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Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity

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ABSTRACT

Few studies compare alternative measures of land use diversity or mix in relationship to body mass index. We compare four types of diversity measures: entropy scores (measures of equal distributions of walkable land use categories), distances to walkable destinations (parks and transit stops), proxy measures of mixed use (walk to work measures and neighborhood housing ages), and land use categories used in entropy scores. Generalized estimating equations, conducted on 5000 randomly chosen licensed drivers aged 25–64 in Salt Lake County, Utah, relate lower BMIs to older neighborhoods, components of a 6-category land use entropy score, and nearby light rail stops. Thus the presence of walkable land uses, rather than their equal mixture, relates to healthy weight.

1. Introduction

Mixing commercial facilities, single-family housing, and multi-family housing has for centuries enabled residents to walk to multiple near-home destinations. In the US, this long tradition was broken with the advent of Euclidian zoning, which allowed localities to separate land uses. Originally intended to protect health by separating noxious industrial land from residential areas (Frumkin et al., 2004), segregated land uses are now implicated in modern health problems associated with less walking, heavier weight, and more automobile pollution (Booth et al., 2005; Johnson, 2001; Saelens and Handy, 2008; Transportation Research Board, 2005).

In contrast, mixed use has been conceptualized as a key ingredient needed to support walking and recent studies suggest mixed use is important in maintaining healthy weight as well. Mixed or diverse land use is one of the "3Ds"—density, pedestrian friendly design, and diversity—that have been found to associate with walking (Cervero and Kockelman, 1997). At this early stage of research, there is much contention about the strength of relationships between land uses and walking or weight outcomes, whether land uses relate more to transportation vs. leisure walking, and the degree to which environments change behavior or people select environments that fit their walking preferences (Cao et al., 2009). Although these issues cannot be settled in this paper, the conceptualization linking land use to walking can be described. The theory is that population density makes walking efficient, decreases the appeal of driving through congested areas where parking is often scarce, and creates demand for destinations. Pedestrian friendly design provides well-connected street networks that create fairly short and direct routes between destinations. Mixed use brings many diverse walking destinations together in an area (Owen et al., 2004), which may be especially important for supporting walking for transportation purposes. We consider the conceptual issues inherent in choosing mixed use measures and examine empirical consequences of relating alternative measures to body mass index (BMI), overweight, and obesity.

2. Mixed use measures

Operationalizing diverse destinations or mixed use into summary scores presents the researcher with a challenging array of options. Dozens of potential land use mix or destination diversity operationalizations exist, including dissimilarity scores, gravity indices, and absolute clustering scores (see reviews in

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Brownson et al., 2009; Forsyth, 2007; Song and Rodriguez, 2004). These measures have been deployed by researchers from a variety of disciplines to measure diverse concepts such as housing segregation, market share of firms, and landscape ecology (Song and Rodriguez, 2004).

In this study, we test entropy measures of mixed use, given how frequently and successfully they have been related to weight outcomes, as reviewed below. Entropy scores equal one when land use is maximally mixed or heterogeneous and zero when land use is maximally homogeneous. Entropy scores arose as variants of the Shannon index (Shannon and Weaver, 1949) originally used to analyze accuracy of information transfer. Later applications from a variety of fields adapted the measures to provide general indices of the evenness of spread across different categories (Krebs, 1999).

3. Mixed use and walking

Several reviews show that mixed use generally supports walking, including a recent review by Saelens and Handy (2008) of 13 prior reviews of walking and the built environment. This meta-review showed extensive support for walking and two overlapping measures of diverse land uses: land use mix and distances to walkable destinations. They reviewed past research showing mixed use related to leisure/exercise and transportation/destination-oriented walking; however, their review indicated that more recent studies (2005—May, 2006) supported the relationship between mixed use and walking for transportation, not leisure (Saelens and Handy, 2008).

Surprisingly negative results emerged, however, in a recent study by Forsyth and colleagues that provided the most comprehensive test of alternative land use scores with walking and accelerometer measures of physical activity. They found only 2 of 44 mixed use measures related to walking (Forsyth et al., 2008). Social land uses (e.g., schools, churches, recreation facilities) related to reports of less walking for leisure ($r=-0.50$) and more walking for transportation ($r=0.42$). Traditional measures of mixed uses, such as entropy scores, and destination proximities were insignificant.

In light of these conflicting results, it is important to consider the conceptualizations underlying land use measures and to compare empirical results for alternative measures. If certain land uses support walking, they might support healthy weight as well. An extra 15-min a day in brisk walking is projected to burn enough calories to prevent a 1–2 pound weight gain per year, an increase many US adults experience (Hill et al., 2003).

3.1. Entropy scores and BMI

Healthier BMIs often relate to greater mixed land uses as measured by entropy scores that assess equality of distribution of designated land uses (Frank et al., 2004; Li et al., 2008; Mobley et al., 2006; Rundle et al., 2007). Entropy scores have not related to BMI (Rutt and Coleman, 2005) or transportation walking (Cerin et al., 2007) when the scores include industrial land uses, which are not typically considered walkable destinations. Thus our analyses focus on entropy scores that combine multiple walkable destinations, such as housing and offices.

We focus on two specific entropy measures developed by Lawrence Frank and colleagues. These are especially promising because they were significantly associated with walking or weight across two different data sets (Frank et al., 2005, 2006). In both equations below, ''area'' referred to square feet of building floor area and scores range from 0, indicating homogeneous use, to 1, indicating equal mixes of categories present in the equation.

3-category mix, adapted from Frank et al. (2005) is

$$\begin{aligned}\text{Landusemix} = (-1)[(b1/a)\ln(b1/a) + (b2/a)\ln(b2/a)\\ + (b3/a)\ln(b3/a)]/\ln(n3),\end{aligned} \tag{1}$$

where a is the total square feet of land for all three land uses present in buffer; $b1$–$b3$ measure areas of land use for: $b1=$ residential, $b2=$ commercial, $b3=$ office, $n3=0$ through 3, summing the number of different land uses present.

6-category mix, from Frank et al. (2006) is

$$\text{Land use mix} = A/(\ln(N)), \tag{2}$$

where

$$\begin{aligned}A = (b1/a)*\ln(b1/a) + (b2/a)*\ln(b2/a) + (b3/a)*\ln(b3/a)\\ + (b4/a)*\ln(b4/a) + (b5/a)*\ln(b5/a) + (b6/a)*\ln(b6/a),\end{aligned}$$

a is the total square feet of land for all six land uses present in buffer, $b1$–$b6$ measure areas of land use for: $b1=$ single-family residential, $b2=$ multi-family residential, $b3=$ retail, $b4=$ office, $b5=$ education, $b6=$ entertainment, $N=$ number of six land uses with area >0.

Frank et al. (2005) found that Eq. (1) entropy score was the most powerful walkability predictor of objectively measured physical activity from a group of predictors that included residential density and street connectivity. Frank et al. (2006) used Eq. (2) entropy score in a walkability index that also included residential density, street connectivity, and retail floor area ratio. Residents in more walkable neighborhoods, assessed spatially as 1-km street network buffers, reported more walking and biking and lower BMIs.

Frank et al. (2006) were careful to vet their sample areas prior to admitting them into studies, which likely assures that their entropy scores adequately operationalize mixed uses that invite walking. Others who adopt entropy measures may not realize the wide range of land use situations that can be represented by entropy scores. We illustrate below several ways in which entropy scores may not provide ideal measures of the walkability potential of mixed use.

