Finding Food Deserts: Methodology and Measurement of Food Access in Portland, Oregon

Andrea Sparks
U.S. Department of Housing and Urban Development

Neil Bania
Department of Planning, Public Policy and Management
University of Oregon

Laura Leete
Department of Planning, Public Policy and Management
University of Oregon

Paper prepared for:

National Poverty Center/USDA Economic Research Service research conference
"Understanding the Economic Concepts and Characteristics of Food Access"
Washington DC
January 23rd, 2009

Finding Food Deserts:
Methodology and Measurement of Food Access in Portland, Oregon

Introduction

In recent years, a growing understanding of the linkages between diet and health has led to increased scrutiny of the accessibility of a wide-range of competitively priced healthful foods in urban environments. Studies in the U.S. first identified 'grocery store gaps', inner-city areas experiencing disinvestment in retail grocery stores leaving low-income inner-city areas underserved by traditional grocery store retailing. This was followed by a number of U.K. studies that further refined the questions and research methodologies for defining 'food deserts' – low income, urban areas with diminished walking distance access to grocery stores (e.g. Wrigley et al., 2002; Wrigley, Warm, and Margetts, 2003; Wrigley, 2002; Clarke, Eyre, and Guy, 2002; Whelan et al., 2002; Wrigley, Guy, and Lowe, 2002). Most recently, a number of studies have asked similar questions for Canadian cities (e.g. Smoyer-Tomic, et al. 2006, Appricio et al, 2007, and Larsen and Gilliland, 2008). A range of patterns have emerged, from findings of pronounced food deserts in some locales (e.g. London, Ontario) to findings of a relatively even distribution of grocery store access in others (Montreal, Quebec and Edmonton, Alberta).

To date, the same research methodology for examining food access has not been as widely applied to U.S. cities. Cotterill and Franklin (1995) documented a statistically significant and negative relationship between public assistance rates, lack of car ownership and square feet of supermarket retail space at the zip code level in 21 major urban areas. Morton and Blanchard (2007) produced U.S. wide county-based measures of access to supermarkets. Zenk et al. (2005) relate disparities in distance to supermarkets to poverty and demographic characteristics in

Detroit, Michigan. However, to our knowledge, to date no researchers have published a city-specific GIS based analysis of food deserts located within a U.S. metropolitan area. In this paper, we seek to fill that gap and conduct an analysis of food deserts and related demographic and methodological issues for the Portland, Oregon metropolitan area.

This study has three major components. First, we follow the methodology employed in recent papers on Canadian cities (Smoyer-Tomic et al., 2006, Apparicio et al., 2007, and Larsen and Gilliland, 2008) to investigate whether the Portland metropolitan area has low-income areas lacking access to supermarkets that one would consider to be 'food deserts'. Second, we investigate whether there is more generally a pattern of unequal supermarket access between higher and lower-income areas, or across areas with different demographic characteristics. Finally, we use the data from the Portland area to examine a number of questions regarding the sensitivity of food access measures to methodological variants. In particular, we are interested in determining whether more and less computationally intensive methodologies yield consistent results.

This latter point is particularly important vis-à-vis the ability of practitioners to compute and use accessibility measures for local planning. Less computationally intensive approaches to food and other access measures may be within reach of local planners and policymakers, while more computationally intensive measures may not be. In particular, we look at two methodological questions. First, we follow up on the investigation by Hewko et al. (2002) of aggregation errors in measuring accessibility to a number of urban park and recreation amenities. We also examine differences in measures that result from using either network distances or the more easily computed Euclidean distance. As Pothukucki and Kaufman (2000) have noted, planners have not systematically considered food provisions systems or food access questions.

Less computationally expensive approaches to measuring accessibility in urban areas could help remedy this situation.

Data and Methodology

Our study area consists of the 243 census tracts that are completely contained within Portland, Oregon's metropolitan area urban growth boundary (UGB), an area encompassing 1,037 km^2 (see Figure 1).[1] These tracts contain 722 census block groups and 18,203 census blocks.[2] Because the focus of this study is an assessment of low-income, urban residents' access to supermarkets, the UGB provides a natural study boundary. In 2000, the US Census reported the 243 tracts in the study area had 1,071,817 residents, 10.6 percent of whom lived below the federal poverty level. Three census tracts in the study area are considered extreme poverty tracts (over 40 percent below the federal poverty line); twenty-four tracts in the study area are high poverty tracts (20 to 39.9 percent below poverty; (Greene, 1991; Jargowsky and Bane, 1990)

Supermarket Data

Supermarkets were included in this study based on criteria consistent with the extant food desert literature: Stores had to sell a full range of products, including fresh fruit and vegetables, dairy and meat, and be part of a chain or be directly affiliated with a distribution system responsible for supplying multiple stores. Supermarket business characteristics and addresses were collected via ReferenceUSA, an online database of business information compiled from phone books, public records, and US Postal Service records ("ReferenceUSA: An infoUSA Company"). Searches within the database were conducted using the 2007 North American

---

[1] Oregon's Urban Growth Boundaries were created by Senate Bill 100, landmark legislation passed in 1973 creating a framework for land use planning across the state and requiring that each city or metropolitan area in the state have an urban growth boundary controlling development and separating urban land from rural. The boundary controls urban expansion onto farm and forest lands; land inside the urban growth boundary supports urban services such as roads, water and sewer systems, parks, schools and fire and police protection.

[2] Tracts that contain census blocks that lie outside the UGB were excluded to reduce aggregation error.

Industry Classification System (NAICS) code for supermarkets, 445110. The resulting database of stores was checked for completeness and accuracy by visiting each chain's corporate website. For some stores, the extent of products carried and ownership details were confirmed by telephone. The final list of 147 supermarkets belong to 18 supermarket chains.[3] Of these 147 stores, 145 were successfully geocoded to street files made available by Portland's metropolitan regional government and planning agency; see Figure 2.[4]

Food Access Measures

We employ four different food access measures in order to evaluate multiple aspects of low-income populations' access to supermarkets: proximity, variety, and competition. Three of these measures have been variously used by Clark et al. (2002), Smoyer-Tomic et al. (2006), Apparicio et al. (2007), and Larsen and Gilliland (2008), among others; the fourth is a slightly altered version of the third. All four measures are based on a concept of walking access in urban areas, taking 1 kilometer to be a reasonable walking distance for an adult in an urban setting. Measure 1 evaluates proximity by measuring the mean distance to the nearest supermarket. Measure 2 evaluates variety by measuring the number of supermarkets located within 1 kilometer. Measures 3a and 3b both measure competition by evaluating the mean distance to three supermarkets belonging to different chains *and* different parent companies (3a), or only to different chains (3b). Because in several cases a single supermarket parent company owns multiple chains within the study area, these two versions allow us to test whether common ownership affects the degree of competition evident. These measures are based on population-

[3] The supermarket chains included were: Albertson's, Cost Cutter, Food 4 Less, Fred Meyer, Grocery Outlet, Haggen Food, Lamb's, Market of Choice, New Seasons, QFC, Safeway, Save-A-Lot, Thriftway (Bale's, Lamb's and independent), Trader Joe's, Whole Foods, Wild Oats, WinCo, and Zupan's Markets.
[4] Geocoding was done using ArcGIS 9.2.

weighted block-level Euclidean distance inputs aggregated to create a tract level access measure. However, as mentioned above, we also test methodological variants of these measures that involve substituting shortest distance along the street network for Euclidean distance, as well as varying the aggregation level of inputs, alternately using block, block group or census tract based data.

Our four measures are calculated as follows:

Measure 1 -- Proximity: $$Z_1 \frac{\sum_{b \in i} w_b (\min | d_{bs} |)}{\sum_{b \in i} w_b},$$

Where: Z_1 = mean distance between census tract and nearest supermarket, d_{bs} = distance between block centroid and supermarket *s*, and w_b = total population of block *b* (entirely included in census tract *i*).

Measure 2 -- Variety: $$Z_2 \frac{\sum_{b \in i} w_b \sum_{j \in s} s_j}{\sum_{b \in i} w_b},$$

Where: Z_2 = mean number of supermarkets within 3280 feet of census tract population, *S* = all supermarkets, S_j = number of supermarkets within 3280 ft of the block centroid (d_{bs} < 3280), and w_b = total population of block *b* (entirely included in census tract *i*).

Measure 3a – Competition (different parent companies): $z_{3a} \frac{\sum_{b \in i} w_b \sum_s \frac{d_{bs}}{n}}{\sum_{b \in i} w_b}$,

Where: z_{3a} = mean distance between census tract population and n different chain-name supermarkets that also belong to different parent companies, d_{bs} = distance between block centroid and supermarket s; d_{bs} is sorted in ascending order, n= number of different chain-name supermarkets belonging to different parent companies to be included in measure (here n=3), and w_b = total population of block b (entirely included in census tract i).

Measure 3b – Competition (same parent companies ok): $z_{3b} \frac{\sum_{b \in i} w_b \sum_s \frac{d_{bs}}{n}}{\sum_{b \in i} w_b}$,

Where: z_{3b} = mean distance between census tract population and n different chain-name supermarkets, d_{bs} = distance between block centroid and supermarket s; d_{bs} is sorted in ascending order, n= number of different chain-name supermarkets to be included in measure (here n=3), and w_b = total population of block b (entirely included in census tract i).

Demographic Data

Data on neighborhood characteristics for the Portland metropolitan area is drawn from the Summary File 3 of the 2000 U.S. Census at the census block group and tract level. Neighborhood characteristics examined include the percent of the population living below the poverty line, neighborhood population density, median household income, the percent of the population that is elderly, African-American or Hispanic, and the percent of households that are owner-occupied and the percent of households without access to an automobile.

Defining Food Deserts

The British government's social and health policy literature of the 1990s "used the term 'food deserts' to describe areas of relative exclusion where people experience physical and economic barriers to accessing healthy food" (Reisig and Hobbiss, 2000, p. 138). As Reisig and Hobbiss (2000) contend, however, "the term [food desert] has remained conceptual rather than being an operational term by which geographical areas can be identified, and indeed is proving hard to define given that the ease with which people access food is a function of more than geography" (p. 138). Similarly, Shaw (2006) contends food deserts have physical, geographical components (lack of nearby access) and attitudinal components (for social or lifestyle reasons people do not purchase healthy food).

