesity. These findings suggest that obesity risk factors lie in multiple neighborhood levels and built environment features need to be defined at a neighborhood size relevant to residents' activity space.

Keywords

Obesity; Built environment; Multilevel modeling; Zip code; County; Utah

Introduction

Obesity is a lifestyle-based risk factor of a wide range of health problems, including heart disease, stroke, diabetes and some of the leading causes of preventable death, and has become a major public health concern in the United States in recent decades (Zhang, Lu, & Holt, 2011). It is now adding a shocking $190 billion to the annual national healthcare from obesity-related conditions; this amount constitutes almost 21% of the total healthcare costs

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(Begley, 2012). Although Utah is among the states with the lowest obesity rates in the U.S., the estimated prevalence of overweight and obesity is over 60% according to the BEE Well Utah (2014).

According to the energy balance theory, an individual's excessive body weight results from a positive balance where total energy intake such as food and drink cumulatively exceeds total energy expenditure including physical activity (Schoeller, 2009). The obesogenic environment thesis suggests that obesity-preventive factors include exposure to a healthy food environment that promotes healthier dietary choices and built environments that encourage physical activities (Hill & Peters 1998; Swinburn, Egger, & Raza 1999). Built environment is broadly defined as “humanformed, developed, or structured areas” (CDC, 2005), and includes walkable urban form, places to be physically active, and attractive and safe environment (Casey, Elliott, & Glanz, 2008; Lovasi, Hutson, Guerra, & Neckerman, 2009; Miles, Panton, Jang, & Haymes, 2008). In this paper, food environment is also considered part of the built environment.

Multilevel modeling is commonly used in research on obesity etiology by incorporating both individual-level risk factors and neighborhood characteristics (Wang, Wen, & Xu, 2013; Wen & Maloney, 2011). Individual variables are often obtained directly from surveys while built environment factors are measured at some neighborhood level(s) from various data sources. One challenge is to determine what constitutes an appropriate neighborhood scale or size in defining the built environment. For example, in analyzing overweight risks, Gordon. Nelson, & Rage (2006) used an 8-km radius around one's residence as a reasonable range to define available physical activity facilities. Rutt and Coleman (2005) defined neighborhood as a 0.25-mile radius around each person's residence to examine the association between mixed land use and BMI. In examining the impact of urban sprawl index on obesity rate, Ewing, Schmid, Killingsworth, Zlot, and Raudenbush (2003) used the county level and Kelly-Schwartz, Stockard, Doyle, and Schlossberg (2004) chose primary metropolitan statistical areas (PMSA). Yamada et al. (2012) examined walkability in Salt Lake City in multiple geographic scales such as census tracts, block group and street network buffers. Other studies in this field also employed smaller area units such as census tracts (Wen & Maloney, 2011) and zip code areas (Wang, Guo, & McLafferty, 2012) to define neighborhoods, depending mainly on what geographic identifiers were available in the research data. The wide variability in neighborhood size without a fair justification of its choice may lead to questions of stability and reliability of research results, an issue related to the modifiable areal unit problem (MAUP) (Fotheringham & Wong, 1991).

More recently, several MLM-based studies examined the issue of appropriate area unit(s) for defining the neighborhood effect in public health. It is widely acknowledged that effective interventions on health behaviors and outcomes occur on multiple levels (Nader, Bradley, Houts, McRitchie, & O'Brien, 2008). Mobley, Kuo, and Andrews (2008) examined how contextual variables in four types of geographic areas (post code areas, primary care service areas, medical service study areas, and county) affected the use of mammography service, and found inconsistent results across the four levels. Another study offered some insights speculating that small local areas might reflect social support while a large area unit might reflect geo-political units and minorities' political influence (Kuo, Mobley, & Anselin, 2011). Wang et al. (2012) constructed a new level of geographic areas from zip code areas with comparable population size to examine the neighborhood effect when neighborhoods are defined in different sizes. Kwan (2012b) used a term “the uncertain geographic context problem (UGCoP)” to refer to unstable results derived from different delineations of contextual units, and went on to suggest that contextual units should be defined in a way that captures people's actual or potential activity spaces (Kwan, 2012a).