First, the entropy formulae that have been used in the land use literature do not imply the presence of a wide range of uses. If the 6-category Eq. (2) above is used, the following examples would both achieve the maximally mixed use scores (see illustrations in Fig. 1).

Example 1a (entropy score = 1.0). $\frac{1}{6}$ multifamily+$\frac{1}{6}$ single family+$\frac{1}{6}$ office+$\frac{1}{6}$ retail+$\frac{1}{6}$ office+$\frac{1}{6}$ entertainment.

Example 1b (entropy score = 1.0). $\frac{1}{2}$ multifamily+$\frac{1}{2}$ single family.

Second, higher scores may not represent more mixed uses when two entropy scores are derived from different equations that involve land use categories that vary in breadth. Notice how the broad category of residential land use, from 3-category Eq. (1), is split into two finer categories, single- and multi-family residential, in 6-category Eq. (2). Multi-family housing is associated with higher density and perhaps the services and facilities that require a certain level of density to support walking, such as transit service, specialized shops, or other retail. A researcher may want to highlight the presence of multi-family housing in particular, given its conceptual link to other aspects of walkability. However, if the researcher highlights the presence of multi-family by adopting the 6-category entropy score, the presence of multi-family housing may actually penalize an area's score:

Example 2a (entropy score = 0.68). 1/100 multifamily+49/100 single family+$\frac{1}{2}$ office.

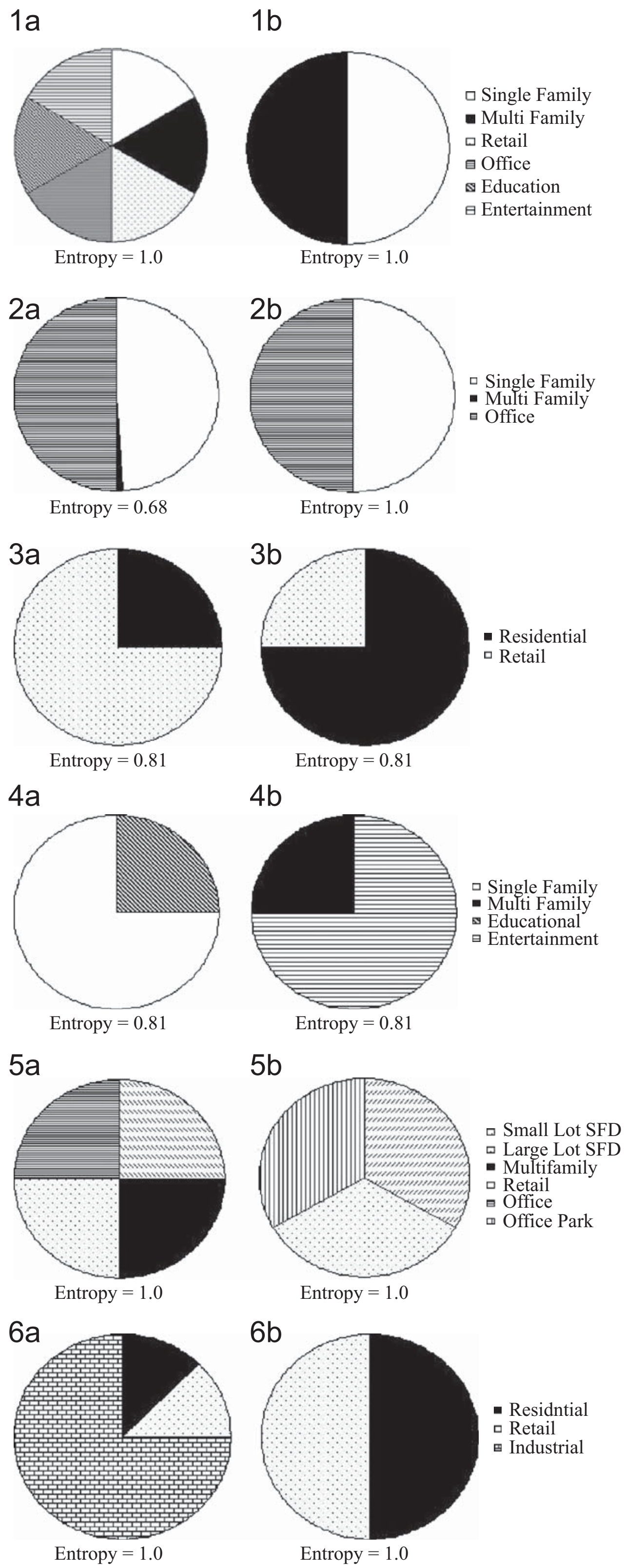

Fig. 1. Examples of different land use configurations and entropy scores.

Example 2b (entropy score = 1.0). 0 multifamily+$\frac{1}{2}$ single family+$\frac{1}{2}$ office.

Third, strong imbalances in land uses, which may alter its walkability, may be assigned the same mixed use score.

Example 3a (entropy score = 0.81). $\frac{1}{4}$ residential+$\frac{3}{4}$ retail.

Example 3b (entropy score = 0.81). $\frac{3}{4}$ residential+$\frac{1}{4}$ retail.

Fourth, qualitatively different mixes of land uses, with different implications for walkability, can have the same entropy values.

Example 4a (entropy score = 0.81). $\frac{1}{4}$ educational+$\frac{3}{4}$ single family.

Example 4b (entropy score = 0.81). $\frac{3}{4}$ entertainment+$\frac{1}{4}$ multi-family.

Fifth, these broad quantitative measures of land use can mask important qualitative differences with respect to walkability within each land use category. Consider how a community designed to be walkable can score the same as a less walkable automobile-oriented suburban fringe community:

Example 5a (entropy score = 1.0). $\frac{1}{4}$ small lot single family detached+$\frac{1}{4}$ multifamily+$\frac{1}{4}$ retail (bookstores, restaurants)+$\frac{1}{4}$ office (small main street shops).

Example 5b (entropy score = 1.0). $\frac{1}{3}$ large lot single family+$\frac{1}{3}$ retail (big box stores just off a freeway exit)+$\frac{1}{3}$ office park.

Finally, in the "missing land" problem, land uses absent from the entropy score may alter the true walkability character in any given area, but without altering the entropy score. If, for example, a neighborhood's walkability is compromised by the presence of a large industrial plant, the entropy measure would simply ignore the industrial land.

Example 6a (entropy score = 1.0). $\frac{1}{8}$ residential+$\frac{1}{8}$ retail+$\frac{3}{4}$ (unscored) industrial.

Example 6b (entropy score = 1.0). $\frac{1}{2}$ residential+$\frac{1}{2}$ retail.

To circumvent this problem, Frank et al. (2004) used the proportion of each land use to the total network buffer area, instead of the sum of land areas in the three or six categories under consideration as in Eqs. (1) and (2), which would yield an entropy score of 0.75 in Example 6a.

In addition to all of the above considerations, there are some practical difficulties in employing broad land use mix scores. Different localities categorize land uses differently and for taxation purposes, not for walkability and weight research. Salt Lake County, for example, posts 167 distinct land uses. Some are easily reduced to frequently used land use categories, such as multi-family residential, while others are not, such as churches, which are classified as "other land use." Researchers might want to create an "institutional" land use code that includes churches and other land uses that contribute to walkability, but journal articles are often too brief to allow such detailed land use categorization decisions to be shared easily. Problems with missing data (Bodea et al., 2008) and variations in unwritten GIS protocols (Forsyth et al., 2006) plague many GIS studies. Finally, as a practical constraint, entropy measures are time-consuming, due to GIS operations to combine neighborhood buffer polygons created around individuals' residential locations with detailed land use polygons. Given these complications, it is important to consider alternative ways to measure mixed use supports for walkability and weight.