Empirical researchers have operationalized the concept of food deserts, however, as urban areas in which residents lack reasonable, spatial access to 1) fresh fruits and vegetables, 2) foods from all the major food groups required for a 'modest but adequate diet', and 3) food items priced competitively compared to the same item in a higher income neighborhood (Wrigley et al., 2002; Wrigley, Warm, and Margetts, 2003; Wrigley, 2002; Clarke, Eyre, and Guy, 2002; Whelan et al., 2002; Wrigley, Guy, and Lowe, 2002). Recent North American studies (Apparicio et al., 2007; Larsen and Gilliland, 2008; Zenk et al., 2005) have defined reasonable access as having a supermarket within walking distance, and all have used supermarkets that belong to chains as a proxy for fresh, affordable food. We follow their lead here and define a food desert as high poverty areas (census tracts with poverty rates at 20 percent or higher) that have low or very low access to supermarkets per the taxonomy below.

Implicit in the above discussion is the understanding that food access involves either walkable distances to grocery stores or access to appropriate transportation for food shopping.

Clark et al. note that “an area might only be classified as a ‘food desert’ if the residents of that area have little or no means of travelling significant distances in order to purchase food” (p. 2049, 2002). In defining food deserts, researchers have relied on the assumption that residents of high-poverty neighborhoods are less likely to have access to automobiles for food shopping, but with the exception of Larsen and Gilliland (2008), none have explicitly modeled the relationship between transportation access and food access. While we do not have the data here to make major inroads on this front, we do take a closer than other researchers look at the relationship between neighborhood poverty, neighborhood car access and food access.

Testing Sensitivity

We test the sensitivity of our results to a number of methodological variants, including the use of network distance and varying the level of aggregation of inputs and outputs. In particular, we are interested in comparing results for methods that are more or less computationally intensive. These variants are listed in Table 1: Variant 1 is our base case discussed above in which we aggregate the (population-weighted) Euclidean distance from block centroids to each supermarket to create tract level access measures. Variants 2 and 3 apply the same methodology, but distances are initially computed at the block group and census tract level respectively. Variant 4 replicates Variant 1, however in this case the initial block level data is only aggregated to the block group level (for the purposes of analyzing area demographics at this level). Finally, Variant 5 replicates Variant 3 (a census tract level measure). However, in this case the Euclidean distance calculations are replaced by the shortest street network distance (using the Network Analyst extension of ArcGIS 9.2).

In the following sections we present the results of our investigation, first looking at whether or not there are neighborhoods in the Portland, Oregon area that match the established criteria for food desert. We then investigate inequality in food access across the metropolitan area, looking at the relationship between food access and demographic characteristics more generally. Finally, we explore the implications of numerous methodological variants.

Finding Food Deserts

As discussed above, we compute four alternate measures of food access for the Portland area. In this analysis, we look at Variant 1 of the four food access measures, in which Euclidean distances to supermarket locations are measured at the census block level (the most disaggregated level possible) and then aggregated with population weights to the census tract level for the purpose of comparing with tract level poverty statistics. Numerous researchers argue that this method results in the least amount of aggregation error and thus is a more reliable measure of obtaining distance measurements from aggregated units to particular facilities (Hewko, et al. 2002, Current and Schilling, 1987, Hillsman and Rhoda, 1978, Hodgson et al., 1997). The descriptive statistics for the four measures are shown in Table 2. The average distance from a census block to a supermarket is just a little over 1 kilometer (3,471 feet); the average number of supermarkets within a kilometer is 0.52. The two measures of competition (that do or do not allow for supermarkets to belong to the same parent companies) yield similar results, that the average distance to the nearest three supermarkets is a little over 1.5 kilometers, or between 5,300 and 5,400 feet.

Do these access measures exhibit spatial autocorrelation? In Table 2, we also show Moran's I for all four measures; the index indicates that each of these measures exhibits a moderate (and statistically significant) departure from randomness (scores ranging from .32 to .67 and z-scores from 7.4 to 15.1). This clustering is apparent in Figures 3a through 3d, showing the spatial distribution of each of the four measures. We adopt the standards set by Apparicio et al. (2007) for distances that constitute Very Low, Low, High and Very High Access.[5] Following these metrics, Figures 3a through 3d show that areas of Very High and High access are more likely to be located in more central portions of the metro area, while Low and Very Low Access areas tend to be more dispersed. It is worth noting that comparing the mean values for all four measures to these metrics, Low to Very Low Access is the norm for the population overall. In particular, very few tracts meet the Low Access standard for Measure 2 of even having one supermarket within a kilometer.

One question is whether these different measures in fact capture different aspects of food access. In Table 3 we show both Pearson and Spearman correlation coefficients between all four measures. The Pearson correlations indicate that all four measures are highly correlated with one another (with coefficients with absolute values in the .67 to .99 range), although Measure 2 somewhat less so. The two versions of Measure 3 are particularly correlated with one another (with a Pearson correlation coefficient of .99); whether or not one accounts for competition within or between parent companies seems to have little effect on the competitive environment in terms of access to three different stores. The Spearman rank correlations (ranging from .81 to .99) also indicate that the ranking of census tracts by their degree of access varies little according to which measure is chosen. We conclude that all four measures tell a consistent story about food access in the area and that, in particular, the two versions of Measure 3 are likely redundant.

---

[5] For Measure 1, tracts whose nearest supermarket was not within walking distance were assigned the Very Low level of access; tracts whose nearest supermarket was located at varying distances within the maximum reasonable walking distance were assigned Low to Very High levels of access. For Measure 2, tracts with an average of fewer than one supermarket within walking distance were assigned the Very Low level of access; tracts with one or more supermarkets within walking distance were assigned Low to Very High levels of access. For Measures 3a and 3b, tracts whose average distance from three different chain-name supermarkets exceeded double the reasonable walking distance were assigned the Very Low level of access; tracts whose three different chain-name stores were closer were assigned Low to Very High levels of access.

In order to identify potential food deserts, we must also consider poverty levels by neighborhood. Compared with many U.S. metropolitan areas, the Portland area has relatively low levels of and less concentrated poverty. The overall poverty rate for the area in the 2000 Census was 10.6 percent; slightly below the national average for that year.[6] Only three of 243 census tracts meet the typical standard for extreme poverty tracts (over 40 percent poverty; Jargowsky and Bane, 1990), and only twenty-four tracts in the study area are high poverty areas (20 to 39.9 percent below poverty). The distribution of poverty over the urban area is shown in Figure 4. As in many metropolitan areas, the extreme and high poverty tracts are somewhat (although not exclusively) concentrated in central city areas; in Portland, the north portion of the city has particularly concentrated poverty levels. Tracts with high poverty levels are also found in northeast and southeast Portland, east Portland/Gresham, and to the far west in Hillsboro. The relative dispersal of poverty in Portland points to another fact, however – that Portland's poor live throughout the metropolitan area in both high and low-income tracts. The implications of this dispersal will be considered below when we take up more general issues of equity of food access across the metropolitan area.

The Pearson correlations shown in Table 4 indicate a positive relationship between poverty rates and food access. In fact, the three extreme poverty tracts in the study area were found to have Very High or High levels of supermarket access by Measures 1, 3A and 3B (and above average access according to Measure 2). This positive overall relationship between poverty and food access is consistent with findings by others for both Montreal and Edmonton (Apparicio et al., 2007, Smoyer-Tomic et al., 2006) but differs from Larsen and Gilliland's (2008) finding for London, Ontario or the pattern evident in Detroit, Michigan (Zenk et al.,

[6] In 2000, the overall U.S. poverty rate of 11.3 percent was a 25-year low.

2005). In Portland, the higher population density in the very lowest income neighborhoods often corresponds to closer proximity to retail services.

Despite this overall pattern, however, 14 of Portland's 24 high poverty tracts had Low or Very Low levels of supermarket access by Measure 1 (and most had Low and Very Low access by all other measures as well). These tracts represent potential food deserts (see Figure 5). An alternative way to visualize the food desert phenomenon is to create a walking distance buffer (1 kilometer or 3280 feet) around each supermarket; Figure 6 shows high poverty tracts that are not within walking distance of any supermarket. A corridor in north Portland is particularly evident, as are the other scattered sites that correspond to our potential food deserts. Among these potential food deserts, all of which have neighborhood poverty rates of 20 percent or higher, the mean (population-weighted) distance to the nearest supermarket is 3,521 feet, the average number of markets within a kilometer is 0.25 and the mean distance to three different stores (regardless of parent companies, Measure 3B) is 5,448 feet; 4.4 percent of the area's population lived in these potential food deserts and 11.3 percent of the population in poverty.

Access across the Urban Area

Beyond identifying potential food deserts, we are also interested in investigating patterns of supermarket access across the urban area more generally, particularly with regard to access by households with different socio-economic and demographic characteristics. Thus, in addition to considering the relationship between food access and poverty, we also look at food access and access to an automobile, racial or ethnic minority status, and the elderly population. The elderly should be of particular interest, as they are more likely than the general population to have or develop mobility issues that impact their access to food shopping. For this analysis we employ three of the four food access measures discussed above (Measure 3a is dropped due to its similarity with Measure 3b) aggregated to the block group level (Variant 4 in Table 1). These food access measures are matched with block group level neighborhood characteristics from the 2000 Census.

In Table 5, we show average (population weighted) block group level characteristics including population density, median household income, poverty rate, percent of housing units that are owner-occupied, percent elderly, African-American, Hispanic and percent of households without access to an automobile. We also show spatial autocorrelation statistics for each characteristic (Moran's I and associated z-score). Moran's I indicates significant spatial clustering of characteristics, with z-scores ranging from 9.5 to 93.6 (all significant at the .0001 level or higher). While all characteristics exhibit spatial autocorrelation, the most clustered characteristic is percent African-American, followed by households lacking access to an automobile; the least clustered characteristic is percent elderly. Despite the high degree of clustering of characteristics, Pearson correlation coefficients suggest only a few systematic relationships between these characteristics and food access measures (Table 6). Among those correlations that are statistically significant, none are particularly large (with the highest absolute value correlation coefficients in the 0.40 range). As one might expect, the strongest relationship is between population density and food access, with higher density being associated with improved food access across the board. As discussed above, the neighborhood poverty rate is positively correlated with food access at the census tract level. Correspondingly, the percent of owner-occupied housing is negatively related to food access and areas with higher concentrations of households without automobiles do systematically have better grocery store access. Accordingly, poverty has a strong positive correlation with lack of automobile access (correlation coefficient of 0.69) and negative correlation with owner-occupied housing (correlation coefficient of -0.62). The remaining associations between demographics and food access are generally close to zero: median household income is not correlated with food access, nor is the percent elderly, and while the Portland area has relatively small racial minority populations, neither the percent Hispanic or the percent African-American is particularly correlated with food access. The latter fact is in stark contrast with Zenk et al.'s (2005) findings for Detroit, Michigan.

