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Mixed land use and obesity: an empirical comparison of alternative land use measures and geographic scales

Ikuho Yamada[a], **Barbara B. Brown**[b], **Ken R. Smith**[b,c], **Cathleen D. Zick**[b], **Lori Kowaleski-Jones**[d], and **Jessie X. Fan**[b]

[a]Assistant Professor, Department of Geography, and, Investigator, Institute for Public and International Affairs, University of Utah

[b]Professor, Department of Family & Consumer Studies, and Investigator, Institute for Public and International Affairs, University of Utah

[c]Director, Pedigree and Population Resource, University of Utah

[d]Associate Professor, Department of Family and Consumer Studies, Investigator, Institute for Public and International Affairs, University of Utah

Abstract

Obesity is a growing epidemic in the United States. Walkable neighborhoods, characterized as having the 3Ds of walkability (population Density, land use Diversity, and pedestrian-friendly Design), have been identified as a potentially promising factor to prevent obesity for their residents. Past studies examining the relationship between obesity and walkability vary in geographic scales of neighborhood definitions and methods of measuring the 3Ds. To better understand potential influences of these sometimes arbitrary choices, we test how four types of alternative measures of land use diversity measured at three geographic scales relate to body mass index for 4960 Salt Lake County adults. Generalized estimation equation models demonstrate that optimal diversity measures differed by gender and geographic scale and that integrating walkability measures at different scales improved the overall performance of models.

Keywords

walkability; obesity; land use diversity; geographic scales of neighborhoods

Introduction

The obesity epidemic is firmly entrenched in the United States (Mokdad et al. 1999; Blanck et al. 2006; Ogden et al. 2006), with 35% of adults considered obese (Hedley et al. 2004; Flegal et al. 2010). The rapid rise in obesity points to contextual causes and has prompted a search for environmental factors that encourage physical activity and prevent obesity (Hill and Peters 1998). Neighborhood walkability, the physical environmental supports for walking, has been identified as an especially promising research direction for better understanding the rise of obesity in the United States. Walking is relatively safe, easy, and affordable. Individuals report that walking, especially in their neighborhoods, is their most preferred physical activity (Giles-Corti and Donovan 2002; Fisher et al. 2004; Lee and Moudon 2004; Booth et al. 1997). A recent extensive review concludes that walkable

Corresponding author: Ikuho Yamada (ikuho.yamada@geog.utah.edu), 260 S. Central Campus Drive, Rm 270, University of Utah, Salt Lake City, UT 84112-0080, Phone: 801-585-3177.

environments, indeed, promote more walking (Saelens and Handy 2008). A less extensive and consistent (Frank et al. 2007) but growing body of research also relates walkable environments to healthier weights (Ewing et al. 2003; Inagami et al. 2006; Laraia et al. 2007; Frank et al. 2008; Smith et al. 2008). However, fundamental questions remain concerning the relationships between human health and walkability and the role of the neighborhood built environment in general. Specifically, what aspects of neighborhood environments should be measured, with what operational definitions, and at what geographic scale? (O'Campo 2003; Forsyth et al. 2006; Hanson 2006; Messer 2007)

Neighborhood walkability is often conceptualized by the 3Ds: population Density, pedestrian-friendly Design, and land use Diversity (Cervero and Kockelman 1997). Density provides a critical mass of people; pedestrian friendly street design allows convenient and fairly direct routes; and diversity creates multiple attractive destinations for pedestrians. Density is often measured by density of population, housing units, or jobs; pedestrian-friendly design is often measured by street intersection density or sidewalk availability. Diversity, also referred to as mixed land use, is operationalized in a variety of ways (Song and Rodriguez 2005; Brown et al. 2009), with little consensus on the best measures. Similarly, researchers adopt a range of geographic scales when defining the extent of the neighborhood. Their choices are often based upon data availability and quantitative considerations rather than theoretical motivations (Messer 2007).

The objective of this study is to enhance this emerging literature by providing empirical guidance on the issues of neighborhood scales and measures of built environment by examining the relationship between body mass index (BMI, defined as weight[kg]/height[m]^2) and four types of mixed land use measures obtained at three geographic scales that define neighborhoods (1 kilometer street-network buffer, census block group, census tract). Our focus on land use diversity among the 3Ds is based upon its multifarious operationalizations mentioned above. We build on prior work by Brown and colleagues (2009), one of few studies that conduct comparisons across different types of mixed use measures. We extend this earlier work by examining a broader range of mixed use measures and three levels of geographic scales, as well as by exploring the utility of integrating multiple scales into a single model. BMI data for this analysis comprise 4,960 licensed drivers in Salt Lake County, Utah. Individual-level BMIs and neighborhood walkability measures are related via generalized estimating equations described in a later section.

Definitions of Neighborhood Scale

Choosing a geographic unit of analysis is a long-standing challenge in any spatial research because spatial data and analytical results depend upon the data aggregation unit or scale, an issue known as the modifiable areal unit problem (MAUP) (Openshaw 1984). Health research is no exception. Although research about neighborhood effects on health is proliferating, the appropriate geographic scale for measuring neighborhoods is still an open question (Hanson 2006; Gauvin et al. 2007; Messer 2007; Weiss et al. 2007; Brownson et al. 2009).

When walking is the health behavior of interest, the neighborhood should reflect the distance that people can walk to and from home. Two approaches are often used to define neighborhoods when measuring walkability. The first and more common is to rely on predefined administrative or census boundaries, with census tracts and block groups being frequent choices in the United States (Krieger et al. 2003; King et al. 2005; Frank et al. 2006; Inagami et al. 2006; Rundle et al. 2007; Smith et al. 2008; Zick et al. 2009). However, census boundaries may not necessarily reflect residents' walking range within their neighborhoods. In addition, walkability measures constructed for these boundaries might mask considerable heterogeneity within each unit.

The second approach is to create a buffer with a specific distance around individuals' home locations. A buffer can be a circle based on the straight-line distance or a polygon created along a given street network based on the shortest-path distance (Frank et al. 2005; Cohen et al. 2006; Norman et al. 2006; Berke et al. 2007; Guo and Bhat 2007; Moudon et al. 2007; Oliver, Schuurman, and Hall 2007). The street-network buffer is conceptually more appealing than the straight-line buffer because the former reflects walking routes imposed by existing streets, although one study found both types of buffers performed similarly in predicting walking (Moudon et al. 2007).

Buffer approaches have the advantage of delineating more individualized neighborhoods although GIS computations can be prohibitive for large datasets. A challenge when using buffers is the choice of the buffer distance—another MAUP concern. The buffer distances used in previous studies vary from 0.1 km (Berke et al. 2007) to 1.6 km (Norman et al. 2006; Forsyth et al. 2008). Several studies cite empirical research to help guide them in defining the limits of a typical walkable distance, but these also vary substantially from 0.8 km (Tilt, Unfried, and Roca 2007) to 1km (Moudon et al. 2007) to 1.5 km (King et al. 2005). Acceptable walking distances have been found to vary by individual factors (e.g., age and health status), environmental factors (e.g., route directness and topography), and destination types and attractiveness (e.g., grocery stores vs. transit stations) (Moudon et al. 2006; Canepa 2007). Morency et al. (2009) also demonstrate that individuals' mobility may vary considerably depending on their demographic characteristics and locational settings. These findings illustrate potential complications in the determination of appropriate buffer distances. They might also imply the need for differential buffer distances across individuals or locations, but we leave this issue for future research.

Here we compare alternative measures of neighborhood walkability constructed for three geographic scales: census tract, block group, and 1km street-network buffer in relation to their association with individual-level BMI. The 1km buffer is chosen because of its proven usefulness in past research and its compatibility with the mixed use measures to be employed. We also explore the possibility that a combination of predictors at different geographic scales might provide a superior ability to predict BMI than predictors at one level of scale, given that appropriate neighborhood definitions may vary across different variables (Galster 2001; O'Campo 2003).

Measures of Mixed Land Use

The literature examining mixed land use and walkability presents somewhat conflicting findings. One comprehensive review by Saelens and Handy (2008) confirms that mixed land use supports physical activity by providing a range of destinations within walking distance, such as transit stations and grocery stores. This review also confirms that measures of mixed use and distances from home to destinations provide overlapping alternatives for capturing land use characteristics that invite neighborhood walking, especially walking for transportation purposes (Saelens and Handy 2008). However, a recent study that examines 44 alternative walkability measures finds that only the measure of "social land use" (e.g., churches, parks) predicts more walking for transportation (Forsyth et al. 2008). In light of these conflicting results, comparative studies of alternative measures are needed. This study investigates four general types of mixed use measures: statistical summaries of mixed use, areas of walkable land uses, distances to specific destinations, and proxy measures.

Statistical summary indices

A common summary statistic of mixed land use is an entropy score that measures the extent to which land use categories are equally distributed in an area (Frank et al. 2005). This measure is often found to be positively associated with more physical activity and healthier weights (Frank, Andresen, and Schmid 2004; Mobley et al. 2006; Rundle et al. 2007; Li et al. 2008). The entropy score varies from 0 to 1, where 0 indicates maximally homogeneous land use and 1 indicates maximally heterogeneous or mixed use. Adapted originally from Shannon’s information theory index (Shannon and Weaver 1949), the entropy score is widely used across disciplines to index the evenness of spread across different categories (Krebs 1989). It has been applied to measure such things as biodiversity (Ravera 2001) and land use mix (Kockelman 1997; Forsyth 2005). Based on findings of Brown et al. (2009), this study adopts an entropy score using six land use categories developed by Frank et al. (2006) shown in Table 1.