3.2. Destination-based measures

Destination-based measures can include a large range of destinations; for the purposes of this paper, we focus on only three destinations that past research has found useful in relationship to walking: light rail stops, bus stops, and parks.

Destination-based measures are often created by noting the presence, density, or average distances for walkable destinations around home. For example, the density of employment establishments near home related to lower weight in one study (Lopez, 2007) and distances to neighborhood retail employment centers related to any reported walking in another (Krizek and Johnson, 2006). Lee and Moudon argue that distances to specific relevant targeted destinations, such as parks or shopping, are easy-to-compute measures that can substitute for both parcel-based mixed land use measures and street connectivity measures of walkability (Lee and Moudon, 2006a), although their review indicates mixed success with how destination-based measures relate to walking (Lee and Moudon, 2006b).

Light rail stops might encourage walking to and from stops, might attract residents who prefer walking, or might, through a combination of environmental opportunity and selection influences, provide environmental supports that allow residents to act on their preferences more easily. For example, within Salt Lake County, a new rail stop construction enabled nearby residents, especially those who were not obese and who held pro-transit attitudes, to more readily express those preferences by becoming rail riders. Their pro-transit attitudes were not sufficient to motivate a longer walk to a more distant stop prior to the new stop construction; however, the new environmental support for walking enabled residents a more convenient opportunity to act on their preferences (Brown and Werner, 2009). Studies elsewhere have shown that rail commuters walked 30% more pedometer-measured steps per day than car commuters (Wener and Evans, 2007) and that residents living in neighborhoods with greater subway stop density have lower BMIs (Rundle et al., 2007).

Parks may also be important venues for physical activity, which may reduce risks for obesity. In low income minority neighborhoods, proximity to a park was associated with park use and physical activity, and more males used parks than females, especially in team sports areas (Cohen et al., 2007). Greater proximity to parks and other recreational uses has also related to lower weight (Giles-Corti et al., 2003). A recent review concluded that parks are generally but not universally associated with greater physical activity (Kaczynski and Henderson, 2007).

Destination-based measures also have limitations and measurement difficulties. These measures can be very specific, leading to cumbersome lists of variables. For example, Tilt et al. (2007) questioned residents about the proximity to 15 distinct destinations. However, most residents reported that many (6 of 15) destinations were not even in their neighborhood. Different destinations also attracted wide variations in walking frequencies; 45% of residents walked to neighborhood grocery stores at least once a week but only 2.2% walked to theaters. It may be difficult to identify in advance a concise list of destinations that generate significant walking. Lists of particular destinations from commercial firms have been shown to have only moderate agreement with field audits and errors in pinpointing locations—although locational errors are reduced when locations are aggregated into broader areas like census-block groups (Boone et al., 2008). In addition, destinations sometimes include large multi-use walkable destinations, such as universities, as well as small specialized destinations, such as bowling alleys (Forsyth et al., 2008), which likely differ substantially in pedestrian traffic. Destinations may also be specialized, attracting only a fraction of the population (e.g., elementary schools, Forsyth et al., 2008). Thus, destination-based measures also have conceptual and measurement limitations. We examine relationships between BMI and three destinations that the literature review showed were particularly promising in supporting healthy weight: nearby rail and bus stops and the presence of a nearby park.

For both entropy- and destination-based measures, sometimes results differ by gender. Sometimes walkability predicts lower BMIs for men only (Berke et al., 2007; Frank et al., 2008), and sometimes proximity to walkable destinations predicts higher BMIs for women only (Boehmer et al., 2007), perhaps reflecting greater fear of crime among women in urban neighborhoods. In sum, our review demonstrates that both destination-based and entropy scores relate to weight, although results are not uniform and sometimes differ by gender.

3.3. *Proxy-based measures*

Our past research demonstrated that two proxy measures of land use mix from the census were useful: the proportion of residents in the block group who walk to work and the average age of housing in the census tract (Smith et al., 2008). Block groups were chosen because they are relatively small areas (i.e., typically about 1500 residents, ranging from 300 to 3000) that approximate walking distance neighborhoods (US Bureau of the Census, 2000). Our study related these two proxies to male and female BMI, overweight, and obesity, based on over 450,000 driver license records in Salt Lake County. In all six models, the greater the proportion of residents who walk to work and the older the housing in the neighborhood, the lower the BMI and the risks of overweight and obesity. The proportion of workers walking to work was very low, averaging only 2–3%, but should indicate a neighborhood where housing and employment sites are within walking distance. Doubling the proportion of residents walking to work decreased an individual's risk of obesity by almost 10%. Adding a decade to the average age of housing in the neighborhood decreased women's risk of obesity by about 8% and men's risk of obesity by about 13%. Therefore, our proxy measures were promising, but we could not compare them with more frequently used entropy measures because the large sample size made such calculations impractical. In order to check the utility and validity of our proxy-based measures, this study compares the proxy mixed use measures to other more explicit mixed use measures.

3.4. *Land use categories*

All three land use measures—entropy scores, proximity scores, and proxy measures—have advantages and disadvantages. Entropy scores have the advantage of including broad land use categories, but the calculation of the entropy index obscures the contribution of the separate land use categories, and the scores have a number of other limitations as outlined above. Proximity measures specify clear types of land uses, but measuring distances to many land uses can yield unwieldy lists of questionable utility. Proxy measures are easily attained in census data bases, but have not been validated against other land use mix and destination measures. We propose to test a fourth type of measure, which is simply the areas of land in the categories used to compute entropy measures of mixed use that have proved useful in past research (Frank et al., 2005, 2006). Assessing areas of walkable destinations is similar to the approach of Forsyth et al. (2008), who found that social land uses related to walking for transportation. Our approach is different from hers in that the land use codes we employ are broader, capturing many different specific types of destinations.

In sum, our research goals are to:

1. Test whether mixed use proxies used county-wide in Smith et al. (2008)—the proportions of residents walking to work and neighborhood housing age—also relate to BMI outcomes in this subsample of 5000.