The distribution of food access according to underlying characteristics can also be illustrated by calculating the mean food access for specific demographic subgroups. Block level access measures are aggregated to the block group level using the population weights for a particular population (e.g. poor, Hispanic, etc.). Table 7 shows these measures, sorted according to food access Measure 1. On average, persons in households without car access exhibit the very best food access (2,743 feet to the nearest supermarket), while the poor, African-American, elderly and Hispanic populations have just slightly better access than the population as a whole. Only those in owner-occupied housing have worse access than the overall population. While the magnitude of most differences between groups is small, a few are worth noting: households without car access have an average of 0.88 supermarkets within a kilometer of their residence; the next best access is among the poor population (0.60 supermarkets) and the figures for Hispanic and owner-occupied households are nearly half the highest figure (0.48 and 0.46, respectively).

The definition of food deserts includes the requirement that an area have a concentration of low-income (or otherwise socio-economically disadvantaged) persons. In Table 8, we examine the food access and other characteristics of block groups according to whether they are low, average and high poverty block groups (less than 10 percent, 10 to 20 percent and over 20 percent poor, respectively). Only high poverty block groups would typically be considered in a definition of food deserts. While the correlations between poverty and food access that we noted above are apparent here (higher poverty being associated with better access), we see that the differences in access between more and less poor neighborhoods lies in the gap between low poverty neighborhoods and all others. Mean food access measures are quite similar for high and average poverty tracts, but are distinctly worse among the low poverty tracts in which nearly 60 percent of the area population resides. This raises the question of food access for the poor, elderly and carless who live outside of concentrated poverty areas and suggests another dimension to the food desert problem: more than one-quarter (28.5 percent) of the Portland area poor population live in these low-poverty block groups where mean food access is low; similarly 31.4 percent of the population in households without an automobile live in such areas, as do 60 percent of the elderly. If the poor, elderly or those lacking automobiles are vulnerable to food access barriers but are spatially dispersed in higher income areas, typical food desert definitions will fail to identify these access problems.

This suggests that there are potentially food access problems that lie outside the scope of food deserts as commonly defined by researchers. In Table 9 we illustrate the magnitude of this problem. For each of three food access measures (M1, M2 and M3B), we show the percent of the population, of the poor population and of the population without car access who live in Low or Very Low food access census block groups that would *not* be identified as food deserts because they are not high poverty block groups. We contrast this with the share of each population living in block groups with Low or Very Low food access that *would be* classified as living in food deserts due to high poverty rates. While between 4.2 and 9.5 percent of the poor population would be identified as living in food deserts (depending on the food access measure employed), another 62.4 to 88.1 percent of the poor population live in Low to Very Low food access areas that would *not* be identified as food deserts. Similarly, while between 12.5 and 25.4 percent of those living without car access are identified as living in food deserts, another 35.5 to 65.5 percent of those without cars have Low or Very Low food access but would *not* be classified as living in food deserts. Thus, as applied in the Portland metropolitan area, the food desert concept captures only a small share of what might be a larger overall food access problem.

Methodological Variants

In this section we investigate the implications of a number of methodological variants in creating food access measures. As noted above, practitioners who want to gauge their community's access to supermarkets may not have the time or technical resources to use thousands of pieces of block-level data as inputs. In the Portland, for example, the 243 census tracts in the study area are comprised of 722 census block groups and 18,203 census blocks. Working with the smaller number of units associated with census tracts will be more accessible to practitioners than managing the larger datasets associated with using census block level data. However, the calculation of distances for aggregated units potentially carries with it difficulties arising from the ecological fallacy (Robinson, 1950). Aggregation error results when the locations of spatially distributed individuals are represented as a single geographic point such as a census tract centroid (Hodgson et al., 1997). Numerous scholars have expressed concern about the impact of aggregation error on the interpretation of spatially based access measures (Hewko, et al. 2002, Current and Schilling, 1987; Hodgson et al. 1997) and have integrated finer resolution data in an attempt to reduce such aggregation error (Hewko, et al., 2002, Current and Schilling, 1987).

With this in mind, we compare variations of our four food access measures by altering the geography and level of aggregation required to produce the measures. Three variations were tested with inputs ranging from the census block to the census tract level. In addition, we examine differences in measurement that arise from using Euclidean distances in place of shortest street network distance (Network Analyst distance in ArcGIS). This last question is particularly important for two reasons: The calculation of street network distances requires mores specialized computer software than does the calculation of Euclidean distances, and Network Analyst computations are particularly demanding of computing resources, especially when computed at detailed levels of geography. The task of computing such distances cannot always be accomplished on an average desktop computer in a reasonable time frame.

Levels of Aggregation

First we will consider the case of three different aggregation levels of inputs to distance measurements. In the case of the first variant, distances between residential areas and supermarket locations are computed at the most disaggregated level – from the geographic center of the census block to the supermarket location – and then aggregated with population weights to the census tract level. In the second and third variants, the underlying distance from neighborhood to supermarket is variously calculated from either the geographic centroid of the census block group and from geographic centroid of the census tract. In the case of block group measurements, these distances are again aggregated to the census tract level using population weights.

Descriptive statistics for these three methodological variants for all four measures of food access display some interesting patterns (Table 10). In all cases measured distances increase slightly when calculations are made with *less* detailed as compared with *more* detailed geography. By the second access measure, when distances are calculated from census block centroids (and population weighted to the tract level) the mean number of supermarkets within 1 kilometer is 0.41. When distances are calculated from the census tract centroid, this number rises to .52, a 27 percent increase in measured access. The pattern is the same but less pronounced when considering the other measures. Distances to the closest supermarket or closest three supermarkets rise between 2 and 5 percent when measured from census tract centroids instead of census block centroids. Similarly, less geographic detail is also associated with higher variability of access measurement. For each access measure, the standard deviation rises 10 to 20 percent as one moves from census block based measures to the census tract based measures.

While the level of geographic detail in the underlying data inputs to food access measures appears to introduce some systematic bias in measurement, we are interested in whether or not these three different methodological variants would result in a substantively different assessment of the pattern of food access across the urban area. Relative measures of access are often of more interest than absolute ones (Dalvi and Martin, 1976). To this end, we examine the Spearman's rank correlations and measures of spatial autocorrelation across the different variants of each measure. The rank correlations across different variants are quite high for all three distance measures – in the 0.96 to 0.98 range for both Measures 3A and 3B and almost as high for Measure 1 (between 0.91 and 0.95) (Table 11). In the case of these three measures, the more aggregate methodological variant is likely to yield about the same geographic pattern as the more time-consuming disaggregated variants. Our conclusion might be somewhat different for Measure 2, however. In this case, the rank correlation between the measure with the most disaggregation (distance measured from the block centroid to the supermarket) and that with the least (distance measured from the tract centroid to the supermarket) is 0.72; when the block group-based measure is compared with the tract level measure, the rank correlation drops to 0.70. Thus, we are less confident that all levels of geographic disaggregation would generate the same pattern when this measure is considered.

An examination of Moran's index of global spatial autocorrelation (I) tells a similar story about the extent to which the three methodological variants do or do not indicate the same geospatial patterns of access. Each panel of Table 12 shows Moran's I (and the associated z-score) for one of the four food access measures along with each methodological variant. Regardless of measure and approach, Moran's I and the associated z-scores indicate a spatial clustering of food access that is both statistically significant and substantively meaningful. In the case of Measures 1, 3A and 3B, the degree of this clustering declines somewhat as one shifts from block level inputs to census tract level inputs (from more to less disaggregation), but the changes in both I and z are relatively slight. Only in the case of Measure 2, does change in the level of aggregation of inputs generate a substantively different level of spatial clustering. When Measure 2 (number of stores within one kilometer) is measured at the block level (and aggregated to the census tract level), the z-score for Moran's I is 15.14. The input distance is calculated at the block group level instead, the z-score drops nearly in half to 8.89.

Taken together with our analysis of access measure means and rank correlations, we conclude that only Measure 2 is sensitive to the level of aggregation of distance measures as inputs. While Measures 1, 3A and 3B are all continuous measures of distance; Measure 2 is a discrete measure of the number of supermarkets within a one kilometer radius. This radius was set to match the usual standard of walkability in the urban environment, however, few neighborhoods in Portland meet this standard and this measure has little variation (with a median value of 0).[7] As such, the changes in distance measurements that occur when one alters the input methodology appear to generate considerable changes in this discrete measure.

Our findings with regard to aggregation error are in some regards similar to those of Hewko et al. (2002). Hewko et al. (2002) examine the impact of aggregation error on distance (access) measures from neighborhoods to three types of recreation facilities in Edmonton, Alberta – neighborhood playgrounds, community halls and leisure centers. As we do, they find that the variability of measured distance falls as one shifts from less to more aggregated inputs. On the other hand, they find that for the first two types of facilities that measured distances *decrease* when one moves from less aggregate input data to more aggregate input data; we find small changes in distances in the other direction. However, when the facility considered was leisure centers, measured distances increased slightly as the level of aggregation increased, similar to what we find for supermarkets. Similarly, they found that the rank correlations of their distance measures were quite stable for the more dispersed facilities (leisure centers) and less so for neighborhood facilities (playgrounds), and that the level of aggregation only changed the pattern of spatial clustering for playgrounds.

Hewko et al. (2002) suggest that the difference in their results for the three types of facilities most likely lies in the different spatial resolution of each type of facility in Edmonton (301 playgrounds, 132 community halls, and 19 leisure centers) and the different average distance to them from the neighborhoods. The short distances to neighborhood playgrounds are

[7] Apparicio et al. (2007) appear to find a much larger proportion of neighborhoods in Montreal that have a supermarket within one kilometer.

more sensitive to the scale of change in measurement than the longer distances computed to the more dispersed facilities. While the Edmonton urban area is smaller in scale than Portland (population of 648,000 and land area of 633 km^2), the spatial density of Portland supermarkets (0.14 per km^2) lies between that of their community halls (0.21 per km^2) and their leisure centers (0.03 per km^2).[8] Thus, while our distances Measures 1, 3A and 3B appear to be relatively stable in the face of methodological variation, it may be that this is a result of the overall level of spatial dispersion of supermarkets in the city (as with Hewko et al.'s community halls and leisure centers) and not necessarily reflective of ironclad stability in the face of methodological variation for *any* access measure. As Hewko et al. (2002) show, distance measures to closer facilities may be inherently more sensitive to such changes.