The current research continues this line of work to examine the neighborhood effects at both zip code and county levels on association of several built environment factors with individual odds of overweight and obesity. We seek to explore appropriate neighborhood units for a particular built environment factor in Utah.

Data and variable definitions

Individual-level data used in this study are from the Utah Behavioral Risk Factor Surveillance Survey (BRFSS) collected in 2007, 2009 and 2011 by the Utah Department of Health in conjunction with the CDC for assessing health conditions and risk in the non-institutionalized Utah adult population (18 years and older). The 2011 BRFSS data reflects a change in weighting methodology (raking) and the addition of cell phone only respondents while the 2007 and 2009 BRFSS were solely based on landline subject recruiting and data collection (http://www.cdc.gov/brfss/annual_data/annual_2011.htm). The BRFSS data (http://health.utah.gov/opha/OPHA_BRFSS.htm) contains rich information on individual socio-demographic characteristics, behavioral factors and health conditions with zip code provided for each respondent. After deleting a small amount of missing data, 21,961 observations are used in the research. Among these records, there are 9962 men and 11,999 women. Some zip code boundaries have changed over time, and a few zip codes are points. By checking the postal service website and other online sources, we were able to construct a unified GIS layer of 299 zip codes in 29 counties as shown in Fig. 1.

Descriptive statistics for the Utah residents in the study sample are shown in Table 1. More than 60% of the study participants are either overweight or obese and the prevalence of obesity in this sample is 24.2%. The majority of the residents are white. About 70% of the sample received college degree or above.

Body mass index (BMI) was calculated based on self-reported height and weight: BMI = mass (kg)/(height (m))^2. According to the CDC, an adult who has a BMI between 25 and 29.9 is considered overweight, while BMI of 30 or higher is obese (http://www.cdc.gov/obesity/adult/defining.html). Two levels of excessive weight were examined in this study, obesity (BMI $\geq$ 30) and overweight plus obesity (BMI $\geq$ 25). Socio-demographic variables including age (continuously measured), gender, race (whites versus non-whites), employment status (categorical), education level (college graduates versus below bachelor's degree), marital status (currently married or not) and smoking status (having smoked 100 cigarette or not) were controlled for in the analysis following previous work (Wen & Kowaleski-Jones, 2012). Age squared was added to further control for potential nonlinear age effect. Race/ethnicity was dichotomously measured into whites versus non-whites given the vast majority of the respondents were white. Employment status was characterized into several groups including “employed for wages” (as the reference category), “self-employed”, “out of work for more than one year”, “out of work for less than one year”, “homemaker”, “student”, and “retired.” Education was dichotomously measured given the threshold effect of college credentials on obesity prevention (Wen & Kowaleski-Jones, 2012).

Place-based socioeconomic status was captured by prevalence of residents living in poverty in a zip code area or a county according to the 2010 Census data. The built environment was captured by the following four variables constructed from multiple data sources.

Street connectivity was measured as the density of intersections, which are identified from the 2008 street centerline data in the ArcGIS 9.3 Data DVD by the ESRI (Aurbach 2010; Wang et al. 2013). Intersections with a starting or ending node of an edge or an intersection of 3-way or more edges were included in the connectivity index calculation. We first obtained the street connectivity in zip codes, and then aggregated to the county level. The aggregation takes population as the weight term such as

$$C_k = \sum_{i=1}^{n_k} P_i * C_i / P_k \quad (1)$$

where C_k is the connectivity in county k, n_k is the number of zip code units in county k, P_i is the population of zip code i within county k, and P_k is the total population in county k. This aggregation process accounts for the uneven spatial distribution of population in a large areal unit such as county, and thus derives a more appropriate “population-adjusted” street connectivity index (Wang et al. 2013).