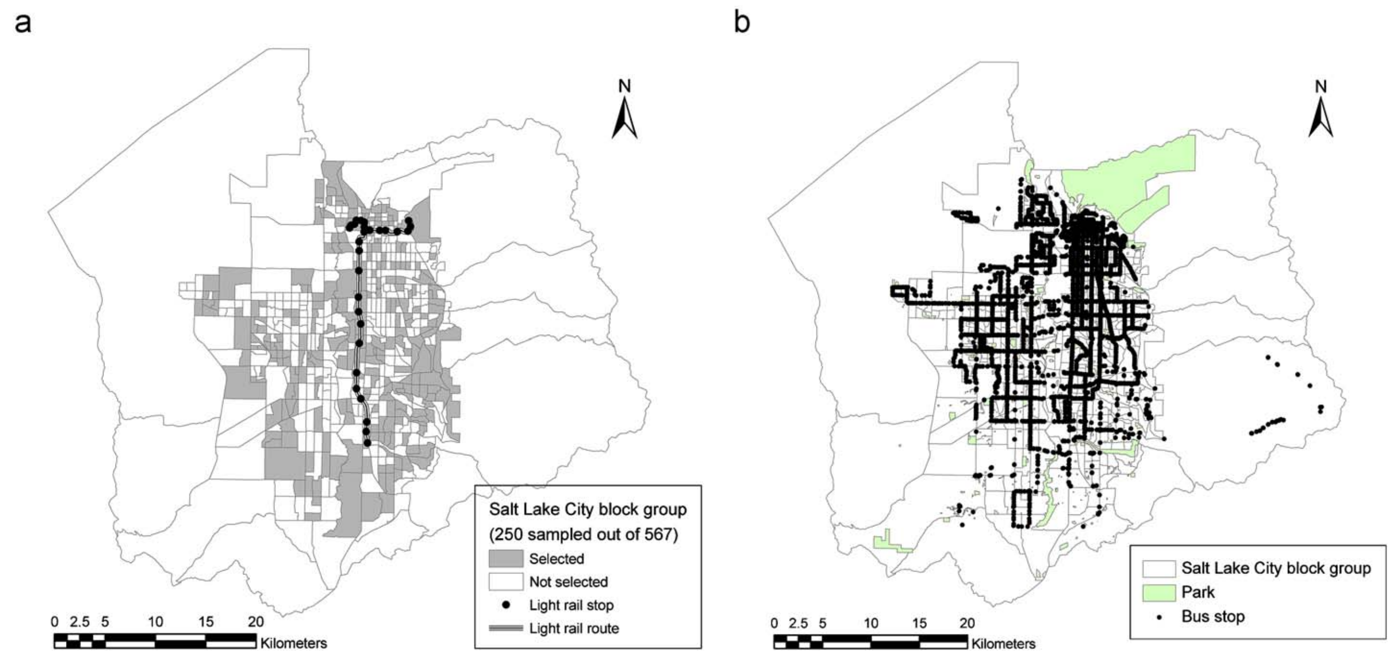

Fig. 2. Sampled block groups, rail line and stops, bus stops and parks in the study region: (a) chosen block groups and rail line and rail stop locations and (b) park land and bus stop locations.

2. Examine relationships among our proxy measures, traditional entropy land use mix scores, destination-specific land uses, and other macro-level predictors of walkability (i.e., street connectivity and population density).
3. Compare our proxy measures with more traditional entropy scores of land use mix and destination-specific measures as predictors of weight outcomes.
4. Compare the aforementioned measures to the set of land use categories that are used in entropy scores as predictors of weight outcomes.

4. Methods

4.1. Sample

Observations were drawn from a larger database of BMIs recorded for residents of Salt Lake County, Utah, based on reported heights and weights from driver licenses. Although self-reported weights may be underestimated (Gorber et al., 2007; Nawaz et al., 2001), there is no evidence of systematic bias or underestimations by neighborhood geographic location. Following standard practice, BMI is defined as weight in kilograms divided by height in meters squared. BMI is used to classify license holders into three categories: healthy weight ($18.5 \leq \text{BMI} \leq 24.9$), overweight ($25 \leq \text{BMI} \leq 29.9$) and obese ($\text{BMI} \geq 30$). Those individuals classified as underweight ($\text{BMI} < 18.5$) are excluded from the sample. We sampled 25–64-year olds, given that we wanted to allow young adults time to establish their own residence and wanted to avoid the additional correlates of BMI for elderly individuals (Smith et al., 2008).

The driver license data from the Utah Department of Public Safety were obtained from the Utah Population Database (UPDB), a health-related research database. 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 was approved by the University of Utah Institutional Review Board 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.

A sample of 5000 participants was drawn from the sample frame of 453,927 Salt Lake County driver license holders to enable the calculation of entropy scores using 1 km land use polygons drawn around each address. After eliminating 18 relatively unpopulated (<150 driver licenses present) or sparsely populated fringe census-block groups from 564 total block groups used by Smith et al. (2008), we randomly sampled 20 participants from each of 250 randomly sampled block groups (Fig. 2). We also retained the seven socio-demographic control variables used by Smith et al. (2008). These include individual age and six census-block group variables: proportions black, Hawaiian/Pacific Islander, Hispanic, and Asian; neighborhood income; and median age of neighborhood residents.

4.2. Land use mix variables

Proxy variables, from Census 2000 Summary File 3, include the proportion of residents who walk to work in the block group (BG) and the median housing age in the census tract.

We computed three entropy scores to represent land use mixes. Two were based on Eqs. (1) and (2) above, from Frank and colleagues' 3-category (2005) and 6-category (2006) measures. Both scores were calculated based on land areas, instead of building floor areas as suggested by Frank, due to a lack of floor area information. The third entropy measure followed the same form, except that it considered two land uses: residential and non-residential walkable destinations. Salt Lake County assigns all parcels in the county to one of 167 land use codes. Three raters classified these into 120 walkable types of destinations, resolving any disagreements through discussion. These land uses include residential ($n = 56$) and non-residential walkable uses ($n = 64$). Residential uses include single and multiple family housing, planned unit developments, condominiums, and trailer parks. Non-residential walkable uses include destinations that characterize Frank et al.'s (2005, 2006) codes as well, such as office spaces, stores, schools, and parks. Nonwalkable land uses excluded from the mixed use score include large-scale land uses that individuals do not typically walk to, such as auto dealerships, airports, warehouses, and farmland, and vacant land.

To measure entropy scores and street connectivity, like Frank et al. we used 1 km street network buffers around each driver license address to define an individual's neighborhood. For greater comparability with Frank, intersection density was calculated for a 1-km street network buffer, removing street intersections that involve interstate highways (Smith et al. (2008) had used 0.25 mile straight line buffer). In Salt Lake County, about 82% of intersections are three-way and are not necessarily associated with less walkable cul-de-sacs. Therefore, intersections of three or more local streets were counted as walkable and averaged into an intersection density measure.

As an alternative category-based measure of land uses related to walkability, we also retained the square kilometers of each of the land use categories used in each entropy score. These alternative 2–3-and 6-variable measures are compared to their respective entropy scores that summarize the equality of mix across the land use categories.

Fig. 2 maps the three destination-oriented measures of mixed land use: distances to the closest light rail and bus stops, and the presence of parks ($1 = \text{yes}$, $0 = \text{no}$) within the 1-km street network buffer.

4.3. Data analysis plan

Zero-order correlations measure associations among alternative land use measures and between those measures and density and street connectivity. Then, partial correlations measure the same associations, but control for socio-demographic variables. Finally, generalized estimating equations test the utility of alternative measures of walkable land uses and distances to predict BMI, overweight (vs. healthy weight; $n = 4248$ in both categories), and obesity (vs. healthy weight, $n = 3299$ in both categories), separately for men and women. Generalized estimating equations were chosen to correct for the clustered nature of the data, with logit link functions used when outcomes are the binary variables of overweight and obesity.

5. Results

Table 1 shows descriptive statistics for all variables in the study. The table confirms that the entropy scores demonstrate variability across the land use categories used, ranging from 0.40 (3-category mix) to 0.75 (2-category mix).

Maps in Fig. 3 show the spatial distributions of average BMIs, computed from the 20 individuals sampled from each of 250 block groups. As was true in the larger study (Smith et al., 2008) higher BMIs tend to be on the western side of Salt Lake County, which has high population growth, especially in the southwest, and substantial minority presence, especially in the northwest. The spatial pattern shows that high BMIs for men are concentrated in the northwest while high BMIs for women are broadly distributed across the west.