Street Network Distances

Our final methodological variant is to consider the impact of computing distances with the shortest street network distance (using Network Analyst) in place of the Euclidean distances used to this point. To evaluate the difference in these measures we recompute our third methodological variant (in which distances are computed from census tract centroids to supermarkets) using street network distances.

The descriptive statistics, rank correlations and spatial autocorrelation statistics for this final variant are shown in Tables 13, 14 and 15 along with its counterpart based on Euclidean distances. As expected, street network distance increases the mean distance for each measure from 35 to 38 percent. In the case of Measure 2 (number of stores within a kilometer) this translates into a (39 percent) lower access measure, as measured distances to stores are longer.

[8] In contrast, the density of playgrounds in Edmonton is 0.48 per km^2.

Despite the overall difference in absolute measurement, however, the rank correlations between measures computed with street network distances and Euclidean distances are still quite high, ranging from 0.89 to 0.93 for Measures 1, 3A and 3B (Table 14). As previously, Measure 2 is somewhat more sensitive to the change in methods with a rank correlation of only 0.81 between the two versions. Finally, comparing the spatial autocorrelation indices for each measure, we see that the use of street network distance raises both I and the associated z-score for each measure, but the changes are relatively minor in all cases.

As an additional benchmark for the relationship between the measures calculated with street network distance and those calculated with Euclidean distance, we estimate OLS regressions explaining food access measures calculated with network distances with those calculated with Euclidean distances. Because street patterns vary considerably from grid patterns in densely developed older parts of the central city to more diffuse suburban road patterns in outlying areas, we suspect that the relationship between the two types of distances may vary between urban and suburban areas. Thus, we include population density of the census tract as a crude proxy for degree of urbanness of the area as well, entering it both by itself and interactively with the Euclidean-distance based access measure. The resulting coefficients are shown in Table 16; in all cases, we see that population density does influence the linear relationship between the two types of measures. In the case of Measures 1, 3A, and 3B, street network distance measures exceed Euclidean distance measures by both a constant term and a multiplicative factor of about 25 percent. However, both factors are moderated by population density. As we might expect, the higher the population density, the smaller the gap between the two types of measures. The same basic result holds for food access Measure 2, however, in this case the constant term (and its interaction with population density) is not statistically significant.

When Measure 2 is calculated with street network distances its value is about half of the value calculated with Euclidean distances, but this share rises with population density as well.

Since street network distance undoubtedly provides a more accurate measure of the actual distance that must be travelled to supermarkets, when one is concerned with identifying absolute levels of access, such as with the identification of food deserts in which residents do not have a supermarket within a certain walkable distance, researchers using Euclidean distance should account for this discrepancy, also noting that the nature of the discrepancy depends on the degree of urbanness of the area. When the concern is evaluating spatial equality and relative levels of access across areas, however, then relative patterns of access are primary. Both the rank correlations and the spatial autocorrelation statistics shown here suggest that the relative ranking of census tracts by access measures is quite stable regardless of exact measurement methods used.

Discussion and Conclusions

To date, there are few published ‘food desert’ studies of U.S. cities against which to benchmark our results. As in the Canadian cities of Edmonton (Smoyer-Tomic, et al., 2006) and Montreal (Apparicio, et al., 2007), poverty and food access in Portland are positively correlated across the urban area as a whole. This contrasts with findings for London, Ontario (Larsen and Gilliland, 2008) and Detroit, Michigan (Zenk et al., 2005), where the relationship between socio-economic disadvantage and food access are reversed, and with findings by Cotterill and Franklin (1995) across a larger number of major U.S. metropolitan areas showing that grocery retail space declines in disadvantaged postal zip codes. It is likely that this range of outcomes across North American cities is a result of distinctly different socio-economic and spatial histories in different regions and among different city sizes and types. Because of Portland's history of relatively recent and steady population growth, Oregon state land-use planning laws that promote continued urban development and infill, and an economic history that has resulted in less concentrated residential poverty, Portland may be likely to exhibit fewer food access problems than many other urban areas. It is possible that other U.S. cities that have developed under similar conditions, particularly in the West, exhibit similar spatial patterns.

Nevertheless, there are still a number of reasons for concern about food access in Portland. First, potential food deserts are not non-existent in Portland. Fourteen of 24 high poverty census tracts in the urban area have Low to Very Low food access; these areas are home to 11 percent of the metropolitan area's poor population. This compares with Apparicio et al.'s (2007) identification of 82 census tracts as food deserts that are home to 17 percent of the Montreal area's low income population.[9] While Portland has fewer apparent 'food deserts', the central city concentration of supermarkets is much lower in Portland than in Montreal and mean supermarket access in Portland's food deserts is considerably lower than in Montreal's (0.25 supermarkets within 1000 meters versus 0.89 in Montreal).

A second reason for concern about food access in Portland has to do with areas that are *not* food deserts. When we consider the share of the poor population or the share of the population without access to an automobile who live in Low or Very Low food access areas, we find that a significant share live in low or average poverty block groups that, as such, do not meet the definition of 'food desert'. By either of our distance measures of food access (distance to nearest supermarket or distance to nearest three supermarkets) 62 percent of the poor live in such areas, as do 35 percent of those without automobile access. We suspect that in cities with socio-

[9] Noting that the Canadian 'low-income' standard is somewhat more generous than the U.S. poverty level.

economic and retail spatial distributions similar to Portland's, that this dispersed lack of access may be widespread and may pose a more significant socio-economic problem than true 'food deserts'.

The methodology used here implies a number of limitations, of course. First, distances measured are only a proxy for time spent traveling to and from grocery stores. We do not incorporate any information about different modes of travel or access to public transit (see Larsen and Gilliland, 2008). Furthermore, the measurement of distances from residences to supermarkets ignores the possibility that individuals food shop as part of other daily or weekly trips or activities (e.g. to and from work or child care locations). Thus, actual access to food shopping has numerous dimensions not captured here.

In this paper we also examine a number of methodological questions regarding measuring food access in urban areas. In particular, we find that the four food access measures used here -- representing proximity, variety and different degrees of supermarket competition -- all produce the same or similar conclusions about relative spatial patterns of food access in the urban area. The rank correlations between these measures across census tracts are quite high and the resulting patterns of spatial autocorrelation are all similar.

In addition, we consider a number of methodological variants to our four basic measures. We check for the effects of aggregation error by altering the level of geographic detail in the input to each of the four measures of food access. We also experiment with two alternate methods of computing distances. When the level of geographic detail is altered, we find that the magnitudes of and spatial patterns exhibited by our three distance-to-store measures (Measures 1, 3A, and 3B) are relatively impervious to change. Regardless of the level of geographic disaggregation, each of these measures generates approximately the same information about food access in the urban area. Only Measure 2 – number of stores within a 1 kilometer radius – is less robust to changes in the level of aggregation. We suspect that this is because this is a discrete measure, which in its current form exhibits less variation than the other measures used here.

When we substitute shortest street network distances for Euclidean distance calculations, we reach similar conclusions. Euclidean distances are noticeably shorter than actual street network distances and the relationship between the two measures varies according to the population density of the area, presumably due to differences between more and less urban street patterns. Nevertheless, both measures yield the same patterns of food access when one considers measures of distances to nearest stores (our Measures 1, 3A, and 3B). As with varying the level of aggregation, however, we find again that the measured number of stores within one kilometer is somewhat less stable in the face of methodological variation.

As the awareness of the link between urban form, diet and public health outcomes grows, practitioners and policy makers will want to develop a better understanding of food access in their communities. While GIS-based information technology is becoming more affordable and accessible, the computation of street network distances and the use of thousands of pieces of geographically detailed data can still be prohibitively expensive, either in terms of hardware or software purchasing costs, or in terms of staff time or expertise. We conclude that for the purposes of considering food access across urban areas as measured by distances to nearest stores, that the use of Euclidean distances and the use of relatively more aggregated census tract level inputs is likely to yield the same substantive conclusions as more resource-intensive methodologies.

References

Apparicio, P., Cloutier, M., and Shearmur, R. (2007). The case of Montreal's missing food deserts: Evaluation of accessibility to food supermarkets. *International Journal of Health Geographics*, 6(1), 4. doi: 10.1186/1476-072X-6-4.

Clarke, G., Eyre, H., and Guy, C. (2002). Deriving indicators of access to food retail provision in British cities: Studies of Cardiff, Leeds and Bradford. *Urban Studies*, 39(11), 2041.

Cotterill, R. W., and Franklin, A. W. (1995). The urban grocery store gap. *University of Connecticut: Food Marketing Policy Center*, 28, 82.

Current J R, and Schilling D A (1987), "Elimination of source A and B errors in p-median location problems" *Geographical Analysis,* vol. 19, pages 95-110.

Dalvi, MQ and Martin K M (1976), "The measurement of accessibility: some preliminary results" *Transportation*, vol. 5, pp. 17-42.

Greene, R. (1991). Poverty concentration measures and the urban underclass. *Economic Geography*, 67(3), 240-252.

Hewko, J., Smoyer-Tomic, K. and M. J. Hodgson, (2002) "Measuring neighbourhood spatial accessibility to urban amenities: does aggregation error matter?" *Environment and Planning A*, 2002, volume 34, pages 1185-1206.

Hillsman, E L, and Rhoda R (1978) "Errors in measuring distances from populations to service centres", *Annals of Regional Science*, vol. 12, pp. 74-88.

Hodgson M J, F. Shmulevitz, and M. Korkel M (1997) "Aggregation error effects on the discrete-space p-median model: the case of Edmonton, Canada", *The Canadian Geographer*, vol. 41, pp. 415-428.

Jargowsky, P. A., and Bane, M. J. (1990). Ghetto poverty: Basic questions. In L. E. Lynn and G. H. McGeary (Eds.), *Inner-city poverty in the United States*. Washington, D.C.: National Academy Press.

Larsen, K., and Gilliland, J. (2008). Mapping the evolution of 'food deserts' in a Canadian city: Supermarket accessibility in London, Ontario, 1961-2005. *International Journal of Health Geographics*, 7(1), 16. doi: 10.1186/1476-072X-7-16.

Morton, L. and T. Blanchard, "Starved for Access: Life in Rural America's Food Deserts", *Rural Realities*, Vol 1., No. 4, 2007.

Pothukuchi, K. and J. L. Kaufman, "LONGER VIEW The Food System: A Stranger to the Planning Field", *Journal of the American Planning Association*, Vol. 66, Part 2, pages 113-124, 2000.