Alternative summary indices might prove better choices than the entropy score, which has several limitations (see extended discussion in Brown et al. 2009). For example, Table 1 shows how Neighborhood A, equally divided across two land uses, and Neighborhood B, equally divided across six land uses, have the same maximum entropy score, despite the fact that Neighborhood B is more diverse. We thus consider two alternative diversity indices used in other fields that can mitigate this limitation of the entropy scores. Shannon’s index (Shannon and Weaver 1949) indicates greater diversity with a variety in uses even if some are rare; Simpson’s index (1949) indicates greater diversity with evenness of dominant uses (Nagendra 2002). Unlike the entropy score, these two indices show higher diversity when greater numbers of land use categories are present, as shown in their computations for Neighborhood B in Table 1. All three proposed statistical summaries are subject to other limitations, however. Specifically, they do not distinguish among qualitative differences nor do they reflect differences in spatial distributions. For example, a fine-grained distribution of many small stores is equivalent to the same area of a big box store, although the former may be more likely to induce residents to walk more.

Walkable land areas

Some studies examine neighborhood land areas or proportions that are considered to be walkable, but without integrating them into statistical summaries (Forsyth et al. 2008; Brown et al. 2009). For example, more public open space (Giles-Corti et al. 2005) and social land uses (Forsyth et al. 2008) relate to walking for leisure and transportation, respectively. Brown et al. (2009) demonstrate that the six land use categories from the Neighborhood B example above relate to BMI better than the corresponding entropy score. In particular, they find that females have lower BMIs when living in a neighborhood with more entertainment and office space and males have lower BMIs when living in a neighborhood with more multi-family residential space (Brown et al. 2009). Such area measures reflect the extent of potentially walkable land uses, but, like entropy measures, they cannot assess whether walkable lands are accessible, well-distributed, or attractive to pedestrians.

Destination-oriented measures

These measures assess the presence, density, or proximity of walkable destinations within a neighborhood. For example, living close to grocery stores, restaurants, and other retail stores relates to more neighborhood walking (Moudon et al. 2007), and living close to employment establishments is associated with lower weight (Lopez 2007). Although easy to conceptualize and compute, the number of destinations studied varies widely, from a single destination such as parks (Cohen et al. 2007) to over 20 destinations (Moudon et al. 2007; Forsyth et al. 2008). Destinations also vary in specificity (e.g., retail vs. drug store), and the geographic clustering of destinations may or may not be considered in some of the measures used. All of these qualities make it difficult to compare studies and isolate any consistent results.

In this study, we examine whether weight relates to proximity to light rail stations, grocery stores, and the central business district (CBD). Light rail stations are chosen because transit use (Wener and Evans 2007) and residential proximity to transit stations (McCormack, Giles-Corti, and Bulsara 2008) are associated with more walking and lower BMI (Rundle et al. 2007; Brown and Werner 2009). Another analysis (Brown et al. 2009) also finds that a resident's BMI is inversely associated with proximity to light rail stations, but not to bus stops or parks.

We examine distance to the CBD because proximity to light rail stations in Salt Lake County relates to proximity to the CBD (see Figure 1). In addition, CBD residents generally walk more (Chen and McKnight 2007; Ewing and Cervero 2001), because CBD's offer more conducive walking environments, resident preferences, and/or difficulties with traffic congestion and parking. Adding "distance to the CBD" to the analysis allows us to determine whether light rail and CBD proximity have distinct effects.

Grocery stores can support walking and healthy eating. One study finds parks and grocery stores are the most frequent walking destinations among 15 surveyed options (Tilt, Unfried, and Roca 2007). Proximity to grocery stores is associated with more walking (Moudon et al. 2007) and healthier BMI (Inagami et al. 2006), although other studies find no relationship (Forsyth et al. 2008; McCormack, Giles-Corti, and Bulsara 2008). These inconsistencies may be due to grocery store variations in price, food selection, and/or quality. We focus on large grocery stores that typically offer lower prices (Kaufman et al. 1997; Kaufman 1999) and healthier foods than smaller ones (Sallis, Nader, and Atkins 1986; Jetter and Cassady 2006).

Proxy scores

We consider two census proxy measures of mixed land use: housing age (i.e., median year when housing structures were built) and proportion of residents who walk to work (U.S. Census Bureau 2000). Neighborhoods with older housing often have more mixed uses as well as a variety of other walkability features including well-connected streets, sidewalks, pedestrian-oriented buildings (Handy 1996a; Handy 1996b), trees, and narrower streets (Southworth and Owens 1993). Similarly, the proportion of residents who walk to work is hypothesized to indicate, at a minimum, the coexistence of residential and employment land uses within walking distance. Few residents walk to work (about 2–3% on average) in Salt Lake County or nationally, so it is unlikely that an analysis of countywide BMIs would be substantially affected by those who walk to work (and presumably have lower BMIs as a result). Neighborhoods with more residents who walk to work will generally have a wider range and number of walkable destinations and more accessible pedestrian pathways (Craig et al. 2002). Both proxies consistently relate to lower BMIs in prior studies (Smith et al. 2008; Brown et al. 2009; Zick et al. 2009), although these studies use only one geographic scale for each proxy unlike the present study.

Although comparisons across types of mixed use measures are rare, Brown and colleagues (2009) compare entropy scores, land areas, destination-oriented measures, and census proxy variables for relationships to weight outcomes. They find that the entropy score with six land use categories adopted from Frank et al. (2006) improves prediction of BMI, but the six categories entered separately improve prediction even more. Proximity to light rail stations and the proxy variables also relate to lower BMI. The present study builds on this work by examining predictors across the three levels of geographic scale and exploring the utility of combining multiple geographic scales in one model. In addition, mixed use measures are expanded to include Shannon's and Simpson's statistical indices, as well as distances to grocery stores and the CBD.

Data and Methods

Sampling and BMI data

Individual-level BMI information is derived from a driver license database that contains all 453,927 license holders in Salt Lake County, Utah, in 2005. This study uses a random subset of 4,960 individuals. Twenty individuals are randomly sampled from 248 census block groups that are also randomly sampled from 549 census block groups in the county (Figure 1); note that 18 relatively unpopulated (with < 150 driver license records) or sparsely populated fringe block groups have been excluded. Young adults (<25 years old) who may not have established their own residence and elderly adults (≥65) whose BMI has more complex associations with health are excluded. Given our interests in problems of higher BMIs compared to healthy BMIs, we also exclude the very small fraction of individuals who are underweight (BMI < 18.5) because they may have underlying health conditions that affect their BMI and its relationship to the built environment differently in comparison with obese individuals. Preliminary analyses confirm that the sample does not differ significantly from the countywide database with respect to gender-specific ages and BMIs (analyses available from the authors upon request). BMIs are calculated from self-reported weight and height taken from Utah driver licenses. The driver license data are obtained from the Utah Population Database (UPDB), a health-related research database that includes records from the Driver License Division of the Utah Department of Public Safety. To protect confidentiality of driver license holders, all personal information from the Driver License Division was removed before the data were provided to the investigators on this research project. This project has been approved by the University of Utah Institutional Review Board (IRB) and the Utah Resource for Genetic and Epidemiologic Research. As part of this process, the UPDB staff retained identifying address information, linked driver license data (height, weight, gender, and age) to census-block groups via Universal Transverse Mercator (UTM) coordinates, and then provided the researchers with a data set without individual addresses.

Measures of walkability

The DIGIT Lab at the University of Utah provides the street centerline data and parcel-level land use data obtained from Salt Lake County Assessor's Office. Utah Transportation Authority provides data on the county's light rail transit system. Dun and Bradstreet business data are used to identify large grocery stores (annual sales volume ≥$1 million). Finally, the socio-demographic measures are obtained from the 2000 U.S. Census (U.S. Census Bureau 2000).

The census block group, tract, and 1km buffer are used to compose all measures of mixed land use, except for the destination-oriented distances. The street network buffers are created around individuals' residences using the street centerline data. For census-based measures (i.e., population density, median year structure built, and percentage of residents who walk to work), a value for each buffer is computed as a weighted average of the values for block groups that overlap with the buffer, where the weight for a block group is proportional to its overlapping area. For mixed use measures based on land use categories, the parcel-level land use data are intersected with boundaries of the three geographic units to identify the areas of the six land uses within each unit. The street intersection density measure is based on the street centerline data and excludes intersections involving interstate highways and intersections of less than three streets.

Figure 1 shows our three destination-oriented measures of mixed use: distance to the closest light rail station (abbreviated as LR), distance to the CBD, and distance to the closest large grocery store. All distances measure the shortest path along street centerlines. The distance to the CBD is measured as the shortest distance from a residence to any intersection within and on the boundary of the CBD as defined by Wood (2005).

Statistical methods

We use generalized estimating equations (GEE) to examine the association between individuals' BMIs and walkability features in their neighborhoods. GEE is an extension of generalized linear models with the quasi-likelihood approach and is designed to analyze longitudinal and other correlated data (Liang and Zeger 1986; Zeger and Liang 1986; Hanley et al. 2003). BMI values for individuals selected from the same block group are correlated with one another according to estimates from a preliminary analysis ($p < .001$). Consequently, our data violates the assumption of uncorrelated error terms when using the ordinary least squares regression, necessitating the use of GEE models.