5.1. Proxy walkabilty measures ("proportion who walk to work" and "housing age") and weight outcomes

Our earlier publication (Smith et al., 2008) tested models for men and women separately, and for three measures of weight:

Table 1
Descriptive statistics.

	Mean	SD
BMI	25.65	4.80
Overweight, proportion	0.40	0.49
Obese, proportion	0.23	0.42
Control variables		
Individual age	41.27	11.10
Proportion black, Block group (BG)	0.01	0.02
Proportion Hawaiian/Pacific Islander, BG	0.01	0.02
Proportion Asian, BG	0.02	0.03
Proportion Hispanic, BG	0.11	0.12
Median family income, BG	56.01	19.35
Median age of population, BG	30.05	5.27
Population density, block group	5541.28	2950.53
Intersection density, 1 km street network	49.29	11.99
Proxy land use mix scores		
Walk to work, proportion	0.02	0.04
Housing age, tract, in years	28.54	15.41
Entropy mix scores		
3-category mix	0.40	0.24
6-category mix	0.49	0.22
2-category mix	0.75	0.17
Six categories of land use in 1 km buffer		
Single family residences (km^2)	0.58	0.27
Multifamily residence (km^2)	0.10	0.10
Retail (km^2)	0.06	0.07
Office (km^2)	0.05	0.07
Education (km^2)	0.02	0.03
Entertainment (km^2)	0.00	0.02
Destination-based measures		
km to light rail stop	5.70	3.69
km to bus stop	0.57	0.55
Park in buffer, proportion	0.74	0.44

BMI and binary indices of overweight ($0 = \text{healthy weight}$; $1 = \text{overweight}$) and obesity ($0 = \text{healthy weight}$; $1 = \text{obese}$). In the original six analyses, the greater the proportion of workers walking to work and the older the neighborhood's housing, the lower the BMI and the lower the odds of overweight and obesity, across all six analyses (BMI, overweight, and obesity, separately for men and women). In the reanalysis, although conducted on a fraction of the original sample size (5000 of 453,927 original cases), 7 of the 12 effects were significant and 2 were marginally significant. Older neighborhood housing age relates to lower risk of weight problems in 5 of 6 analyses (and is marginally significant, $p = 0.06$ for overweight men in the sixth analysis). The proportion of residents walking to work is significant in 2 of 6 analyses and marginally significant in a third case (for women: odds for BMI and overweight are significant; for men: only the odds of obesity is marginally significant, $p = 0.09$).

5.2. Relationships among varied measures of mixed use

The walk to work and neighborhood housing age proxies are both significantly related to other indices of mixed use or proximal destinations (Table 2). Generally, walking to work is more strongly related to traditional entropy measures of mixed use than is housing age (see correlations in columns 3 and 4). Thus, we will consider walking to work as a measure of mixed use. Housing age is retained in subsequent analyses, along with density and street connectivity, as a broader measure of walkability.

The three entropy measures are also all highly intercorrelated (r's range from 0.70 to 0.85, columns 5, 6, and 7). Among the three measures of proximity to walkable destinations, entropy mixed

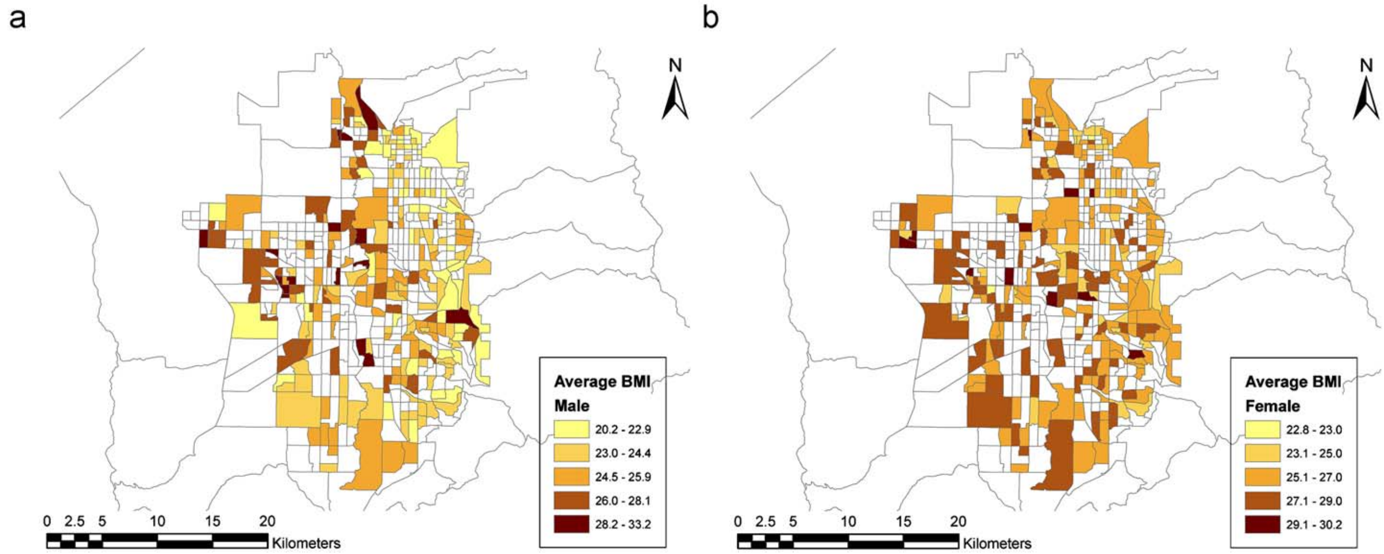

Fig. 3. Spatial distributions of average BMI: (a) male and (b) female.

Table 2
Correlations among density, pedestrian friendly street deign, and multiple diversity measures.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Population density, BG	1.00														
2	Intersection density, BG	0.42**	1.00													
3	Walk to work %, BG	0.17**	−0.08**	1.00												
4	Housing age, tract	0.29**	0.20**	0.37**	1.00											
5	3-category mix	−0.04**	−0.34**	0.46**	0.21**	1.00										
6	6-category mix	0.07**	−0.21**	0.42**	0.29**	0.85**	1.00									
7	2-category mix	0.00	−0.19**	0.26**	0.12**	0.72**	0.70**	1.00								
8	Single family homes (km^2)	0.20**	0.45**	−0.34**	0.11**	−0.60**	−0.58**	−0.50**	1.00							
9	Multifamily units (km^2)	0.29**	0.04**	0.36**	0.30**	0.39**	0.64**	0.28**	−0.33**	1.00						
10	Retail (km^2)	0.02	−0.19**	0.38**	0.21**	0.74**	0.60**	0.43**	−0.30**	0.36**	1.00					
11	Office (km^2)	0.11**	−0.14**	0.62**	0.31**	0.69**	0.55**	0.39**	−0.39**	0.40**	0.54**	1.00				
1-2	Education (km^2)	0.22**	0.18**	0.18**	0.22**	−0.05**	0.09**	0.08**	0.21**	0.04*	0.01	0.08**	1.00			
13	Entertainment (km^2)	−0.09**	−0.06**	−0.07**	−0.07**	0.10**	0.01	0.09**	0.00	−0.04**	−0.05**	−0.07**	−0.07**	1.00		
14	km to light rail stop	−0.08**	0.03*	−0.42**	−0.46**	−0.49**	−0.55**	−0.38**	0.30**	−0.49**	−0.41**	−0.44**	−0.02	0.04**	1.00	
15	km to bus stop	−0.31**	−0.22**	−0.25**	−0.40**	−0.25**	−0.35**	−0.22**	−0.11**	−0.25**	−0.33**	−0.25**	−0.20**	0.11**	0.28**	1.00
16	Park in buffer	0.14**	0.15**	0.13**	0.15**	0.06**	0.03*	0.14**	0.05**	0.06**	0.00	0.19**	0.15**	−0.02	−0.16**	−0.05**

BG = block group.