ReferenceUSA: An infoUSA Company.*ReferenceUSA: Our Quality*. Retrieved May 4, 2008, from http://www.referenceusa.com/au/ourquality.asp?si=8146440052900.

Reisig, V., and Hobbiss, A. (2000). Food deserts and how to tackle them: A study of one city's approach. *Health Education Journal*, 59(2), 137-149. doi: 10.1177/001789690005900203.

Robinson WS (1950) "Ecological correlations and the behavior of individuals", *American Sociological Review*, vol. 15, pp. 351-357.

Shaw, H.J. (2006), "Food Deserts: towards the development of a classification", *Geografiska Annaler: Series B, Human Geography*, 88(2), pp. 231 – 247.

Smoyer-Tomic, K., J. Spence and C. Amrhein (2006) "Food Deserts in the Prairies? Supermarket Accessibility and Neighborhood Need in Edmonton, Canada", *The Professional Geographer*, 58(3), pp. 307-326.

Whelan, A., Wrigley, N., Warm, D., and Cannings, E. (2002). Life in a 'food desert'. *Urban Studies*, 39(11), 2083.

Wrigley, N. (2002). 'Food deserts' in British cities: Policy context and research priorities. *Urban Studies*, 39(11), 2029.

Wrigley, N., Guy, C., and Lowe, M. (2002). Urban regeneration, social inclusion and large store development: The Seacroft Development in context. *Urban Studies*, 39(11), 2101.

Wrigley, N., Warm, D., and Margetts, B. (2003). Deprivation, diet and food retail access: Findings from the Leeds 'food deserts' study. *Environment and Planning A*, 35(1), 151-88.

Wrigley, N., Warm, D., Margetts, B., and Whelan, A. (2002). Assessing the impact of improved retail access on diet in a 'food desert': A preliminary report. *Urban Studies*, 39(11), 2061.

Zenk, S. N., Schulz, A. J., Israel, B. A., James, S. A., Bao, S., and Wilson, M. L. (2005). Neighborhood racial composition, neighborhood poverty, and the spatial accessibility of supermarkets in metropolitan Detroit. *American Journal of Public Health*, 95(4), 660-667.

Figure 1. *Study area. Portland, Oregon's metropolitan urban growth boundary (UGB)*

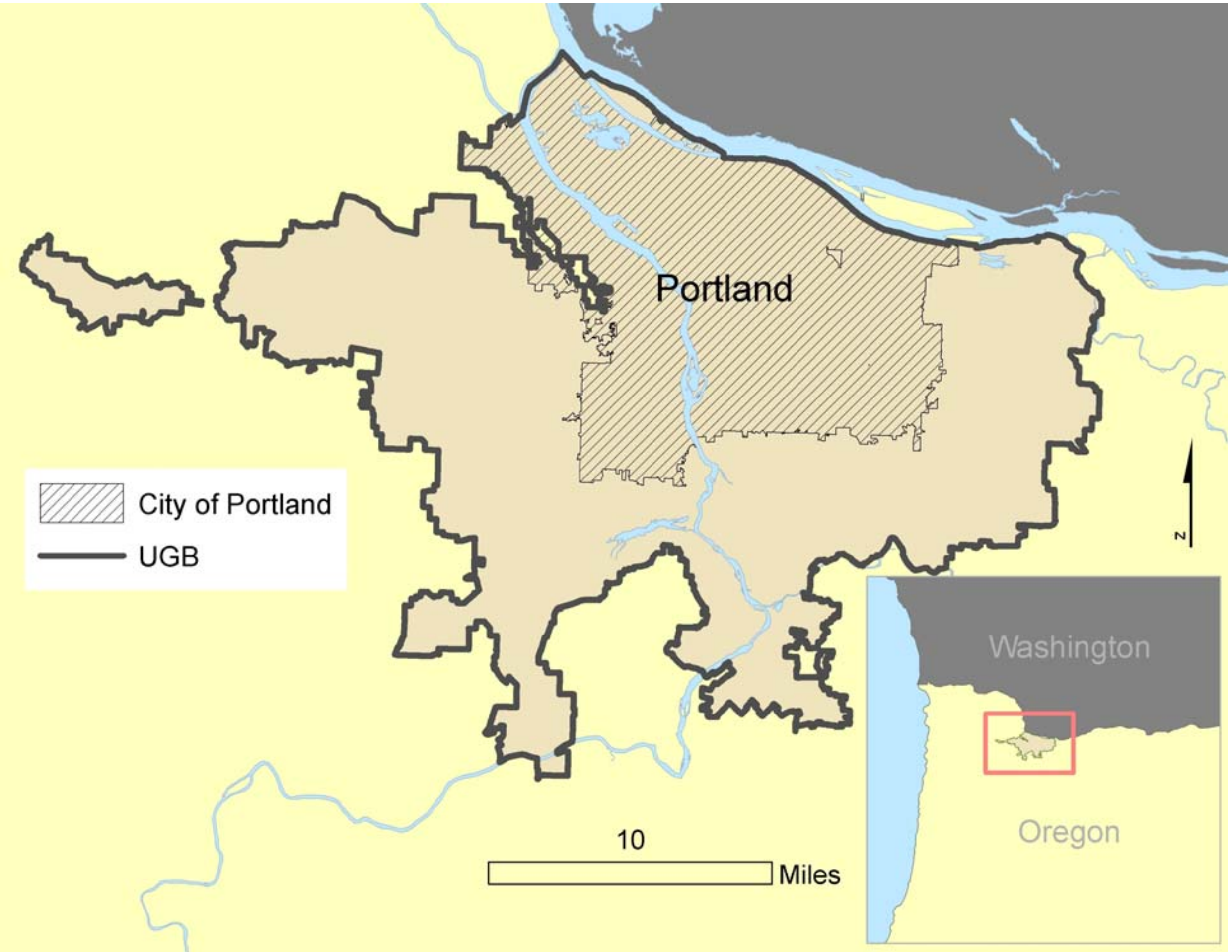

Figure 2. *Spatial distribution of supermarkets, Portland, Oregon metropolitan area*

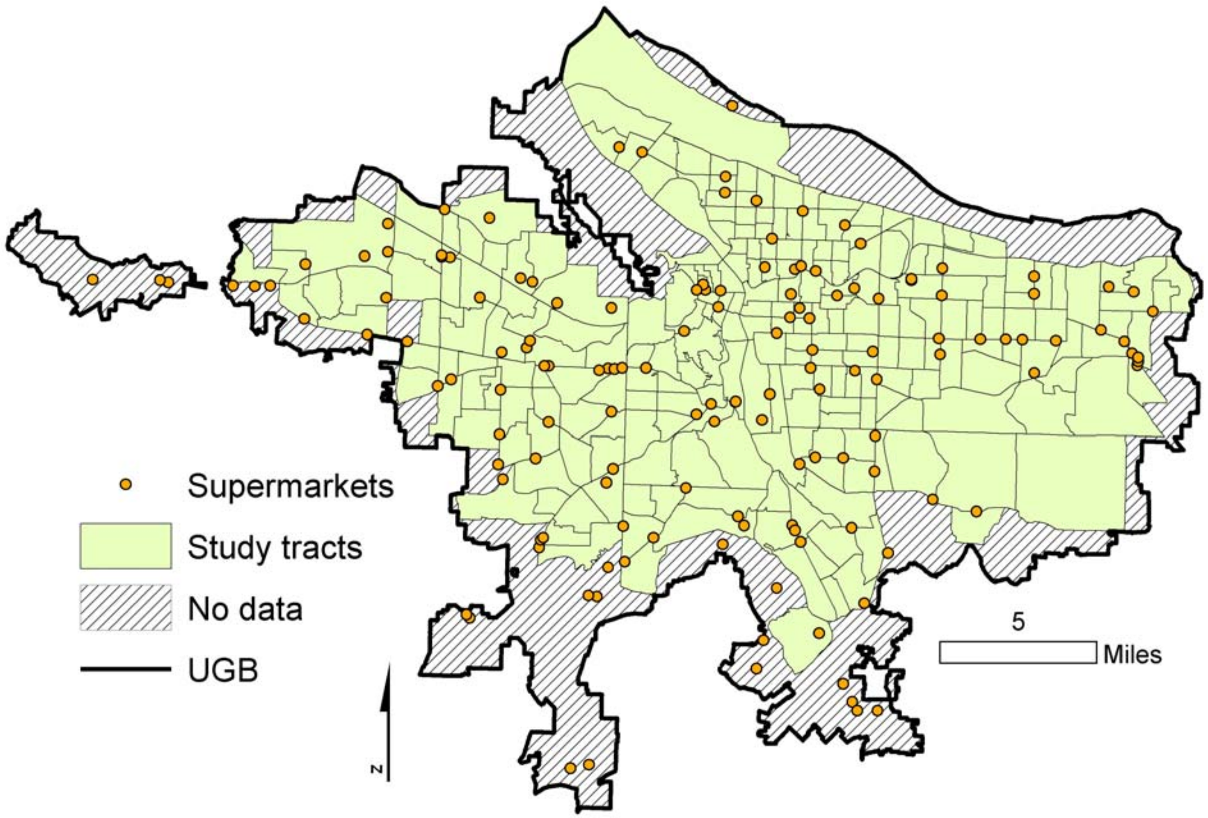

Figure 3a. *Measure 1 access categories: Average distance to nearest supermarket*