The literature indicates that neighborhood socio-demographic status relates to residents' health including obesity independently of their own socio-demographic status (Krieger and Gordon 1999; Yen and Syme 1999; Robert and Reither 2004; Janssen et al. 2006; Zick et al. 2009; Smith et al. 2008). Some studies also suggest that census-based aggregate measures may be used as valid proxies for individual-level socio-demographic status especially at smaller geographic scales (Krieger 1991, 1992; Soobader et al. 2001). We thus control for individual age and six neighborhood socio-demographic variables (neighborhood income, median age of neighborhood residents, and proportions of African American, Hawaiian/ Pacific Islander, Hispanic, and Asian). Because the potential impact of neighborhood socio-demographic status is not necessarily limited to the walkable proximity of individuals' home, the block group scale is chosen to measure the six neighborhood variables.

We use models that include only the seven control variables as a baseline (called Level-0 model) and evaluate the goodness-of-fit of other models relative to the baseline. We first create models for the three geographic scales separately and examine the utility of each. Then we combine measures of mixed use at each scale to test whether the overall model fit is improved by selecting appropriate neighborhood scales differently for each of mixed use measures.

Results

Table 2 presents descriptive statistics for all of the variables. The street intersection density for the street-network buffer scale is over 15% higher than for the block group and census tract scales because the network buffers are more compact and concentrated along the streets. In terms of mixed land use measures, the block group and buffer scales tend to be more similar than the census tract scale. This likely reflects the size difference of the three geographic scales; the average size of census tracts, block groups, and 1km buffers are 3.34 km^2 (Standard deviation (SD) = 2.88), 1.21 km^2 (SD = 1.73), and 1.28 km^2 (SD =0.39), respectively. Such large differences across geographic scales underscore the possibility that choices of scale may be important for BMI prediction. Table 3 shows partial correlations between walkability measures and BMI, controlling for the seven socio-demographic variables. Most correlations are modest, but the distance to LR, the distance to the CBD, and the two census proxies all have significant associations with BMI in the expected directions, consistently across gender and geographic scales. Evidence for variability is present as well, with variables significant for 12 of 39 gender comparisons in varying degrees; additionally, 7 of 13 variables are significant at one geographic scale but not at other scales.

Table 4 summarizes goodness-of-fit statistics for models with various combinations of built environment variables at the three geographic scales. Model fit is measured by “corrected quasi-likelihood under the independence model criterion” (QICC), which penalizes goodness-of-fit measures for model complexity. Lower values of QICC indicate better fitting models.

Population density and pedestrian-friendly design

Level-1 models add population density and street intersection density to the baseline Level-0 models, resulting in large improvements in QICC at every geographic scale. Increased population density is significantly associated with lower BMI, except among females at the block group scale. Higher intersection density is unexpectedly associated with higher male BMI. Subsequent models also show positive associations (for both genders but more consistently for males), suggesting intersection density is a poor walkability measure in this sample when using BMI as the health outcome. All subsequent models add one or more measures of mixed land use to the Level-1 model.

Land use diversity

Among the three summary indices of mixed use that are based on areas of the six land use categories listed in Table 1, Simpson’s index is preferable because it yields superior QICCs in three of six gender-scale combinations and it never has the worst QICC (see Levels 2a–2c in Table 4). Increased diversity measured by any summary index is always associated with lower BMI although the association is not necessarily significant. However, in all six gender-scale combinations summary indices do not perform as well as the six land use categories added separately (Level-2d, QICC improvements of 11 to 271 points). This finding, which is consistent with those reported by Brown et al. (2009), may be an indication that what matters to neighborhood walkability is the presence of walkable land uses rather than their level of mixture.

Destination-oriented measures of mixed use yield varied results (Levels 3a–3d). The distance to LR considerably improves model fit for all gender-scale combinations, especially among females (Level-3a). The LR variable is also significant with increased distance associated with higher BMI. Adding the distance to the CBD to Level-3a models further improves model fit and the variable is significant for all gender-scale combinations. The significance of the distance to LR disappears for male models, however, perhaps reflecting moderate but significant correlations between the two variables (0.486 for males and 0.475 for females). The result implies that the proximity to the CBD offers some benefit to both males and females in terms of their weight status, but the proximity to LR is beneficial only for females. The distance to the closest large grocery store, on the other hand, leads to much smaller model improvements (Table 4, Level-3c and -3d).

Both census proxy variables (Level-4a and -4b) yield large QICC improvements, with a higher percentage of residents who walk to work and older neighborhood housing (i.e., earlier “median year built”) both significantly associated with lower BMI. Older housing is especially powerful and consistent across all gender-scale combinations.

Comparisons of models of Levels 2–4 reveal several interesting patterns. First, the six land use categories included separately (Level-2d) perform best among the four area-based measures of mixed use, but their QICC improvements are much smaller than those achieved by the combination of distances to LR and the CBD (Level-3b) and the “median year built” variable (Level-4b). The “walk to work” variable also outperforms the six categories for some gender-scale combinations. Second, the combination of distances to LR and the CBD consistently performs best for females, while the “median year built” variable consistently performs best for males. Third, models at the 1km buffer scale generally achieve the best QICC, except among females, where distances to LR and the CBD perform best when other variables (i.e., Level-0 population and intersection densities) are aggregated to the census tract scale.

Combination of multiple mixed use measures

Using multiple area-based measures in a single model makes little sense because of their similarity in the conceptualization of mixed use. Other measures, however, may be combined together to achieve a better understanding of neighborhood characteristics that relate to individual BMI. Perhaps measures such as housing age and proximities to LR and the CBD indicate not only mixed use but also other walkable features of neighborhoods, for example, green space and sidewalks. Therefore, the following analyses examine whether models can be improved by combining multiple mixed use measures.

Level-5 models combine the best single mixed use measures from above (Level-3b distances to LR and the CBD and Level-4b housing age) and yield QICC improvements from 25 to 375 points compared to the original two models. As in the original models, the "median year built" variable is significant in all gender-scale combinations and the distance to LR is significant only for females. The significance of the distance to the CBD disappears, which likely reflects its relatively high correlation with the "median year built" variable (partial *r*'s are about 0.6–0.7). Interestingly, the block group scale provides the best model fit for females, which rarely happened in earlier models.

Level-6 models add the six land use categories, the "walk to work" variable, or both, to Level-5 models. Noticeable improvements in QICC are attained by the six land use categories (Level-6a) in most gender-scale combinations, whereas improvements by the "walk to work" variable is marginal except for females at the census tract and buffer scales (Level-6b). Adding both variables simultaneously (Level-6c) barely improves the model fit in comparison with Level-6a models, with an exception of the female model at the buffer scale. The "walk to work" variable is insignificant in most cases, although several of the six land uses are significant in both Level-6a and -6c models for some gender-scale combinations. Overall, the best model fit is achieved by Level-6a model for males (i.e., distances to LR and the CBD + housing age + six land use areas) and Level-6c model for females (i.e. male model above + proportion walk to work) both at the buffer scale.

Finally, in order to examine the potential benefit of choosing geographic scales for individual built environment measures rather than choosing one for the entire model, we modify Level-6a model for males and Level-6c model for females to include measures at geographic scales that give the strongest partial correlations in Table 3. For the six land use categories, the buffer scale is chosen since it led to the largest QICC improvements in Level-2d, -6a, and -6c models. The resulting QICC values improve upon the previously best models in Table 4 for both genders. Table 5 presents details of these best-fit models. For males, lower BMIs are associated with lower intersection density at the census tract level (p=0.006), older housing at the block group level (p=.001), and more multifamily residential use at the buffer level (p=0.027). Lower BMIs of females are associated with closer light rail stations (p=0.009) and more entertainment use at the buffer level (p=0.021). These significant associations are in the hypothesized directions, except for the intersection density for males.

Summary and Discussions

Despite the growing literature on walkability and health, few guidelines exist for researchers to decide upon proper geographic scales and walkability measures, especially mixed land use measures. In this paper, we examine three geographic scales and four types of mixed land use measures in relationship to BMI. Analyses indicate that the use of the street network buffer generally results in relatively better fitting models.

The advantage of buffer measures is not necessarily consistent across genders or measures of the built environment, however. Further, the best fitting models demonstrate that the performance of models could be improved by choosing an appropriate geographic scale for each measure of the built environment instead of choosing one scale for all variables. We recognize that our results may not generalize to all geographic circumstances. We chose the best scale simply by relying on partial correlations and we limit testing to three levels of geographic scale. This analysis nonetheless illustrates a potential pitfall when any fixed neighborhood definition is used to measure all built environmental features.

Almost all of the alternative measures of mixed use examined in this study are useful in predicting individual BMI. The census proxy of the median housing age and the distance to the closest light rail station are particularly promising, followed by the six land use categories included separately. None of the three statistical summary indices depicted in Table 1 outperform the six land use categories included separately. In addition, some combinations of the alternative measures demonstrate further improvement in model fit. Together, these findings suggest that no single measure of mixed use will likely fully capture how land use relates to neighborhood BMIs; mixed use is complex and merits complex and multiple measures.