Walk score (http://www.walkscore.com/) is a measure of resource proximity and density based on the summed total of distance between a point of interest to nearby amenities (Brewster, Hurtado, Olson, & Yen, 2009). The algorithm is developed by the Front Seat Management (http://www.frontseat.org/) as a pending patent system, and produces a valid measure of walkability (Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011). The algorithm uses location data of amenities such as restaurants, grocery stores, schools, parks, and movie theaters. The location data are sourced from Google, Education.com, Open Street Map, and Localeze. The Walk Score algorithm calculates a linear combination of the Euclidean distance from point of interest to the amenities. The weights in the linear combination are determined by facility type priority and a distance decay function (Front Seat, 2013). The Walk Score ranges from 0 (the lowest) to 100 (the highest). Font Seat provides an application programming interface (API) to query the Walk Score database through URL calls, eliminating the need to use the website interface (Front Seat, 2013). A Python program is composed to automatically request Walk Scores from the server through the Walk Score API. Similarly, walk score was first obtained in zip codes and then aggregated to the county level by using the weighted average formula in Equation (1).

The *distance to the nearest park* was constructed from the 2008 park dataset, also from the aforementioned ESRI Data DVD. National, state and local parks and forests are included in the dataset. There were 275 public parks and forest units in Utah, and 24 of them with areas smaller than 4000 square feet were not included in this study. For better accuracy, distance to the nearest park was calculated from each census block centroid (Zhang et al. 2011) and then aggregated to zip code and county levels as described above.

Food environment was captured by fast-food restaurant presence. Food consumption relying on fast food restaurants is likely to promote more meals or increase consumption of high fat meals, leading to higher caloric intake (Lopez, 2007). The restaurant data was from the U.S. Economic Census (http://www.census.gov/econ/).We used the most recent data available in 2007, with restaurants classified into fast-food and full-service. At the county level, food environment was measured as the *ratio of fast-food and full-service restaurants*. In our study area, many of the zip code areas did not have any restaurants, and calibrating such a ratio would be infeasible. Therefore, at the zip code level, we used the *fast-food accessibility* to capture the food environment. The accessibility measure follows the widely adopted accessibility index such as

$$A_i=\sum_{j=1}^{n}\left[S_j f(d_{ij})/\left(\sum_{k=1}^{m}P_k f\left(d_{kj}\right)\right)\right]$$

where P_k is population at location (i.e., zip code) k, and S_j is the number of fast food restaurants at location j, d is the travel time between them, and the common gravity model (i.e., power function with $\beta = 1$) is adopted to define the distance decay function $f(d)$ (Wang, 2012).

Table 2 reports mean, median, and ranges of neighborhood variables for the zip code areas and counties. We are aware of the gaps in dates among the data sources for the variables: BRFSS data 2007e2011, census data for poverty in 2010, street connectivity and distance from park in 2008, food environment in 2007 and walk score derived from the contemporary sources in 2013 (when most the data extraction and processing were conducted). It is considered acceptable given the limitation of data availability and the slow pace of neighborhood changes.

MLM analysis

After eliminating cases with missing data for BMI or demographic characteristics at the individual level, the analysis included 21,961 individuals nested within 299 zip codes that were nested within 29 counties. In other words, the hierarchical structure of the data has three levels: individuals (level 1) in zip codes (level 2) in county (level 3). Individuals living in the same zip code area or the same county share the same environmental characteristics at the corresponding level. That is to say, the neighborhood contextual variables are defined at two levels (zip code and county). Three-level random intercept logistic regression analyses were performed using SAS ProcGlimmix (Gibbs, 2008). Model 1 tested the effect of individual and zip code variables. Model 2 added county-level factors to Model 1. Model 3 was the final model including all significant place-based contextual variables in previous models. Akaike Information Criterion (AIC) value for each model was also reported to gauge a model's balance between its fitness of power and degrees of freedom.

Table 3 presents the odds ratios of multilevel logistic models for the risk of obesity (BMI ≥ 30). The effects of all the individual variables are fairly consistent across all models. White is not significant in any models. Female gender, college education, self-employment, homemaker, married and smoking are negatively associated with the odds of obesity. Age is positively associated with the odds of obesity, but the negative and significant coefficient for the “age squared” variable suggests this trend is reversed after reaching a certain age. Zip code level poverty prevalence (Models 1, 2 and 3) and county level ratio of fast-food to full-service restaurants (Models 2 and 3) are the only two place-based covariates exhibiting significant and positive associations with individual-level odds of obesity. Based on the AIC values, Model 3 is preferred.