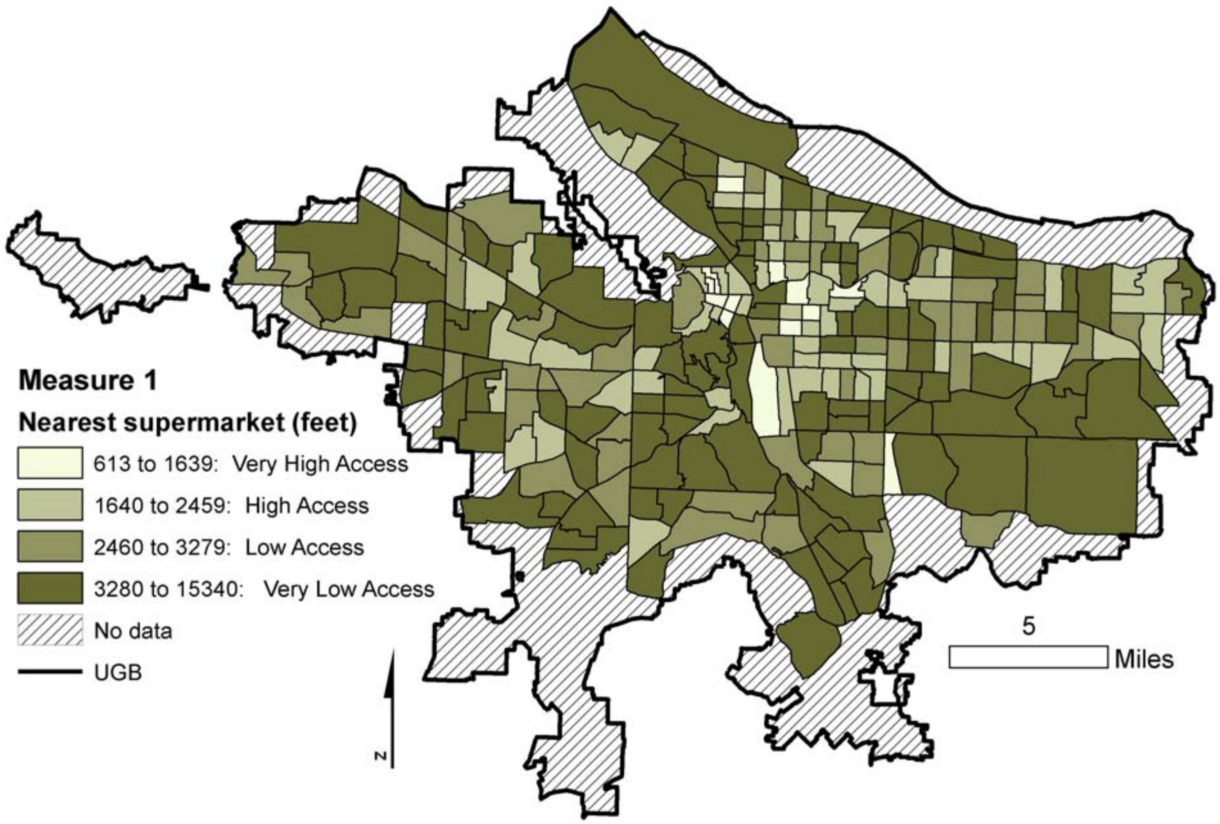

Figure 3b. *Measure 2 access categories: Number of supermarkets within walking distance*

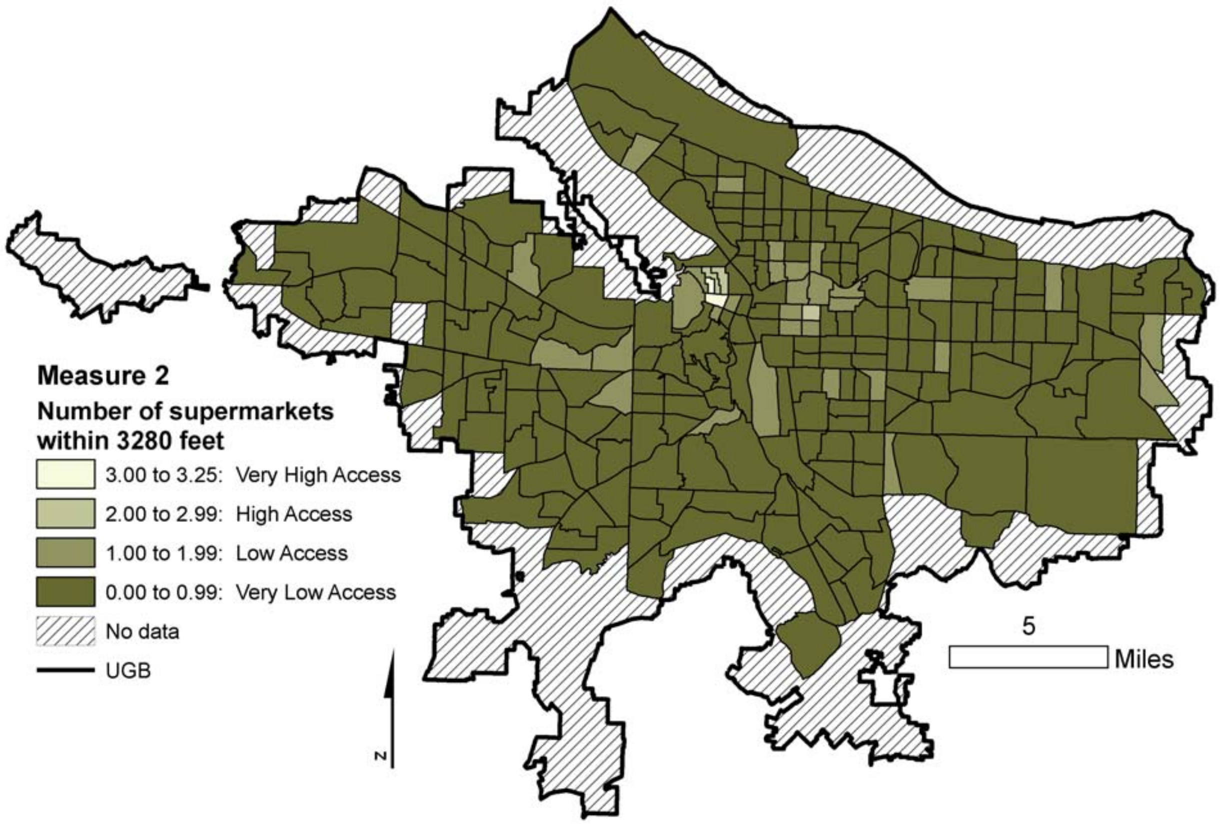

Figure 3c. *Measure 3a access categories: Average distance to 3 closest chain-name supermarkets (different parent companies)*

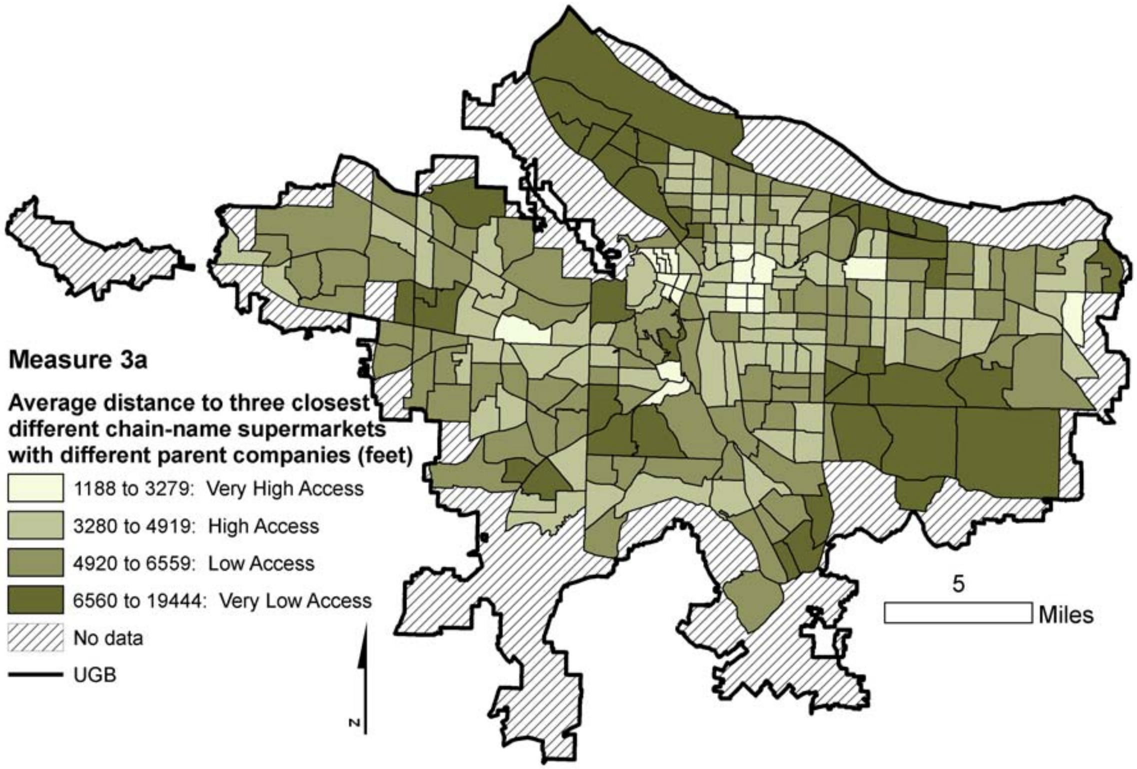

Figure 3d. *Measure 3b access categories: Average distance to three closest different chain-name supermarkets*