The variable measuring proximity to large grocery stores is notable for its failure to improve model fit. This might happen because common shopping patterns of Americans require motorized transportation to carry multiple, heavy bags. Motorized transportation also allows them to choose stores not in the proximity of their residence. Additionally, grocery stores provide not only healthy food but also less nutritious food and they may be located near unhealthy food outlets such as fast food restaurants. Weight status is determined by physical activity and eating behavior, thus food environments that relate to both components may have more complex associations with BMI than what could be measured by the proximity to grocery stores alone. Another unexpected, notable finding in this study is that mixed use measures at the census tract scale generally resulted in better model fit than those at the block group scale. This is counterintuitive as the smaller block group scale more closely approximates walkable distances. These unexpected findings might result from the fact that walkability in this study is solely restricted to residential neighborhood. Although this is a widely adopted approach in studies concerned with neighborhood effects on human health, individuals travel to many areas for work and shopping, including those outside their residential neighborhoods. Consequently, walkability measures that take into consideration human spatial behaviors such as space-time accessibility developed in time geography (Kwan 1998; Miller 1999) might be justified to better capture the built environmental features that are relevant to individuals' health.

Results also demonstrate gender differences in the association between individual BMI and built environment measures as well as in the preferred geographic scales of analysis for several measures. Consistent with prior research (Rundle et al. 2007; Brown and Werner 2009; Brown et al. 2009), proximity to light rail stations relates to lower female BMI, regardless of the proximity to the CBD. In contrast, proximity to LR relates to lower male BMI only when proximity to the CBD is not controlled. This may reflect gender differences in transit use (Crane 2007; Pucher and Renne 2003) and/or private vehicle ownership. In addition, different subsets of the six land use categories show significant associations with male and female BMIs. These results suggest the importance of examining how walkability features are used and perceived differently by men and women.

To the best of our knowledge, self-reported weight and height information on driver license has rarely been used in obesity research. An advantage of driver license data is its extensive coverage of the adult population. The original UPDB driver license data includes almost 90% of Salt Lake County residents between the ages of 25 and 64, which enhances the external validity of the study's finding.

A possible disadvantage of using driver license data is that they may exclude the most economically disadvantaged individuals who may also have a higher obesity risk. The use of driver license data also imposes potential limitations of self-reported weight and a time lag between the physical environment and weight measures. Past studies find a tendency for individuals to under-report weight and over-report height (Nawaz et al. 2001; Gorber et al. 2007). Nevertheless, self-reported weights, such as those in the Behavioral Risk Factor Surveillance System (BRFSS) and the National Health and Nutrition Examination Survey (NHANES), have proved valuable for monitoring obesity trends in the United States (Centers for Disease Control and Prevention 2007; Ezzati et al. 2006).

Individuals' records in the data correspond to their most recent renewal; in Utah, renewals are required every five years or after address changes, name changes, or loss of license. The data therefore represent the most recent height and weight data from 1995 through 2005, while census and other built environment measures are from different years. In addition, for individuals who changed their residences during this time period, reported BMI measures may not correspond to the built environment of their current residences; we are currently investigating this issue of residential change. Given these potential limitations and the fact that adults 25–64 typically gain weight over time (U.S. Department of Agriculture 2005), BMI measures in this study are likely to underestimate true BMIs and thus our findings should be viewed as conservative.

There are additional research questions that are beyond the scope of this study. First, the buffer distance of 1km is chosen primarily for compatibility with prior studies; we do not test for optimal buffer distances. Studies that examine multiple buffer distances find differences across distances in terms of the magnitude of associations (Berke et al. 2007) and the associated built environment features (McCormack, Giles-Corti, and Bulsara 2008). This implies that optimal distances likely vary for different measures of built environment. Consequently, it is essential to develop theoretical as well as empirical bases to decide upon appropriate buffer distances. Second, the six land use categories used in this study are from Frank et al. (2006). They may be classified differently in other municipalities or data sets, which may hamper comparative studies. Third, data were not available that would allow us to control for additional individual-level covariates (e.g., income) and behaviors (e.g., walking). Some studies suggest that women are more likely to use public transit than men (Crane 2007; Pucher and Renne 2003), which may explain the gender differences we observed in proximity to LR. However, future research is needed to fully understand the sources of these differences. Fourth, these results are cross sectional and do not consider residential self-selection. Most past studies that relate walkability to physical activity or obesity risk do not explicitly investigate this issue. If more physically active individuals self-select into more walkable neighborhoods, this could introduce a bias into the estimated relationships. Thus, care must be taken so as not to interpret our estimated relationships as causal.

Three variables used in the current study merit special attention in future research. The census proxy measures—median year structure built and the percentage of residents walking to work—are useful measures, given their ease of collection and consistent relations with BMI (Smith et al. 2008; Brown et al. 2009; Zick et al. 2009). However, the question of exactly how these variables affect walkability and BMI deserves further attention. If our findings are replicated elsewhere, census proxy variables might enable researchers and policy makers to identify potential hot spots of obesity risk without requiring detailed land use information. Similarly, the observed health benefit of the proximity to transit stations merits wider study, including investigations of effects that are direct (walking to rail stations) and indirect (walking to other destinations clustered around rail stations). Light rail offers societal benefits of less pollution and oil dependence; if light rail consistently relates to lower BMI, then the health benefits of light rail deserve broader consideration from policy makers and researchers.

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References

U.S. Department of Agriculture. Dietary Guidelines for Americans. U.S. Department of Health and Human Services; 2005.

Berke EM, Koepsell TD, Moudon AV, Hoskins RE, Larson EB. Association of the built environment with physical activity and obesity in older persons. American Journal of Public Health. 2007; 97(3): 486–492. [PubMed: 17267713]

Blanck HM, Dietz WH, Galuska DA, Gillespie C, Hamre R, Khan LK, Serdula MK, Ford ES, Garvin WS, Mokdad AH, Densmore D. State-specific prevalence of obesity among adults - United States, 2005. Morbidity and Mortality Weekly Report. 2006; 55(36):985–988. [PubMed: 16971886]

Booth ML, Bauman A, Owen N, Gore CJ. Physical activity preferences, preferred sources of assistance, and perceived barriers to increased activity among physically inactive Australians. Preventive Medicine. 1997; 26(1):131–137. [PubMed: 9010908]

Brown BB, Werner CM. Before and after a new light rail stop: Resident attitudes, travel behavior, and obesity. Journal of the American Planning Association. 2009; 75(1):5–12.

Brown BB, Yamada I, Smith KR, Zick CD, Kowaleski-Jones L, Fan JX. Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity. Health & Place. 2009; 15:1130–1141. [PubMed: 19632875]

Brownson RC, Hoehner CM, Day K, Forsyth A, Sallis JF. Measuring the built environment for physical activity: State of the science. American Journal of Preventive Medicine. 2009; 36(Supplement 1)(4):S99–S123. e12. [PubMed: 19285216]

Canepa B. Bursting the bubble: Determining the transit-oriented development's walkable limits. Transportation Research Record: Journal of the Transportation Research Board. 2007; 1992:28–34.

Centers for Disease Control and Prevention. Health risks in the United States: Behavioral Risk Factor Surveillance System at a glance 2007. 2007

Cervero R, Kockelman K. Travel demand and the 3Ds: Density, diversity, and design. Transportation Research Part D-Transport and Environment. 1997; 2(3):199–219.

Chen C, McKnight CE. Does the built environment make a difference? Additional evidence from the daily activity and travel behavior of homemakers living in New York City and suburbs. Journal of Transport Geography. 2007; 15(5):380–395.

Cohen DA, Ashwood S, Scott M, Overton A, Evenson KR, Voorhees CC, Bedimo-Rung A, McKenzie TL. Proximity to school and physical activity among middle school girls: The Trial of Activity for Adolescent Girls. Journal of Physical Activity and Health. 2006; 3(S1):S129–S138.

Cohen DA, Sehgal A, Williamson S, Golinelli D, Lurie N, McKenzie TL. Contribution of Public Parks to Physical Activity. American Journal of Public Health. 2007; 97(3):509–514. [PubMed: 17267728]

Craig CL, Brownson RC, Cragg SE, Dunn AL. Exploring the effect of the environment on physical activity - A study examining walking to work. American Journal of Preventive Medicine. 2002; 23(2):36–43. [PubMed: 12133736]

Crane R. Is there a quiet revolution in women's travel? Revisiting the gender gap in commuting. Journal of the American Planning Association. 2007; 73(3):298–316.

Ewing R, Cervero R. Travel and the built environment - A synthesis. Transportation Research Record. 2001; 1780:87–114.

Ewing R, Schmid T, Killingsworth R, Zlot A, Raudenbush S. Relationship between urban sprawl and physical activity, obesity, and morbidity. American Journal of Health Promotion. 2003; 18(1):47–57. [PubMed: 13677962]

Ezzati M, Martin H, Skjold S, Hoorn SV, Murray CJL. Trends in national and state-level obesity in the USA after correction for self-report bias: analysis of health surveys. Journal of the Royal Society of Medicine. 2006; 99(5):250–257. [PubMed: 16672759]

Fisher KJ, Li FZ, Michael Y, Cleveland M. Neighborhood-level influences on physical activity among older adults: A multilevel analysis. Journal of Aging And Physical Activity. 2004; 12(1):45–63. [PubMed: 15211020]

Flegal KM, Carroll MD, Ogden CL, Curtin LR. Prevalence and Trends in Obesity Among US Adults, 1999–2008. Journal of the American Medical Association. 2010; 303(3):235–241. [PubMed: 20071471]

Forsyth A, Hearst M, Oakes JM, Schmitz KH. Design and Destinations: Factors Influencing Walking and Total Physical Activity. Urban Studies. 2008; 45(9):1973–1996.