Table 4 presents the results for overweight and obesity. Currently married is not significant anymore and student becomes negatively significant in Model 1. Other individual variables have the same effects as Table 3. In Model 1, fast food restaurant accessibility is negatively associated with the odds of overweight and obesity. Poverty prevalence (Models 1 and 2) and distance to the closest parks (Model 2) are positive covariates at zip code level but the effect of poverty is rendered insignificant in Model 3. At the county level, only the ratio of fast-food to full-service restaurants is a significant covariate positively associated with the odds of overweight or obesity (i.e., BMI ≥ 25) (Models 2 and 3). Based on the AIC values, Model 3 is preferred.

Discussion

The study simultaneously examines several built environmental features in their associations with odds of excessive body weight at two geographic aggregation levels: zip code and county. We also examined two different levels of excessive body weight, overweight plus obesity and obesity alone. The results suggest that observed built environmental influences on overweight and obesity are sensitive to these nuances. Net of individual controls and place-based poverty prevalence, distance to parks seems to be the only significant built environmental variable that is consistent with our hypothesis, that is, the longer distance to parks, the less spatial park accessibility, the higher odds of overweight and obesity. However, this effect is only manifested for the odds of being overweight or obese rather than being obese alone. Meanwhile, the results on the food environment are inconsistent across zip code and county level analyses. In addition, walk score and street connectivity, measures of neighborhood walkability, are not significantly linked to odds of individuals' excessive body weight in this sample.

Poverty rate is the only placed-based socio-demographic variable included in the analyses as a control variable. Both zip code and county level poverty rates were examined. It turns out the zip code-level poverty effect is more stable across the model configurations and body weight outcomes compared to built environment features. By contrast, county-level poverty was never significant in the presence of zip code-level poverty. This finding suggests that socioeconomic status, captured by poverty rate, should play a more important role at smaller geographic unit. County-level poverty has a weaker influence on the individual compared to zip code-level poverty as the latter captures socioeconomic contexts of more immediate social surroundings.

We examined three types of built environment features including walkability, park accessibility and food environment. Unexpectedly, none of the two walkability measures, namely street connectivity and walk score, were significant. Both variables were objectively measured and theoretically expected to be conductive to leisurely or non-leisurely walking and thus help with prevention against excessive weight gain. The empirical discrepancies are intriguing but not without antecedent (Berke, Koepsell, Moudon, Hoskins, & Larson, 2007). Several reasons are possible for this result. Our measures of walkability are not precise enough and the exposure mis-specification may partly explain the null finding. Lacking information on individual address, we used geographic centroids of each zip code area as the focal point to measure street connectivity and walk score. Within-area variations cannot be captured in this way. In addition, there may be interaction effects between walkability and other neighborhood factors such as socioeconomic status and ethnic composition. A recent study conducted in Baltimore found that walkability was only negatively linked to lower odds of obesity among individuals living in predominantly white and high-SES neighborhoods whereas the association between walkability and obesity among individuals living in low-SES neighborhoods was not significant after accounting for the confounders (Casagrande, Gittelsohn, Zonderman, Evans, & Gary-Webb, 2011). Other interaction effects may also exist. It is also possible that walkability effects are simply just weaker compared to other built environment features like food environments and park accessibility in Utah. However, population-based studies also conducted in Utah (Smith et al. 2008; Zick et al. 2013) used different walkability indicators and examined the walkability and obesity link reporting that increasing levels of walkability decrease the risks of excess weight. Perhaps empirical results of the walkability and excessive weight link are to some extent to the specific walkable-environment measures used in the analysis.

Distance to parks captures spatial inaccessibility to local parks representing one type of neighborhood activity-promoting public amenities. A significant and positive effect of this variable was found at the zip code level but not at the county level. This is consistent with previous findings that the association between neighborhood environments and health outcomes are stronger for smaller units such as zip code and census tracts (Krieger et al. 2003; Sturm & Datar, 2005). The result also makes intuitive sense, that is, individuals' exercise levels are likely to be more responsive to parks nearby rather than those located distantly. Compare to walkability, presence of local parks is a stronger built environment factor of individuals' odds of excessive weight in our analysis.