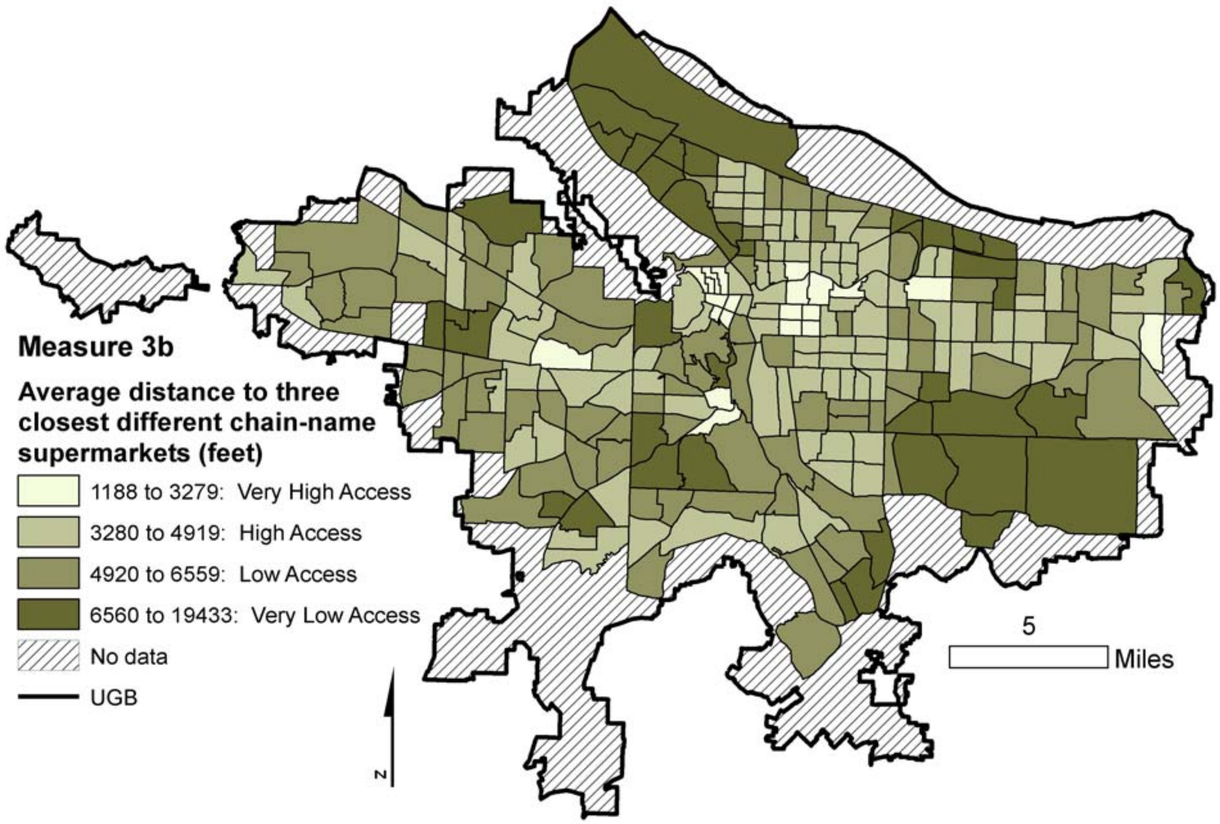

Figure 4. *Poverty rate by census tract, Portland, Oregon metropolitan area*

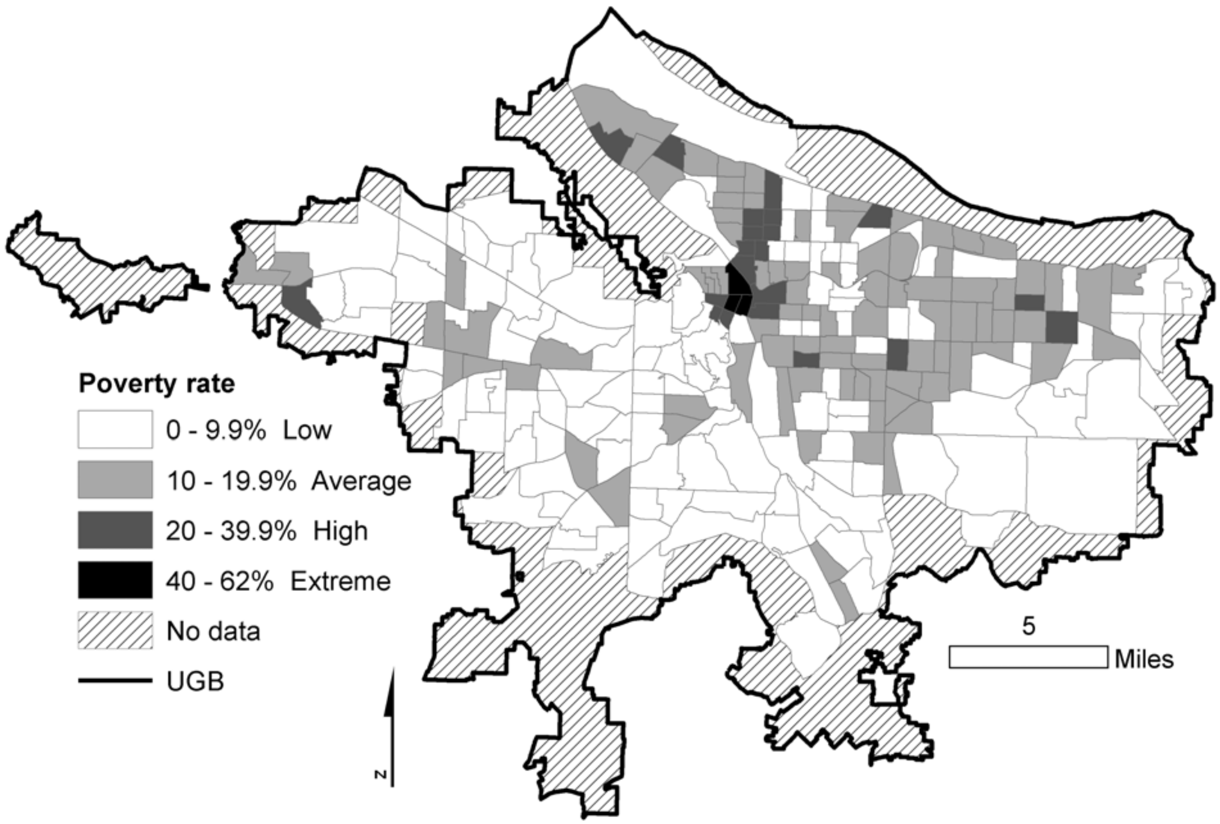

Figure 5. *Poverty rate and food deserts*

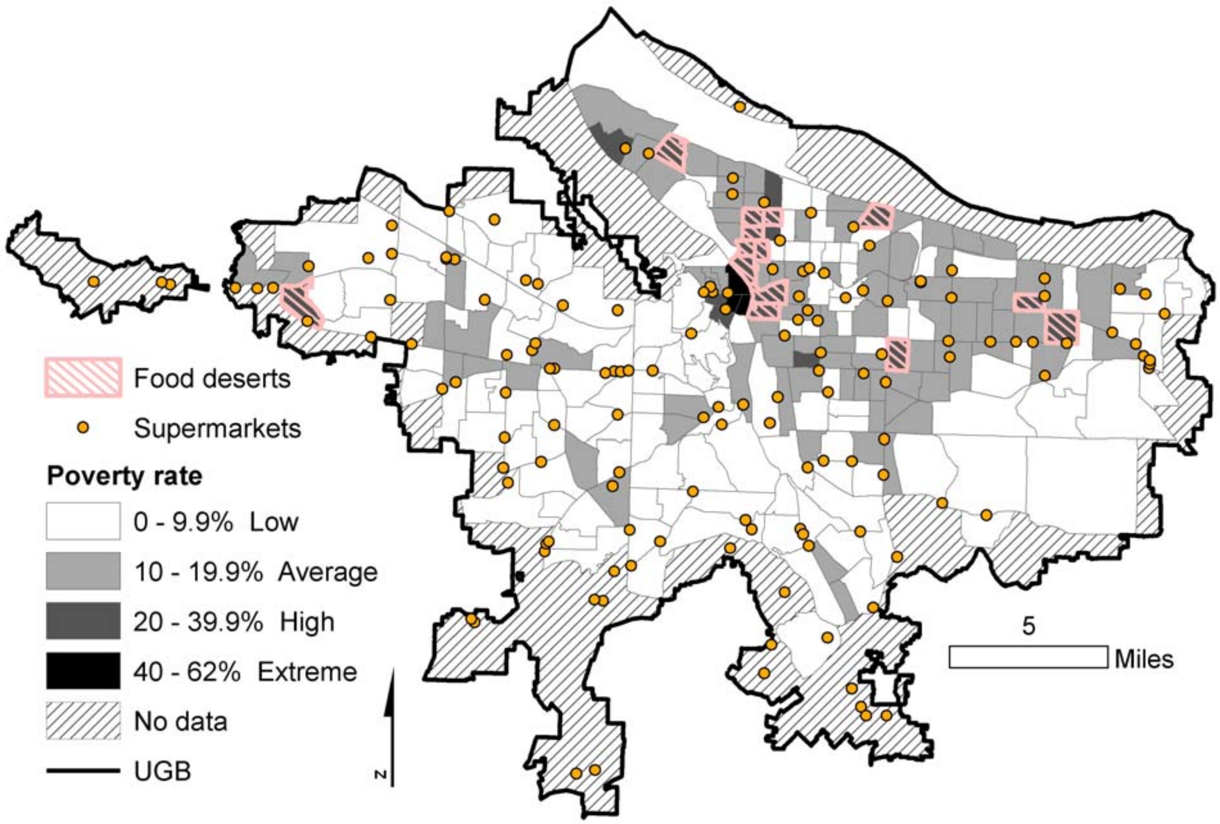

Figure 6. *Areas located within walking distance of supermarkets*

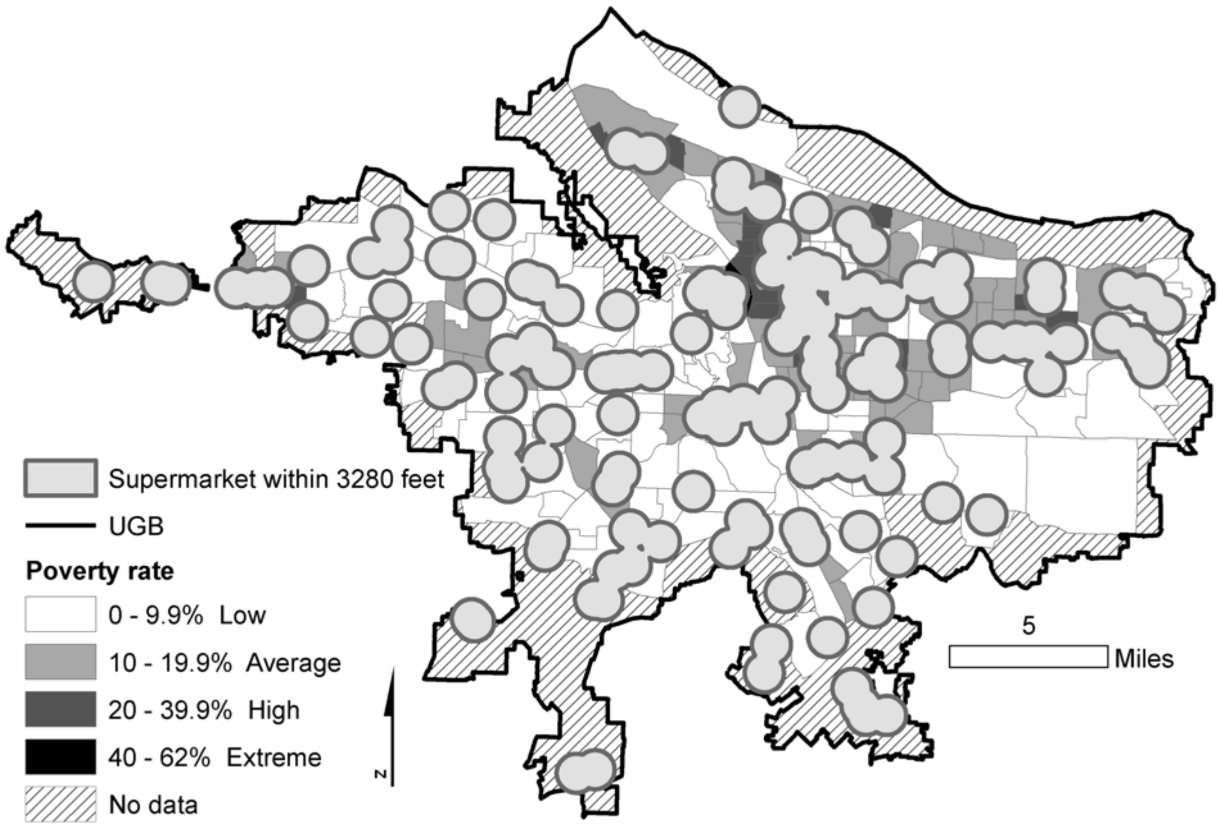

Table 1. Measurement Variants for Food Access Measures

Variant	Distance from Supermarket to:	Aggregation Level	Distance Calculation
1	Block centroids	Tract	Euclidean
2	Block Group centroids	Tract	Euclidean
3	Tract centroids	Tract	Euclidean
4	Block centroids	Block Group	Euclidean
5	Tract centroids	Tract	Network Distance