Forsyth A, Schmitz KH, Oakes M, Zimmerman J, Koepp J. Standards for environmental measurement using GIS: Toward a protocol for protocols. Journal of Physical Activity and Health. 2006; 3(Suppl. 1):S241–S257.

Forsyth, AE., editor. Environment and Physical Activity: GIS Protocols. Minneapolis: Metropolitan Design Center, University of Minnesota; 2005.

Frank L, Schmid T, Sallis J, Chapman J, Saelens B. Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. American Journal of Preventive Medicine. 2005; 28(Supplement 2):117–125. [PubMed: 15694519]

Frank LD, Andresen MA, Schmid TL. Obesity relationships with community design, physical activity, and time spent in cars. American Journal of Preventive Medicine. 2004; 27(2):87–96. [PubMed: 15261894]

Frank LD, Kerr J, Sallis JF, Miles R, Chapman J. A hierarchy of sociodemographic and environmental correlates of walking and obesity. Preventive Medicine. 2008; 47:172–178. [PubMed: 18565576]

Frank LD, Saelens BE, Powell KE, Chapman JE. Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? Social Science & Medicine. 2007; 65(9):1898–1914. [PubMed: 17644231]

Frank LD, Sallis JF, Conway TL, Chapman JE, Saelens BE, Bachman W. Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. Journal of the American Planning Association. 2006; 72(1):75–87.

Galster GC. On the nature of neighborhood. Urban Studies. 2001; 38(12):2111–2124.

Gauvin L, Robitaille E, Riva M, McLaren L, Dassa C, Potvin L. Conceptualizing and operationalizing neighbourhoods - The conundrum of identifying territorial units. Canadian Journal of Public Health-Revue Canadienne De Sante Publique. 2007; 98:S18–S26. [PubMed: 18047157]

Giles-Corti B, Broomhall MH, Knuiman M, Collins C, Douglas K, Ng K, Lange A, Donovan RJ. Increasing walking: how important is distance to, attractiveness, and size of public open space? American Journal of Preventive Medicine. 2005; 28(Suppl 2)(2):169–176. [PubMed: 15694525]

Giles-Corti B, Donovan RJ. The relative influence of individual, social and physical environment determinants of physical activity. Social Science & Medicine. 2002; 54(12):1793–1812. [PubMed: 12113436]

Gorber SC, Tremblay M, Moher D, Gorber B. A comparison of direct vs. self-report measures for assessing height, weight and body mass index: a systematic review. Obesity Reviews. 2007; 8(4): 307–326. [PubMed: 17578381]

Guo JY, Bhat CR. Operationalizing the concept of neighborhood: Application to residential location choice analysis. Journal of Transport Geography. 2007; 15(1):31–45.

Handy SL. Understanding the link between urban form and nonwork travel behavior. Journal of Planning Education and Research. 1996a; 15(3):183–198.

Handy SL. Urban form and pedestrian choices: A study of four Austin neighborhoods. Transportation Research Record. 1996b; 1552:135–144.

Hanley JA, Negassa A, Edwardes MDd, Forrester JE. Statistical analysis of correlated data using generalized estimating equations: An orientation. American Journal of Epidemiology. 2003; 157(4):364–375. [PubMed: 12578807]

Hanson S. Active living research in light of the TRB/IMO report. Journal of Physical Activity and Health. 2006; 3(Suppl. 1):S258–S266.

Hedley AA, Ogden CL, Johnson CL, Carroll MD, Curtin LR, Flegal KM. Prevalence of overweight and obesity among U.S. children, adolescents, and adults, 1999–2002. Journal of American Medical Association. 2004; 291(23):2847–2850.

Hill JO, Peters JC. Environmental contributions to the obesity epidemic. Science. 1998; 280(5368): 1371–1374. [PubMed: 9603719]

Inagami S, Cohen DA, Finch BK, Asch SM. You are where you shop - Grocery store locations, weight, and neighborhoods. American Journal of Preventive Medicine. 2006; 31(1):10–17. [PubMed: 16777537]

Janssen I, Boyce WF, Simpson K, Pickett W. Influence of individual- and area-level measures of socioeconomic status on obesity, unhealthy eating, and physical inactivity in Canadian adolescents. American Journal of Clinical Nutrition. 2006; 83(1):139–145. [PubMed: 16400062]

Jetter KM, Cassady DL. The availability and cost of healthier food alternatives. American Journal of Preventive Medicine. 2006; 30(1):38–44. [PubMed: 16414422]

Kaufman PR. Rural Poor Have Less Access to Supermarkets, Large Grocery Stores. Rural Development Perspectives. 1999; 13(3):19–26.

Kaufman, PR.; MacDonald, JM.; Lutz, SF.; Smallwood, DM. Agricultural Economics Report. Washington DC: U.S. Department of Agriculture, Food and Rural Economics Division, Economic Research Service; 1997. Do the poor pay more for food? Item selection and price differences affect low-income household food costs.

King WC, Belle SH, Brach JS, Simkin-Silverman LR, Soska T, Kriska AM. Objective measures of neighborhood environment and physical activity in older women. American Journal of Preventive Medicine. 2005; 28(5):461–469. [PubMed: 15894150]

Kockelman K. Travel behavior as function of accessibility, land use mixing, and land use balance: Evidence from San Francisco Bay area. Transportation Research Record: Journal of the Transportation Research Board. 1997; 1607(1):116–125.

Krebs, CJ. Ecological Methodology. New York: Harper & Row; 1989.

Krieger N. Women and social class: a methodological study comparing individual, household, and census measures as predictors of black/white differences in reproductive history. Journal of Epidemiology and Community Health. 1991; 45(1):35–42. [PubMed: 2045742]

Krieger N. Overcoming the absence of socioeconomic data in medical records: validation and application of a census-based methodology. Am J Public Health. 1992; 82(5):703–710. [PubMed: 1566949]

Krieger N, Chen JT, Waterman PD, Rehkopf DH, Subramanian SV. Race/ethnicity, gender, and monitoring socioeconomic gradients in health: A comparison of area-based socioeconomic measures - The public health disparities geocoding project. American Journal of Public Health. 2003; 93(10):1655–1671. [PubMed: 14534218]

Krieger N, Gordon D. Re: Use of census-based aggregate variables to proxy for socioeconomic group: Evidence from national samples. American Journal of Epidemiology. 1999; 150(8):892–894. [PubMed: 10522661]

Kwan M-P. Space-time and integral measures of individual accessibility: A comparative analysis using a point-based framework. Geographical Analysis. 1998; 30(3):191–216.

Laraia B, Messer L, Evenson K, Kaufman JS. Neighborhood factors associated with physical activity and adequacy of weight gain during pregnancy. Journal of Urban Health-Bulletin of the New York Academy of Medicine. 2007; 84(6):793–806. [PubMed: 17710552]

Lee C, Moudon AV. Physical activity and environment research in the health field: Implications for urban and transportation planning practice and research. Journal of Planning Literature. 2004; 19(2):147–181.

Li FZ, Harmer PA, Cardinal BJ, Bosworth M, Acock A, Johnson-Shelton D, Moore JM. Built environment, adiposity, and physical activity in adults aged 50–75. American Journal of Preventive Medicine. 2008; 35(1):38–46. [PubMed: 18541175]

Liang KY, Zeger SL. Longitudinal data analysis using generalized linear models. Biometrika. 1986; 73:13–22.

Lopez RP. Neighborhood risk factors for obesity. Obesity. 2007; 15(8):2111–2119. [PubMed: 17712130]

McCormack GR, Giles-Corti B, Bulsara M. The relationship between destination proximity, destination mix and physical activity behaviors. Preventive Medicine. 2008; 46(1):33–40. [PubMed: 17481721]

Messer LC. Invited commentary: Beyond the metrics for measuring neighborhood effects. American Journal of Epidemiology. 2007; 165(8):868–871. [PubMed: 17329714]

Miller HJ. Measuring space-time accessibility benefits within transportation networks: Basic theory and computational procedures. Geographical Analysis. 1999; 31:187–212.

Mobley LR, Root ED, Finkelstein EA, Khavjou O, Farris RP, Will JC. Environment, obesity, and cardiovascular disease risk in low-income women. American Journal of Preventive Medicine. 2006; 30(4):327–332. [PubMed: 16530620]

Mokdad A, Serdula M, Dietz W, Bowman B, Marks J, Koplan J. The spread of the obesity epidemic in the United States, 1991--1998. JAMA. 1999; 282:1519–1522. [PubMed: 10546690]

Morency C, Paez A, Roorda MJ, Mercado R, Farber S. Distance traveled in three Canadian cities: Spatial analysis from the perspective of vulnerable population segments. Journal of Transport Geography. 2009

Moudon AV, Lee C, Cheadle AD, Garvin C, Johnson DB, Schmid T, Weathers RD, Lin L. Operational definitions of walkable neighborhood: Theoretical and empirical Insights. Journal of Physical Activity and Health. 2006; 3(S1):S99–S117.

Moudon AV, Lee C, Cheadle AD, Garvin C, Johnson DB, Schmid TL, Weathers RD. Attributes of environments supporting walking. American Journal of Health Promotion. 2007; 21(5):448–459. [PubMed: 17515010]

Nagendra H. Opposite trends in response for the Shannon and Simpson indices of landscape diversity. Applied Geography. 2002; 22(2):175–186.