* $p<0.05$.
** $p<0.01$.

use measures correlate best with rail stop proximity. Thus, some proximity measures likely indicate the existence of broader patterns of mixed use as well.

Maps in Fig. 4 show the spatial variations of the three entropy measures, constructed from polygons indicating the 1 km street network buffers around individuals' addresses. Not surprisingly, Frank and colleagues' 3- and 6-category measures correspond well with each other. The 6-category entropy score shows greater spatial diffusion of high mixed use areas because any combination of the 6 categories will lead to the maximum entropy score if each category has the same land area. The 2-category measure, on the other hand, has a distinct spatial pattern where buffers with high scores are widely distributed. This measure collapses all possible non-residential walkable categories into one group, creating the highest average entropy scores among the three possibilities (see Table 1). In addition, the maximum differences between the three entropy measures in each buffer range from 0.01 to 0.99. These comparisons demonstrate that the correlations between the three entropy measures are high overall, but their average values differ.

5.3. Partial correlations between land uses and weight

An examination of partial correlations of weight outcomes with land uses in Table 3 shows that results are significant but modest, as might be expected for large and diverse samples with multiple determinants of weight. The results generally demonstrate stronger relationships for the proxy land use measures than for the traditional land use entropy measures. Moreover, the components of the 6-category land use entropy variable show significant and perhaps more informative relationships with weight than the 6-category entropy score itself. Both the 3-category and 6-category entropy variables show that men have lower BMIs and are less likely to be obese when land use is mixed. The land use category data show that men and women often have fewer weight problems when more office land use is present and that men have fewer weight problems when more multi-family residential land is present. The simplest 2-category entropy score is non-significant. Of the distance measures, greater distance between home and a light rail stop

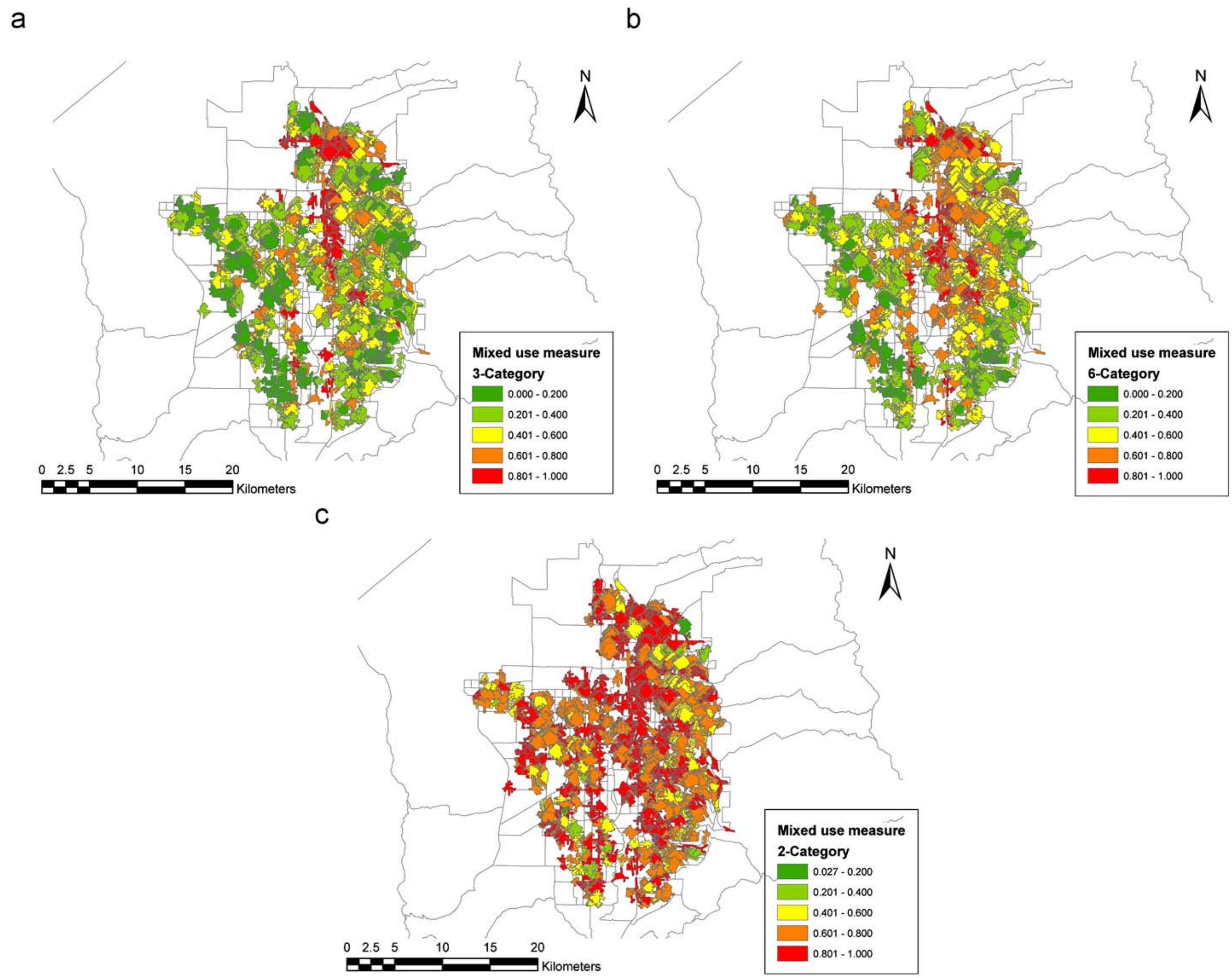

Fig. 4. Spatial distributions of the three entropy measures of mixed land use: (a) 3-category entropy measure, (b) 6-category entropy measure, and (c) 2-category entropy measure.

relates to greater BMI for men and women and greater risk of overweight for women and obesity for men and women.

5.4. *Model fit for alternative land use measures: proxies, entropy, categories, and destinations*

By examining multivariate tests of alternative measures, some consistencies in land use mix relationships with weight outcomes become clear. Compared to the analysis that contained proxy measures from Smith et al. (2008), some of the alternative mixed use measures provide a better model fit. The baseline analysis retained walkability features distinct from mixed use (i.e., housing age, density, and street connectivity) and the seven socio-demographic control variables, so that the effects of adding alternative measures of mixed use variables could be compared to baseline.

In Table 4, generalized estimating equations for different multivariate tests of land use are summarized. We use as goodness of fit the "quasi-likelihood under independence criterion" (QICC), which penalizes models with greater complexity, and where values decrease when fit improves. All models have fairly similar QICC values for the outcomes of overweight and obesity, with the maximum difference of 7. However, land use measure choices become significant when the outcome is BMI. Models that include the six land use categories used in Frank et al. (2006) provide superior model fit in predicting BMI. QICC scores associated with the six categories of land use are substantially lower than baseline for male BMI (132 points better) and female BMI (361 points better). These improvements in model fit are substantially better than the improvements in fit provided by models that include the 6-category entropy score for males (20 points better than baseline) and females (28 points better than baseline). Neither the 3- or 2-category scores or their respective entropy scores fare better than the 6-category or entropy models (with the exception that the 3-category entropy score provides better fit—by 22 points—than the 6-category entropy score for female BMI).