While walkability and park accessibility are both hypothesized to be environmental factors promoting physical activity, the food environment is supposed to affect the other key energy balance factor, dietary intake. There are many ways to capture the food environment and calculating the number of fast food restaurant per capita is a common method in many studies (Jay, 2004;Wang, Kim, Gonzalez, MacLeod, & Winkleby, 2007). In this study, we captured density of BMI-unhealthy food outlets by focusing on per-capita exposure to fast food. Instead of using the conventional method, we operationalized the presence and density of fast food outlets differently for the two spatial units, zip code areas and counties. Fast-food restaurant accessibility was defined at the zip code level and the ratio of fast-food outlets to full-service outlets was used at the county level. Results show that there is a small and negative association between fast food accessibility and risk of overweight and obesity at the zip code level in Model 1 from Table 4. Although the association at the zip code level is counterintuitive, it is no longer significant after adding the county-level variables in Model 2 from Table 4. For fast food ratio at the county level, it is strongly positively associated with the risk of unhealthy outcome (overweight or obesity) in Models 2 and 3 from Table 4 ($p \leq 0.001$). The explanation is that full-service restaurants are typically providing healthy food, while fast-food restaurants are typically main source of unhealthy, energy dense processed foods (Michimi & Wimberly, 2010). This is the only variable that is significant at the county level. Since people normally drive to buy fast food beyond the zip code they live, perhaps the adequate scale for defining food environment needs to be expanded beyond zip code areas.

Concluding comments

Based on the BRFSS data in Utah, this research examines the associations between neighborhood built environments and individual odds of overweight and obesity after controlling for individual risk factors. Four neighborhood built environment factors measured at both zip code and county levels are street connectivity, walk score, distance to parks, and food environment. Two additional neighborhood variables, namely the poverty rate and urbanicity, are also included as control variables.

Several study limitations should be kept in mind when interpreting study findings. First of all, this study is cross-sectional without considering temporal effects. The built environment variables describe an individual's residential neighborhood contexts at a specific time but do not account for how long the resident has lived there. For example, high BMI may have resulted from cumulative neighborhood obesogenic exposure but only information on the respondent's current neighborhood contexts can be captured in the analysis. The cross-sectional analysis cannot tell whether neighborhood environment factors cause individuals to live healthy or whether healthy individuals choose to live in neighborhood with good environment. To better sort out selection versus causation, longitudinal analyses should be conducted in the future. Secondly, the measurement of overweight/obesity relied on self-reported weight and height and thus was subject to response bias. Lastly, some important built environment factors were not examined in this study. For example, mixed land use may increase people's physical activities and reduce obesity. Highly mixed commercial and residential land uses can provide goods and services within individuals' walking or bicycling distances.

Despite the limitations, several strengths of this study are note-worthy. A key contribution of the current study is its simultaneously examining built environment at two different geographic units. To the best of our knowledge, this is the first 3-level study examining contextual effects of the built environments on individuals' odds of excessive weight in Utah. The MLM results show that among the four built environment variables, (1) at the zip code level, distance to parks is the only significant (and negative) covariate of the odds of overweight and obesity; and (2) at the county level, food environment is the sole significant factor with stronger fast food presence linked to higher odds of overweight and obesity. As residents normally walk to parks for recreational activities but drive to restaurants for food, the relevant built environments vary in spatial range. The findings suggest that obesity risk factors lie in multiple neighborhood levels and built environment need to be defined at a neighborhood size relevant to residents' activity space. This raises the issue of "uncertain geographic context problem (UGCoP)" and suggests that the contextual variables need to be defined in a way that reflects human mobility patterns pertaining to the specific trip purposes.

Acknowledgments

Support by the National Institute of General Medical Sciences of the National Institutes of Health under award number R01CA140319-01A1 is gratefully acknowledged. Wang also acknowledges the support of a visiting professorship at Yunnan University of Finance and Economics in the summer of 2014.