Nawaz H, Chan W, Abdulrahman M, Larson D, Katz DL. Self-reported weight and height: Implications for obesity research. American Journal of Preventive Medicine. 2001; 20(4):294–298. [PubMed: 11331120]

Norman GJ, Nutter SK, Ryan S, Sallis JF, Calfas KJ, Patrick K. Community design and access to recreational facilities as correlates of adolescent physical activity and body-mass index. Journal of Physical Activity and Health. 2006; 3(Suppl. 1):S118–S128.

O'Campo P. Invited commentary: Advancing theory and methods for multilevel models of residential neighborhoods and health. American Journal of Epidemiology. 2003; 157(1):9–13. [PubMed: 12505885]

Ogden CL, Carroll MD, Curtin LR, McDowell MA, Tabak CJ, Flegal KM. Prevalence of Overweight and Obesity in the United States, 1999–2004. JAMA. 2006; 295(13):1549–1555. [PubMed: 16595758]

Oliver LN, Schuurman N, Hall AW. Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands. International Journal of Health Geographics. 2007; 6

Openshaw, S. The modifiable areal unit problem. Norwich, England: GeoBooks; 1984.

Pucher J, Renne JL. Socioeconomics of urban travel: Evidence from the 2001 NHTS. Transportation Quarterly. 2003; 57(3):49–77.

Ravera O. A comparison between diversity, similarity and biotic indices applied to the macroinvertebrate community of a small stream: the Ravella river (Como Province, Northern Italy). Aquatic Ecology. 2001; 35(2):97–107.

Robert SA, Reither EA. A multilevel analysis of race, community disadvantage, and body mass index among adults in the US. Social Science and Medicine. 2004; 59:2421–2434. [PubMed: 15474198]

Rundle A, Roux AVD, Freeman LM, Miller D, Neckerman KM, Weiss CC. The urban built environment and obesity in New York City: A multilevel analysis. American Journal of Health Promotion. 2007; 21(4):326–334. [PubMed: 17465178]

Saelens BE, Handy SL. Built environment correlates of walking: A review. Medicine and Science in Sports and Exercise. 2008; 40:S550–S566. [PubMed: 18562973]

Sallis JF, Nader R, Atkins J. San Diego surveyed for heart healthy foods and exercise facilities. Public Health Reports. 1986; 101:216–218. [PubMed: 3083479]

Shannon, CE.; Weaver, W. The Mathematical Theory of Communication. Urbana: The University of Illinois Press; 1949.

Simpson EH. Measurement of diversity. Nature. 1949; 163:688.

Smith KR, Brown BB, Yamada I, Kowaleski-Jones L, Zick CD, Fan JX. Walkability and Body Mass Index: Density, design, and new diversity measures. American Journal of Preventive Medicine. 2008; 35(3):237–244. [PubMed: 18692736]

Song Y, Rodriguez DA. The measurement of the level of mixed land uses: a synthetic approach. Carolina Transportation Program White Paper Series. 2005

Soobader M, LeClere FB, Hadden W, Maury B. Using aggregate geographic data to proxy individual socioeconomic status: does size matter? Am J Public Health. 2001; 91(4):632–636. [PubMed: 11291379]

Southworth M, Owens PM. The evolving metropolis: studies of community, neighborhood, and street form at the urban edge. Journal of the American Planning Association. 1993; 59(3):271–287.

Tilt JH, Unfried TM, Roca B. Using objective and subjective measures of neighborhood greenness and accessible destinations for understanding walking trips and BMI in Seattle, Washington. American Journal of Health Promotion. 2007; 21(4):371–379. [PubMed: 17465183]

U.S. Census Bureau. Census 2000. 2000. http://factfinder.census.gov

Weiss L, Ompad D, Galea S, Vlahov D. Defining neighborhood boundaries for urban health research. American Journal of Preventive Medicine. 2007; 32(6S):S154–S159. [PubMed: 17543706]

Wener RE, Evans GW. A morning stroll: Levels of physical activity in car and mass transit commuting. Environment and Behavior. 2007; 39(1):62–74.

Wood, JA. Economic benchmarks for Salt Lake City's central business district. Salt Lake City: The Downtown Alliance; 2005.

Yen IH, Syme SL. The social environment and health: A discussion of the epidemiologic literature. Annual Review of Public Health. 1999; 20:287–308.

Zeger SL, Liang KY. The analysis of discrete and continuous longitudinal data. Biometrics. 1986; 42:121–130. [PubMed: 3719049]

Zick CD, Smith KR, Fan JX, Brown BB, Yamada I, Kowaleski-Jones L. Running to the store? The relationship between neighborhood environments and the risk of obesity. Social Science & Medicine. 2009; 69(10):1493–1500. [PubMed: 19766372]

Biographies

IKUHO YAMADA is an Assistant Professor in the Department of Geography and Investigator at the Institute for Public and International Affairs (IPIA) at the University of Utah, Salt Lake City, UT 84112. Email: ikuho.yamada@geog.utah.edu. Her primary research interests reside in spatial statistics, GIScience, and spatial-temporal approaches to public health and urban transportation issues.

BARBARA B. BROWN is a Professor in the Department of Family and Consumer Studies and Investigator at IPIA at the University of Utah. Email: barbara.brown@fcs.utah.edu. She is an environmental psychologist who studies environmental, psychological, and social aspects of neighborhoods as they relate to walkability, new urbanism, neighborhood revitalization, and transit-oriented designs.

KEN R. SMITH is at the University of Utah where he is a Professor in the Department of Family and Consumer Studies, an Investigator with the Institute for Public and International Affairs, and is Director of the Pedigree and Population Resource. Email: ken.smith@fcs.utah.edu. He is a biodemographer interested in familial aspects of health, aging and longevity.

CATHLEEN D. ZICK is a Professor in the Department of Family and Consumer Studies and Investigator at IPIA at the University of Utah. Email: zick@fcs.utah.edu. She is a family and consumer economist interested in household time allocation, household structure and economic well-being, and family/consumer policy.

LORI KOWALESKI-JONES is an Associate Professor in the Department of Family and Consumer Studies and Investigator at IPIA as well as at the Huntsman Cancer Institute at the University of Utah. Email: lori.kowaleski-jones@fcs.utah.edu. She is interested in the ways in which youth are affected by family structure, community resources, and public policy.

JESSIE X FAN is a Professor in the Department of Family and Consumer Studies and Investigator at IPIA at the University of Utah. Email: fan@fcs.utah.edu. She is a consumer and family economist interested in consumer expenditure, saving, and credit use decisions and relevant policy issues.