The models with the distances to rail and bus stops and the presence of park land provide similar model fit to the 6-categories model, with QICC scores within 7 points, except the 6-category model provides substantially better fit (by 106 points) for male BMI. Rail stop proximity was the best predictor among the distance measures of lower BMI. Consequently, the final line in Table 4 combines rail stop proximity with the 6 categories of land

Table 3
Partial correlations between walkability and weight outcomes.

	Male			Female		
	BMI	Over-weight	Obese	BMI	Over-weight	Obese
Density	−0.03	−0.02	−0.05*	−0.02	0.00	0.00
Street connectivity	0.04*	0.02	0.03	0.00	0.04	0.00
Walk to work %	−0.05*	−0.04*	−0.08**	−0.08**	−0.06**	−0.04
Housing age	−0.08**	−0.04*	−0.11**	−0.11**	−0.05*	−0.09**
3-category mix	−0.04*	−0.03	−0.06*	−0.04	−0.04	−0.02
6-category mix	−0.04*	−0.03	−0.07*	−0.03	−0.04	−0.02
2-category mix	−0.02	−0.02	−0.05	0.00	0.00	−0.01
Single family home area	0.02	0.01	0.04	0.01	0.04*	0.00
Multifamily unit area	−0.07**	−0.04*	−0.09**	−0.02	−0.02	−0.01
Retail area	−0.02	−0.02	−0.04	−0.05*	−0.04	−0.03
Office area	−0.05*	−0.07**	−0.08**	−0.07**	−0.05*	−0.04
Education area	−0.02	−0.05*	−0.04	0.03	0.00	0.03
Entertainment area	0.01	0.02	0.02	−0.03	0.00	−0.04
km to TRAX stop	0.05**	0.03	0.06*	0.11**	0.05*	0.10**
km to bus stop	0.01	0.03	0.01	0.02	0.01	0.00
km to park	−0.01	−0.03	−0.04	−0.03	0.01	−0.04

Controlling neighborhood income; proportions black, Hawaiian/Pacific Islander, Hispanic, Asian; median age of neighborhood residents; and individual age.

* $p<0.05$.
** $p<0.01$.

Table 4
Differences from baseline QICC goodness of fit indicator for: scores, land use categories, or distance/presence of walkable destinations.

Measure	BMI		Overweight		Obese	
	Male	Female	Male	Female	Male	Female
Replication QICC: Housing age, walk to work proxies, controls	51,055	51,610	2962	2307	1715	1489
Baseline QICC: Housing age, density, street connectivity and controls	51,071	51,719	2961	2309	1717	1488
Difference from baseline (higher scores indicate improved fit over baseline)						
3-Category entropy	14.91	49.02	−1.39	−0.85	2.70	−0.77
3 Categories	31.53	227.16	0.63	−0.86	−0.94	−3.56
6-Category entropy	20.31	27.74	−2.11	0.45	1.49	−2.33
6 Categories	131.90	360.73	0.81	−6.49	−1.81	−1.23
2-Category entropy	0.28	−1.73	−1.79	−1.89	0.46	−1.77
2 Categories	14.67	144.82	1.74	0.61	2.36	−1.66
Rail stop distance, bus stop distance, park present	25.48	364.92	−3.72	−3.07	−3.36	5.58
6 Categories and rail stop distance	130.52	635.53	−1.07	−7.06	−2.13	6.08

Note: All analyses control for individual age, median income in the neighborhood, neighborhood racial/ethnic composition, and median age of residents in the neighborhood. Smaller QICC goodness of fit measures indicates that models have better explanatory power while controlling for model complexity. 3 categories = residential, commercial, and office; 6 categories = single family residential, multifamily residential, retail, office, education, and entertainment; 2-categories = residential, nonresidential walkable.

use, to test whether combining the two different types of land use mix indicators improves model fit. The resulting model that adds rail stop proximity substantially improves model fit for female BMI (by 275 points), but does not improve model fit for male BMI.

Table 5 shows the detailed results of the final model that combines the best of the land use-based measures, namely the 6 land use categories, and the best of the destination-based measures, namely the distance to the closest light rail stop. Individual equations for males and females, and for BMI, overweight, and obesity, indicate that walkable land use categories are generally, but inconsistently related to lower BMI and risk of overweight or obesity. Specifically, among males, lower BMIs relate to more multi-family housing ($p = 0.03$), and lower risks of overweight relate to more office space ($p<0.01$) and more educational institution space ($p = 0.05$). Thus, the classification of housing land uses matter when predicting male BMI. Note that a significant coefficient for housing emerged only when housing was divided into single-family and multi-family residential, which explains the lower performance of simpler 2- and 3-category mix entropy indices and their respective components, which had a single category for all housing.

No land uses uniquely predict male obesity risk or female overweight risk when all other predictors are controlled. Among females, lower BMIs are associated with more office space ($p = 0.05$), more entertainment space ($p = 0.02$), and closer rail stops ($p = 0.00$). Among females, higher risks of obesity relate to more educational institution space ($p = 0.04$), less entertainment space ($p = 0.04$) and more distant rail stops ($p = 0.00$).

6. Summary

Researchers often choose mixed use measures for studies of weight and other health-related outcomes without knowing how alternative measures relate to weight in the same data set. This study uses county-wide data to provide comparisons and best combinations of alternative measures. We examined three entropy measures with varying degrees of detail in the

Table 5
Generalized estimating equations of BMI and best predictors from walkability indicators.

	Males			Females		
	B	SE	*p*	*B*	SE	*p*
BMI						
Population density	0.00	0.00	0.18	0.00	0.00	0.91
Intersection density	0.02	0.01	0.01	0.00	0.01	0.72
Tract housing age	−0.02	0.01	0.00	−0.03	0.01	0.00
Single family area	0.10	0.49	0.84	0.04	0.50	0.93
Multifamily area	−2.27	1.03	0.03	1.99	1.59	0.21
Retail area	0.30	1.31	0.82	−1.57	2.16	0.47
Office area	−1.33	1.48	0.37	−3.48	1.78	0.05
Education area	−2.14	3.07	0.48	7.18	6.08	0.24
Entertainment area	3.13	8.13	0.70	−7.24	3.12	0.02
Km to rail stop	0.01	0.03	0.85	0.12	0.04	0.00
QICC fit index	50940			51084		
Overweight (overweight = 1; healthy weight = 0)						
Population density	0.00	0.00	0.78	0.00	0.00	0.98
Intersection density	0.01	0.00	0.21	0.00	0.01	0.39
Tract housing age	0.00	0.00	0.19	−0.01	0.00	0.01
Single family area	−0.05	0.24	0.82	0.37	0.26	0.15
Multifamily area	−0.68	0.60	0.26	0.17	0.74	0.81
Retail area	0.33	0.70	0.64	−0.83	1.07	0.44
Office area	−2.35	0.82	0.00	−0.61	0.98	0.53
Education area	−3.38	1.69	0.05	−0.09	1.68	0.96
Entertainment area	3.03	3.74	0.42	−1.12	2.77	0.69
km to rail stop	0.00	0.02	0.58	0.01	0.02	0.39
QICC fit index	2960			2316		
Obese (obese = 1; healthy weight = 0)						
Population density	0.00	0.00	0.08	0.00	0.00	0.83
Intersection density	0.01	0.01	0.15	0.00	0.01	0.73
Tract housing age	−0.02	0.01	0.00	−0.02	0.01	0.00
Single family area	0.50	0.34	0.13	0.05	0.31	0.87
Multifamily area	−1.04	0.74	0.16	0.85	0.83	0.30
Retail area	−0.88	0.86	0.31	0.09	1.26	0.95
Office area	−1.06	1.05	0.31	−1.61	1.1	0.14
Education area	−2.29	2.26	0.31	4.16	2.02	0.04
Entertainment area	2.71	6.64	0.68	−12.1	5.97	0.04
km to rail stop	0.00	0.02	0.96	0.06	0.02	0.00
QICC fit index	1719			1481		

classification of land uses, three sets of the specific categories used in the computation of entropy scores, and three destination-based measures (bus stops, rail stops, and parks). Generalized estimating equations demonstrated that entropy measures with 3 and 6 land use categories, the 6 categories constituting the 6-category entropy measure, and the distance to the closest light rail stop had significant, if not consistent, associations with weight outcomes, especially BMI.