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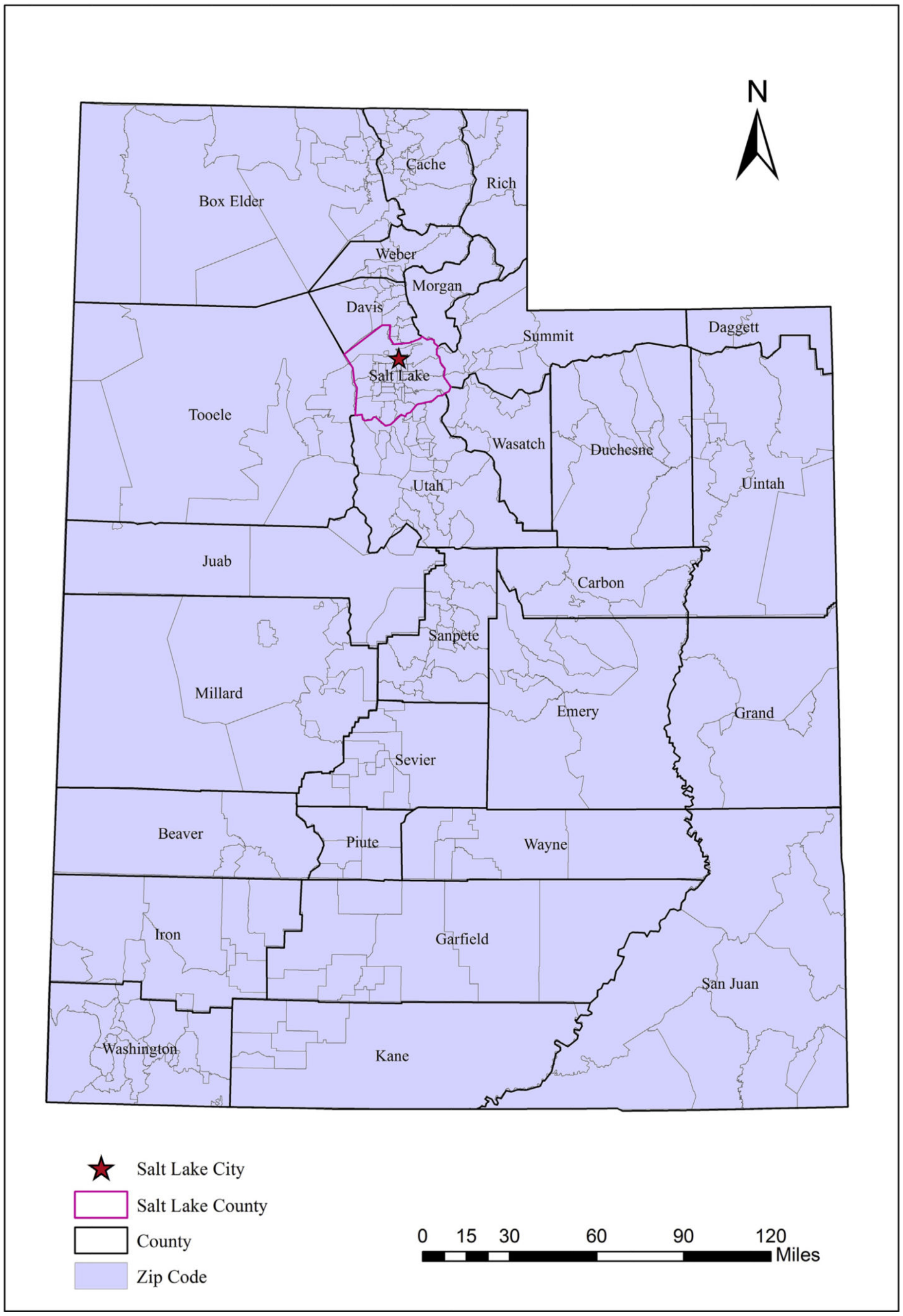

Fig. 1.
Zip code and county boundaries in Utah.

Table 1

Individual variables from the BRFSS (2007, 2009, 2011; *n* = 21,961).

Variables	Sample size	Sample %
Female	11,999	54.6
Non-Hispanic Whites	20,505	93.3
College degree or above	15,433	70.3
Currently married	15,255	69.5
Having smoked 100 cigarettes	6229	28.4
Employed for wages	10,616	48.3
Self-employed	2289	10.4
Out of work for more than 1 year	438	2.0
Out of work for less than 1 year	550	2.5
Homemaker	2750	12.5
Student	489	2.2
Retired	4829	22.0
Obese (BMI 30.0 and above)	5315	24.2
Overweight or obese (BMI 25.0 and above)	13,281	60.5

Table 2

Variables at the zip code and county levels.