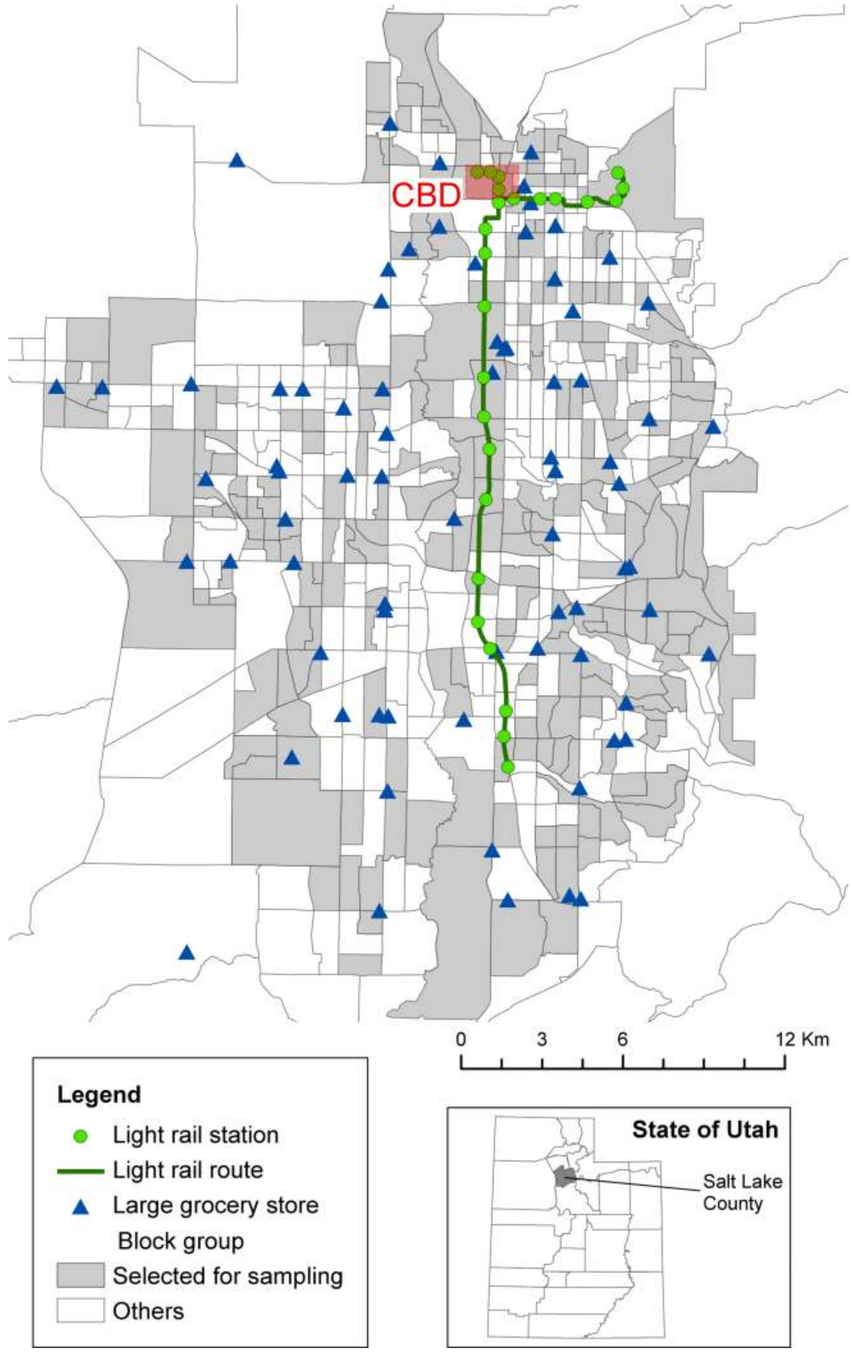

Figure 1.
Study area – Salt Lake County, Utah

Table 1

Statistical summary indices of mixed land use

	Frank's entropy score	Shannon's index	Simpson's index
Formulae	$-\sum_{i=1}^{6}(b_i/a)\ \ln\ (b_i/a)/\ \ln\ (N)$ $= -\sum_{i=1}^{6}p_i\ \ln\ (p_i)/\ \ln\ (N)$	$-\sum_{i=1}^{6}p_i\ \ln\ (p_i)$	$\sum_{i=1}^{6}b_i(b_i-1)/\{a(a-1)\}$
Value range (Low to high heterogeneity)	0 – 1	0 – positive infinity	1 – 1/6 (or more generally, 1/*K*); lower numbers are more diverse
Neighborhood A (1/2 each land uses 1 & 3)	1.00	0.69	0.50
Neighborhood B (1/6 each land uses 1 – 6)	1.00	1.79	0.17

Notation:

Land uses: 1=single-family residential; 2=multifamily residential; 3=retail; 4=office; 5=education; 6=entertainment

a: total square feet of land for all six land uses present in a neighborhood

N: number of six land uses with area > 0

K = number of land use categories (in this specification, K=6)

b_i (i =1, …, 6): area of a specific land uses, from 1 to 6 above

$p_i = b_i/a$: percent of area of a specific land use

Table 2

Descriptive statistics by gender

	Male (N=2617)		Female (N=2343)	
	Mean	**(SD)**	**Mean**	**(SD)**
Weight status				
BMI, individual	26.51	(4.52)	24.72	(4.94)
Sociodemographic measures				
Age, individual	40.85	(10.99)	41.74	(11.20)
Median age (both sexes), BG	30.08	(5.29)	30.02	(5.24)
Proportion African American (%), BG	0.01	(0.02)	0.01	(0.02)
Proportion Hawaiian and Pacific Islander (%), BG	0.01	(0.03)	0.01	(0.02)
Proportion Hispanic (%), BG	0.12	(0.13)	0.10	(0.11)
Proportion Asian (%), BG	0.02	(0.03)	0.02	(0.03)
Median family income (in $1,000), BG	55.07	(19.63)	57.05	(18.99)
Density measure				
Population density (per sq. kilometer), BG	2167.26	(1189.19)	2165.40	(1165.17)
Population density (per sq. kilometer), CT	2064.36	(1015.62)	2080.88	(991.62)
Population density (per sq. kilometer), buffer	2084.30	(801.92)	2093.80	(758.75)
Design measure				
Intersection density (per sq. kilometer), BG	42.14	(16.91)	43.28	(16.90)
Intersection density (per sq. kilometer), CT	40.40	(13.68)	41.32	(13.35)
Intersection density (per sq. kilometer), buffer	49.00	(12.02)	49.87	(11.78)
Area-based measures of mixed use				
Block group scale				
Area of single family residential (in sq. kilometers), BG	0.398	(0.390)	0.412	(0.382)
Area of multifamily residential (in sq. kilometers), BG	0.065	(0.088)	0.062	(0.094)
Area of retail (in sq. kilometers), BG	0.071	(0.133)	0.062	(0.120)
Area of office (in sq. kilometers), BG	0.065	(0.170)	0.060	(0.182)
Area of education (in sq. kilometers), BG	0.019	(0.120)	0.024	(0.153)

	Male (N=2617)		Female (N=2343)	
	Mean	**(SD)**	**Mean**	**(SD)**
Area of entertainment (in sq. kilometers), BG	0.009	(0.059)	0.007	(0.051)
Total area (in sq. kilometers), BG	0.628	(0.584)	0.628	(0.603)
Frank's entropy score, BG	0.508	(0.236)	0.493	(0.232)
Shannon's index, BG	0.760	(0.377)	0.732	(0.363)
Simpson's index, BG	0.598	(0.211)	0.614	(0.205)
Census tract scale				
Area of single family residential (in sq. kilometers), CT	1.170	(0.757)	1.230	(0.770)
Area of multifamily residential (in sq. kilometers), CT	0.216	(0.224)	0.206	(0.224)
Area of retail (in sq. kilometers), CT	0.198	(0.236)	0.179	(0.217)
Area of office (in sq. kilometers), CT	0.176	(0.322)	0.160	(0.312)
Area of education (in sq. kilometers), CT	0.047	(0.142)	0.053	(0.180)
Area of entertainment (in sq. kilometers), CT	0.024	(0.101)	0.020	(0.090)
Total area (in sq. kilometers), CT	1.831	(1.095)	1.847	(1.099)
Frank's entropy score, CT	0.551	(0.201)	0.532	(0.193)
Shannon's index, CT	0.898	(0.345)	0.865	(0.330)
Simpson's index, CT	0.543	(0.192)	0.562	(0.185)
1km street network buffer scale				
Area of single family residential (in sq. kilometers), buffer	0.567	(0.274)	0.593	(0.268)
Area of multifamily residential (in sq. kilometers), buffer	0.101	(0.099)	0.099	(0.103)
Area of retail (in sq. kilometers), buffer	0.067	(0.077)	0.060	(0.066)
Area of office (in sq. kilometers), buffer	0.051	(0.067)	0.047	(0.065)
Area of education (in sq. kilometers), buffer	0.019	(0.027)	0.019	(0.031)
Area of entertainment (in sq. kilometers), buffer	0.004	(0.017)	0.004	(0.019)
Total area (in sq. kilometers), buffer	0.808	(0.262)	0.822	(0.262)
Frank's entropy score, buffer	0.499	(0.224)	0.479	(0.219)
Shannon's index, buffer	0.786	(0.371)	0.749	(0.361)
Simpson's index, buffer	0.600	(0.208)	0.620	(0.203)
Destination-oriented measures of mixed use				
Distance to the closest light rail station (in kilometers)	5.54	(3.65)	5.80	(3.72)

	Male (N=2617)		Female (N=2343)	
	Mean	**(SD)**	**Mean**	**(SD)**
Distance to CBD (in kilometers)	14.02	(8.19)	14.78	(8.16)
Distance to the closest large grocery store (in kilometers)	1.65	(0.81)	1.66	(0.82)
Census proxy measures				
Block group scale				
Proportion walk to work (%), BG	2.55	(4.30)	2.24	(3.99)
Median year structure built, BG	1969.9	(15.5)	1970.2	(15.8)
Census tract scale				
Proportion walk to work (%), CT	2.62	(3.89)	2.39	(3.58)
Median year structure built, CT	1970.5	(15.3)	1970.5	(15.7)
1km street network buffer scale				
Proportion walk to work (%), buffer	2.51	(3.58)	2.28	(3.33)
Median year structure built, buffer	1970.0	(14.2)	1970.3	(14.7)

(SD = standard deviation; BG = block group; CT = census tract)

Table 3

Partial correlation between individuals' BMI and built environment measures

	Male BMI	Female BMI				
Distance to the closest light rail station (in kilometers)	0.054 **	0.112 **				
Distance to CBD (in kilometers)	0.082 **	0.113 **				
Distance to the closest large grocery store (in kilometers)	−0.008	0.025				
	BG		CT		Buffer	
	Male BMI	Female BMI	Male BMI	Female BMI	Male BMI	Female BMI
Population density (per sq. kilometer)	−0.024	−0.012	−0.040 *	−0.037	−0.037	−0.040
Intersection density (per sq. kilometer)	0.014	0.015	0.000	−0.008	0.039 *	−0.003
Frank's entropy score (higher scores, more diversity)	−0.036	−0.032	−0.043 *	−0.010	−0.043 *	−0.032
Shannon's index (higher scores, more diversity)	−0.044 *	−0.028	−0.040 *	−0.006	−0.047 *	−0.044 *
Simpson's index (lower scores, more diversity)	0.042 *	0.030	0.043 *	0.016	0.046 *	0.046 *
Area of single family residential (in sq. kilometers)	0.048 *	0.012	0.047 *	0.050 *	0.022	0.008
Area of multifamily residential (in sq. kilometers)	−0.014	0.030	−0.008	0.050 *	−0.069 **	−0.021
Area of retail (in sq. kilometers)	−0.007	−0.007	0.015	0.021	−0.020	−0.049 *
Area of office (in sq. kilometers)	−0.007	−0.016	0.015	0.020	−0.049 *	−0.071 **
Area of education (in sq. kilometers)	−0.008	−0.029	−0.009	−0.024	−0.021	0.028
Area of entertainment (in sq. kilometers)	−0.027	−0.040	0.008	−0.011	0.006	−0.028
Proportion walk to work (%)	−0.046 *	−0.076 **	−0.050 *	−0.103 **	−0.065 **	−0.103 **
Median year structure built (larger value = newer housing)	0.081 **	0.111 **	0.076 **	0.110 **	0.079 **	0.119 **

(Significance level: * 5%; ** 1%.