The superior performance of the BMI model with six categories over the entropy score suggests that it is the presence of walkable land uses, not the entropy score representation of land use mixture, that might improve walkability of a neighborhood. For example, one might walk to a neighborhood grocery store even if it does not comprise an equal one-sixth of the land along with five other equal amounts of different types of walkable land uses.

Not only were all approaches to measuring mixed land useful in predicting some outcomes, but the 6 land use categories and rail stop proximity were sufficiently unique that they did not cancel out each others' effects in the final combined model for this data set. We should note that retaining several land use categories in a model raises the possibility that the contribution of single categories may be obscured. For example, the highest correlation among the categories was between office and retail ($r = 0.54$), which means their individual coefficients may not show significance, although their combined presence may improve model fit.

Consistent with Smith et al. (2008), older housing was related to lower risks of overweight and obesity in 5 of 6 final models (and was marginally significant for the sixth model of male overweight), demonstrating a fairly robust effect in relation to weight outcomes. Older housing age likely indexes a broad array of neighborhood properties that support walking for pleasure, including aesthetic qualities such as tree cover and narrow streets, and walking to destinations, such as a fine-grained mix of attractive destinations (Handy, 1996a, 1996b) and merits replication efforts in other communities.

Results also demonstrated differences in the association between neighborhood walkability and the weight status of males and females. Although office space relates to lower weight outcomes (lower BMI for women, lower overweight risk for men), no other land use category predicts lower weight for both genders, net of other predictors. Residing in a block group with more educational institution space is not directly related to weight for either gender (Table 4), but in combination with other predictors, has positive relations to female obesity and negative to male overweight (Table 5). Among adults, proximity to schools has been associated with more transportation walking (McCormack et al., 2008) and direct routes to school associated with more general walking in other studies (Moudon et al., 2007), consistent with findings for males in this study. Among females, and consistent with prior research, proximity to entertainment spaces (Cohen et al., 2007; Giles-Corti et al., 2003) and especially light rail stops (Rundle et al., 2007) relates to lower BMI and obesity risk. Perhaps women walk more when nearby destinations generate other foot traffic throughout the day and evening; women feel more comfortable when socially safe others provide "eyes on the street" (Jacobs, 1961; Loukaitou-Sideris and Fink, 2009). Alternatively, perhaps women who prefer walking move to areas of town where walking can be a more useful means of transportation.

This evaluation yields several suggestions for future researchers. First, entropy measures should be chosen carefully, with an understanding of how similar entropy scores can represent very different walking environments. In addition to finding superior empirical results for the land use categories over the entropy scores, our earlier review highlighted several conceptual limitations in the ability of entropy scores to serve as ideal indicators of mixed use. The uncounted land, the interconnections between types of land, and the unused categories within a mix equation can all make a difference. Thus, researchers may want to consider examining carefully their components of entropy scores, scrutinizing unscored land, and complementing entropy scores with other mixed use and walkability measures, including population density, street connectivity, and housing age and distances to transit. In addition, future researchers are encouraged to provide more comprehensive comparisons using a wide range of mix measures, which have not been used in BMI-related outcomes but have been reviewed by other researchers who focus on walking and other outcomes (Brownson et al., 2009; Forsyth, 2007; Song and Rodriguez, 2004).

Second, the components of entropy scores have not been examined in past research that uses entropy measures, yet they often provided a superior model fit in our tests. Researchers may want to consider reporting the effects of the underlying components, even when they also use entropy scores. Third, directions and magnitudes of associations with BMI varied across the six land use categories. This implies that the simple dichotomy between residential and non-residential walkable uses implemented by a 2-category entropy score may be incapable of capturing the complexities of neighborhood land use relationships to residents' weight outcomes. The weaker performance of the 2-category entropy score in this study also supports this finding.

Fourth, destination-based measures may become unwieldy, so researchers may need to adapt methods (e.g., use GPS indicators of individual destinations) or use careful conceptualizations to select destinations most likely to draw pedestrians, such as light rail stops. Fifth, we found no clear statistically preferred measure of land use mix when the outcomes were overweight or obesity, perhaps due to the reduced sample size or a less sensitive categorical outcome measure of obesity or overweight compared to a continuous BMI outcome; researchers who test for effects only on obesity and/or overweight may want to examine BMI outcomes as well.

Several important issues not investigated in this study should also be noted. First, our destination-based measures only considered public transportation facilities and parks when a broader variety of destinations are likely to promote walking, especially transportation walking; similarly, food-related destinations may also affect BMI. Second, we chose to examine the 1-km street network buffer for compatibility with prior research, but other geographic scales might provide better, or at least different, predictors of weight outcomes. Third, we used land use data from one county and it is not clear how comparable land use codes are to those used in other geographic areas, although we used multiple raters to classify land as closely as possible to the categories used by Frank and colleagues. Although many municipalities classify land uses for tax purposes, future work is needed to determine whether there is an optimal way to classify land uses for health outcomes. A more optimal solution might depend on some combination of careful comparisons across tax codes, business listings, and even remote sensing. Finally, the role of resident selection into neighborhoods was not assessed in this study or in most cross-sectional studies that relate land use to health outcomes, but may affect BMI. Selection should be examined in future studies using longitudinal designs, statistical models that address selection (i.e., propensity score models or instrumental variable models), and through direct measurement and control of neighborhood preference self-reports.

For policy makers, by retaining the separate types of land uses that are often combined into entropy indices, the implications for land use recommendations may become clearer. For example, the presence of multi-family dwellings was associated with better weight outcomes in some analyses, but single-family detached housing was not. Given how controversial it can be to add multi-family housing to neighborhoods (Basolo and Hastings, 2003; Pendall, 1999), it is useful to know they have positive associations as well. The distance to light rail stops was another measure that may be of importance to policy makers and was the most powerful destination-based measure among women. Transit-oriented development often combines multiple factors, such as the encouragement of higher densities, less convenience for cars, and special consideration for pedestrians, that may provide for better walking conditions overall. Rail stop permanence and rail's ability to serve many riders may encourage business development in addition to supporting healthy walkability and weight. A recent cost benefit analysis estimated that rail stop users can accrue 8.3 min of walking per day walking to transit, which over time may prevent weight gain and prevent estimated expenditures of $5500 per person in additional health costs (Edwards, 2008). As countries consider ways to reduce reliance on oil and automotive travel, the positive correlates of living near transit may make the transition to rail-serviced neighborhoods more attractive.

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