Data source (Year)	Neighborhood Characteristics	Mean		Median		Range	
		Zip code	County	Zip code	County	Zip code	County
Decennial Census (2010)	% Poverty	0.74	11.73	0.09	11.20	0.00–48.86	4.80–25.80
ESRI Data DVD (2008)	Street Connectivity	8.45	29.13	1.13	13.15	0.02–83.79	0.91–173.46
Online (2013)	Walk score	10.25	6.20	0.00	0.00	0.00–92.00	0.00–32.84
ESRI Data DVD (2008)	Distance to park	12.00	13.04	10.49	9.67	0.38–2.17	0.80–46.06
Economic Census (2007)	Food environment[a]	84.64	2.87	35.84	3.10	2.17–958.49	0.00–5.33

[a]Food environment means fast-food restaurant accessibility at zip code level and the ratio of fast-food restaurant to full-service restaurant at county level.

Table 3

Adjusted odd ratios (95% Confidence interval) of the multilevel logistic models for odds of obesity (BMI ≥ 30).

	Model 1	Model 2	Model 3
Individual-level variables			
Age (18+)	1.133***	1.133***	1.133***
Age^2	0.999***	0.999***	0.999***
Female	0.845***	0.846***	0.845***
White	1.063	1.063	1.059
Married	0.886**	0.885**	0.887**
College	0.834***	0.835***	0.827***
Self-employed	0.748***	0.749***	0.752***
Out of work for more than 1 year	1.142	1.144	1.129
Out of work for less than 1 year	1.119	1.123	1.113
Homemaker	0.829***	0.828***	0.826**
Student	0.879	0.876	0.838
Retired	1.054	1.055	1.050
Smoker	0.930*	0.931*	0.933*
Zip code-level variables			
Poverty	3.149**	3.686**	3.471**
Street connectivity	1.002	1.002	
Walk Score	0.999	1.000	
Distance to park	1.007	1.011	
Fast food accessibility	1.000	1.000	
Metro	1.037	1.025	
County-level variables			
Poverty		0.996	
Street connectivity		1.000	
Walk Score		1.004	
Distance to park		0.991	
Ratio of fast-food to full-service		1.172***	1.160***
Metro		0.875	
AIC	23,599.08	23,595.30	23,581.16

Sample size: 21,961 individuals living in 299 zip codes, 29 counties.

*** $p \leq 0.001$,

** $p \leq 0.01$,

* $p \leq 0.05$ (two-tailed tests).

Table 4

Adjusted odd ratios (95% Confidence interval) of the multilevel logistic models for odds of overweight or obesity (BMI ≥ 25).

	Model 1	Model 2	Model 3
Individual-level variables			
Age (18+)	1.135***	1.136***	1.136***
Age^2	0.999***	0.999***	0.999***
Female	0.475***	0.475***	0.475***
White	1.058	1.058	1.054
Married	1.039	1.039	1.040
College	0.823***	0.824***	0.820***
Self-employed	0.820***	0.821***	0.821***
Out of work for more than 1 year	0.964	0.964	0.962
Out of work for less than 1 year	0.967	0.970	0.969
Homemaker	0.734***	0.734***	0.734***
Student	0.861*	0.859	0.858
Retired	0.941	0.941	0.942
Smoker	0.945*	0.945*	1.768*
Zip code-level variables			
Poverty	2.104**	2.376*	1.768
Street connectivity	1.000	1.000	
Walk Score	1.000	1.000	
Distance to park	1.009	1.014*	1.012***
Fast food accessibility	0.999*	0.999	
Metro	1.003	0.975	
County-level variables			
Poverty		0.997	
Street connectivity		1.000	
Walk Score		1.005	
Distance to park		0.991	
Ratio of fast-food to full-service		1.128***	1.120***
Metro		0.926	
AIC	27,604.79	27,599.70	27,585.17

Sample size: 21,961 individuals living in 299 zip codes, 29 counties.

*** $p \leq 0.001$,

** $p \leq 0.01$,

* $p \leq 0.05$ (two-tailed tests).