Abbreviation: BG = block group; CT = census tract)

Note: Correlation coefficients control for individual age, neighborhood income, median age of neighborhood residents, and race/ethnic composition of neighborhoods measured at the block group scale.

Table 4

Goodness of fit statistics for models associating individual BMI with various combinations of built environment measures by corrected quasi-likelihood under the independence criterion (QICC)

			BG scale		CT scale		Buffer scale	
			Male	**Female**	**Male**	**Female**	**Male**	**Female**
Level 0	**Only 7 controls, without any 3D variables**	QICC	51456.5	52088.7				
Level 1	**Level 0 + population density and intersection density**							
		QICC	51354	52010.2	51221.5	51964.7	51101.9	51983.2
		Improvement from Level 0	*−102.5*	*−78.5*	*−235.0*	*−124.0*	*−354.6*	*−105.5*
Level 2	**Level 1 + area-based diversity measures**							
Level 2a	Frank's index	QICC	51293.1	52002	51149.7	51962.6	51062.3	51930
		Improvement from Level 0	*−163.4*	*−86.7*	*−306.8*	*−126.1*	*−394.2*	*−158.7*
Level 2b	Shannon's index	QICC	51254.8	52013.1	51156.1	51965	51048.9	51895.8
		Improvement from Level 0	*−201.7*	*−75.6*	*−300.4*	*−123.7*	*−407.6*	*−192.9*
Level 2c	Simpson's index	QICC	51266	52006.9	51140.7	51952.7	51051.5	51879.3
		Improvement from Level 0	*−190.5*	*−81.8*	*−315.8*	*−136.0*	*−405.0*	*−209.4*
Level 2d	Frank's 6 categories	QICC	51213.2	51894.4	51129.4	51697.6	50934.8	51608.16
		Improvement from Level 0	*−243.3*	*−194.3*	*−327.1*	*−391.1*	*−521.7*	*−480.5*
Level 3	**Level 1 + destination-based diversity measures**							
Level 3a	Distance to light rail station	QICC	51230.8	51412.4	51101.1	51338.6	51006.2	51377.6
		Improvement from Level 0	*−225.7*	*−676.3*	*−355.4*	*−750.1*	*−450.3*	*−711.1*
Level 3b	Distances to LR & CBD	QICC	51062.2	51184.4	50982.3	51171.9	50882.2	51191.1
		Improvement from Level 0	*−394.3*	*−904.3*	*−474.2*	*−916.8*	*−574.3*	*−897.6*
Level 3c	Distance to large grocer	QICC	51351.8	52008.2	51210.3	51952.9	51084.7	51977.9
		Improvement from Level 0	*−104.7*	*−80.5*	*−246.2*	*−135.8*	*−371.8*	*−110.8*
Level 3d	Distances to LR, CBD, & large grocer	QICC	51048.3	51172.2	50959.4	51167.9	50856.9	51186.6
		Improvement from Level 0	*−408.2*	*−916.5*	*−497.1*	*−920.8*	*−599.6*	*−902.1*
Level 4	**Level 1 + proxy-based diversity measures**							

			BG scale		CT scale		Buffer scale	
			Male	**Female**	**Male**	**Female**	**Male**	**Female**
Level 4a	Percentage walk to work	QICC	51296.4	51787.6	51167.6	51524.4	50983.1	51503.8
		Improvement from Level 0	*−160.1*	*−301.1*	*−288.9*	*−564.3*	*−473.4*	*−584.9*
Level 4b	Median year structure built	QICC	51020.0	51382.4	50947.9	51381.1	50844.3	51327.9
		Improvement from Level 0	*−436.5*	*−706.3*	*−508.6*	*−707.6*	*−612.2*	*−760.8*
Level 5	**Combination of Levels 3b and 4b Level 1 + distances to LR & CBD + median year structure built**							
		QICC	50960.5	51007.2	50908.4	51030.1	50819	51028.1
		Improvement from Level 0	*−496.0*	*−1081.5*	*−548.1*	*−1058.6*	*−637.5*	*−1060.6*
		Improvement from Level 3b	−101.7	−177.2	−73.9	−141.8	−63.2	−163
		Improvement from Level 4b	*−59.5*	*−375.2*	*−39.5*	*−351.0*	*−25.3*	*−299.8*
Level 6	**Level 5 + six land uses, % walk to work, or both Level 1 + distances to LR & CBD + median year structure built + more**							
Level 6a	Level 5 + six land uses	QICC	50859.2	50802.6	50877.5	50744.7	50737.5	50743.6
		Improvement from Level 0	*−597.3*	*−1286.1*	*−579.0*	*−1344.0*	*−719.0*	*−1345.1*
		Improvement from Level 5	*−101.3*	*−204.6*	*−30.9*	*−285.4*	*−81.5*	*−284.5*
Level 6b	Level 5 + % walk to work	QICC	50958.4	50992.9	50910.4	50980.2	50806.8	50960.3
		Improvement from Level 0	*−498.1*	*−1095.8*	*−546.1*	*−1108.5*	*−649.7*	*−1128.4*
		Improvement from Level 5	*−2.1*	*−14.3*	*2.0*	*−49.9*	*−12.2*	*−67.8*
Level 6c	Level 5 + six land uses + % walk to work	QICC	50855.9	50795.4	50879.3	50712.4	50738.6	50679.2
		Improvement from Level 0	*−600.6*	*−1293.3*	*−577.2*	*−1376.3*	*−717.9*	*−1409.5*
		Improvement from Level 5	*−104.6*	*−211.8*	*−29.1*	*−317.7*	*−80.4*	*−348.9*

Note: Values in italics show improvement of fit in comparison with other models, where larger negative values are associated with larger improvement. Shaded values indicate the best fit model for each level of models by gender.

Table 5

Best estimated models relating individual BMI and built environment measures

Independent variables	Beta	(Std. error)	*p*-value
Male (Intercept)	−30.190	(16.510)	0.067
Age, individual	0.072	(0.008)	0.000**
Median age (both sexes), BG	0.022	(0.019)	0.247
Proportion African American (%), BG	7.229	(5.711)	0.206
Proportion Hawaiian and Pacific Islander (%), BG	3.546	(3.168)	0.263
Proportion Hispanic (%), BG	0.963	(0.927)	0.299
Proportion Asian (%), BG	−6.407	(3.177)	0.044*
Median family income (in $1,000), BG	−0.020	(0.006)	0.001**
Population density (per sq. kilometer), CT	0.000	(0.000)	0.113
Intersection density (per sq. kilometer), buffer	0.025	(0.009)	0.006**
Distance to the closest light rail station (in kilometers)	0.003	(0.033)	0.920
Distance to CBD (in kilometers)	0.003	(0.020)	0.875
Median year structure built, BG	0.027	(0.008)	0.001**
Area of single family residential (in sq. kilometers), buffer	0.253	(0.491)	0.606
Area of multifamily residential (in sq. kilometers), buffer	−2.319	(1.051)	0.027*
Area of retail (in sq. kilometers), buffer	0.839	(1.259)	0.505
Area of office (in sq. kilometers), buffer	−1.218	(1.522)	0.424
Area of education (in sq. kilometers), buffer	−1.697	(3.170)	0.592
Area of entertainment (in sq. kilometers), buffer	3.455	(7.933)	0.663
Female (Intercept)	−33.285	(31.768)	0.295
Age, individual	0.099	(0.009)	0.000**
Median age (both sexes), BG	0.037	(0.020)	0.065
Proportion African American (%), BG	8.686	(7.606)	0.253
Proportion Hawaiian and Pacific Islander (%), BG	11.168	(3.451)	0.001**
Proportion Hispanic (%), BG	3.515	(1.583)	0.026*
Proportion Asian (%), BG	−9.398	(3.770)	0.013*
Median family income (in $1,000), BG	−0.051	(0.009)	0.000**
Population density (per sq. kilometer), buffer	0.000	(0.000)	0.434
Intersection density (per sq. kilometer), BG	0.005	(0.007)	0.456
Distance to the closest light rail station (in kilometers)	0.103	(0.039)	0.009**
Distance to CBD (in kilometers)	0.014	(0.034)	0.681

Independent variables	Beta	(Std. error)	*p*-value
Median year structure built, buffer	0.028	(0.016)	0.085
Proportion walk to work (%), buffer	−0.086	(0.059)	0.142
Area of single family residential (in sq. kilometers), buffer	−0.266	(0.549)	0.627
Area of multifamily residential (in sq. kilometers), buffer	2.361	(1.631)	0.148
Area of retail (in sq. kilometers), buffer	−1.384	(2.175)	0.525
Area of office (in sq. kilometers), buffer	−1.245	(2.186)	0.569
Area of education (in sq. kilometers), buffer	9.256	(5.691)	0.104
Area of entertainment (in sq. kilometers), buffer	−7.191	(3.114)	0.021 *

(Significance level: * 5%; ** 1%)