Table 2. Descriptive Statistics for Food Access Measures, Portland, Oregon (Area within Urban Growth Boundary)
(Variant 1 -- Block Level Measures Aggregated to Census Tract Level Using Population Weights)

Access Measure	N	Mean	Std Dev	Median	Minimum	Maximum	Moran's I[a]	z-Score[b]
M1: Distance to Nearest Supermarket (feet)	243	3,471	100,505	3,251	614	15,340	0.32	7.35
M2: Number of Supermarkets within 1 km (3280 feet)	243	0.52	33.52	0.40	0.00	3.25	0.67	15.14
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)	243	5,384	120,372	5,147	1,189	19,444	0.48	10.91
M3B: Average Distance to Three Closest Supermarkets	243	5,318	122,155	5,126	1,189	19,433	0.48	10.92

[a] Calculated with a weighted connectivity matrix with a lag distance of 1.5 km.
[b] All z-scores different from 0 at the .0001 level or higher.

Table 3.
Pearson and Spearman Correlations between Food Access Measures at the Census Tract Level(n=243)
Portland, Oregon (Area within Urban Growth Boundary)

(Variant 1: Block Level Measures Aggrgated to Census Tract Level Using Population Weights)

Pearson Correlation Coefficients

Access Measure	Measure 1	Measure 2	Measure 3A
M1: Distance to Nearest Supermarket (feet)	--		
M2: Number of Supermarkets within 1 km (3280 feet)	-0.692		
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)	0.857	-0.668	
M3B: Average Distance to Three Closest Supermarkets	0.864	-0.669	0.993

Spearman's Rho - Rank Correlation Coefficients

Access Measure	Measure 1	Measure 2	Measure 3A
M1: Distance to Nearest Supermarket (feet)	--		
M2: Number of Supermarkets within 1 km (3280 feet)	-0.924		
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)	0.818	-0.812	
M3B: Average Distance to Three Closest Supermarkets	0.830	-0.823	0.986

Note: All coefficients significant at the .001 level or higher

Table 4. Pearson Correlations between Food Access Measures and Poverty Rate at the Census Tract Level (n=243)
Portland, Oregon (Area within Urban Growth Boundary)

Access Measure	Correlation with Poverty Rate
M1: Distance to Nearest Supermarket (feet)	-0.216
M2: Number of Supermarkets within 1 km (3280 feet)	0.182
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)	0.187
M3B: Average Distance to Three Closest Supermarkets	0.188

Note: All coefficients significant at the .001 level or higher

Table 5. Block Group Level Socio-Economic and Demographic Characteristics from the 2000 U.S. Census (Population Weighted Means, n=722) Portland, Oregon (Area within Urban Growth Boundary)

Variable	Mean	Std Dev	Minimum	Maximum	Moran's I[a]	z-score[b]
Population density (persons/square mile)	6,020	128,526	76	28,818	0.42	31.2
Median household income	23,704	352,726	7,825	77,439	0.40	29.5
Percent of population in poverty	0.106	3.31	0.0	0.623	0.35	26.3
Percent of population elderly (65+)	0.106	2.42	0.0	0.582	0.13	9.5
Percent of population African-American	0.038	3.06	0.0	0.590	1.26	93.6
Percent of population Hispanic	0.082	3.66	0.0	0.800	0.28	20.8
Percent of households owner-occupied	0.599	9.14	0.0	1.000	0.29	21.7
Percent of households without automobile access	0.093	3.98	0.0	0.915	0.54	40.4

[a] Calculated with a weighted connectivity matrix with a lag distance of 1.5 km.
[b] All z-scores different from 0 at the .0001 level or higher.

Table 6. Pearson Correlation Coefficients between Food Access Measures and Socio-Economic Characteristics
Block Group Level Analysis, Portland, Oregon Metropolitan Area (n=722)

	Food Access Measure		
Socio-Economic and Demographic Characteristics	Measure 1: Mean Distance to Closest Supermarket	Measure 2: Number of Supermarkets within 3280 feet (1 kilometer)	Measure 3B: Averge Distance to Closest 3 Supermarkets
Population density (persons/square mile)	-0.36 ***	0.36 ***	-0.41 ***
Percent of population in poverty	-0.17 ***	0.14 ***	-0.15 ***
Percent of households owner-occupied	0.29 ***	-0.32 ***	0.31 ***
Percent of households without automobile access	-0.26 ***	0.31 ***	-0.27 ***
Median household income	0.07	-0.002	-0.003
Percent of population elderly (65+)	-0.05	0.06	-0.05
Percent of population African-American	-0.04	-0.03	0.01
Percent of population Hispanic	0.01	-0.08 *	0.02

* .01 < p =< .05
** .001 < p =< .01
*** p < .001

Table 7. Block Level Access Measures Aggregated to Block Group Level with Alternate Weights (n=722)

	Measure 1: Mean Distance to Closest Supermarket	Measure 2: Number of Supermarkets within 3280 feet (1 kilometer)	Measure 3B: Averge Distance to Closest 3 Supermarkets
<u>Weight:</u>			
Population in households without car access	2,743	0.88	4,437
Population below poverty level	3,204	0.60	5,046
African-American population	3,290	0.50	5,322
Elderly population	3,409	0.55	5,214
Hispanic population	3,424	0.48	5,271
Whole Population	*3,471*	*0.52*	*5,318*
Population in owner-occupied households	3,620	0.46	5,503

BG level Access measures are then aggregated to the metro area total using various weights

Table 8. Mean Access Measures and Population Characteritsics by Block Group Poverty Level (n=722)

	Percent Poverty in Block Groups:		
	Extreme & High (> 20%) (n=94)	**Average (10 to 20%) (n=220)**	**Low (< 10%) (n=408)**
Access Measure			
M1: Distance to Nearest Supermarket (feet)	3,073	3,172	3,700
M2: Number of Supermarkets within 1 km (3280 feet)	0.61	0.63	0.44
M3B: Average Distance to Three Closest Supermarkets	5,000	4,980	5,550
Percent of:			
Population	11.6%	29.6%	58.8%
Poor Population	30.8%	40.7%	28.5%
Elderly Population	9.9%	30.0%	60.1%
Households with No Car Access	29.0%	39.6%	31.4%

Table 9. Population Percentages According to Degree of Food Access and Poverty Level of Block Group (n=722)

	Percent in Block Groups with Low or Very Low Food Access and Low or Medium Poverty			Percent in Block Groups with Low or Very Low Food Access and High Poverty		
	Overall Population	Poor Population	Population w/out Car Access	Overall Population	Poor Population	Population w/out Car Access
M1: Distance to Nearest Supermarket (feet)	71.2	62.4	35.5	1.9	4.2	12.5
M2: Number of Supermarkets within 1 km (3280 feet)	94.8	88.1	65.5	3.9	9.5	25.4
M3B: Average Distance to Three Closest Supermarkets	68.5	62.2	36.4	2.3	5.0	13.1

Table 10. Descriptives Statistics for Census Tract Food Access Measures by Measure and Methodological Variant (n=243)

Access Measure and Variant		Mean	Std Dev	Median	Minimum	Maximum
M1: Distance to Nearest Supermarket (feet)						
1	Block to Tract	3,471	100,505	3,251	614	15,340
2	Block Group to Tract	3,602	106,682	3,411	652	14,813
3	Tract Level	3,651	122,804	3,418	265	16,625
M2: Number of Supermarkets within 1 km (3280 feet)						
1	Block to Tract	0.52	33.5	0.40	0.00	3.25
2	Block Group to Tract	0.49	38.7	0.32	0.00	3.00
3	Tract Level	0.41	47.3	0.00	0.00	5.00
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)						
1	Block to Tract	5,384	120,372	5,147	1,189	19,444
2	Block Group to Tract	5,440	124,201	5,173	1,156	18,920
3	Tract Level	5,513	130,876	5,318	1,027	19,596
M3B: Average Distance to Three Closest Supermarkets						
1	Block to Tract	5,318	122,155	5,126	1,189	19,433
2	Block Group to Tract	5,372	126,149	5,159	1,156	18,920
3	Tract Level	5,431	133,261	5,254	1,027	19,596

Table 11. Spearman Rank Correlations of Census Tract Level Food Access Measures by Measure and Methodological Variant (n=243)

Access Measure and Variant		Input Data Level*: Variant 1: Block to Tract	Input Data Level*: Variant 2: Block Group to Tract
M1: Distance to Nearest Supermarket (feet)			
1	Block to Tract	--	
2	Block Group to Tract	0.95	
3	Tract Level	0.91	0.93
M2: Number of Supermarkets within 1 km (3280 feet)			
1	Block to Tract	--	
2	Block Group to Tract	0.84	
3	Tract Level	0.72	0.70
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)			
1	Block to Tract	--	
2	Block Group to Tract	0.98	
3	Tract Level	0.96	0.96
M3B: Average Distance to Three Closest Supermarkets			
1	Block to Tract	--	
2	Block Group to Tract	0.98	
3	Tract Level	0.96	0.96

* All coefficients significant at the .001 or higher

Table 12. Moran's I Measure of Spatial Autocorrelation for Food Access Measures by Measure and Methodological Variant (n=243)

Access Measure and Variant		Moran's I	z*
M1: Distance to Nearest Supermarket (feet)			
1	Block to Tract	0.324	7.35
2	Block Group to Tract	0.276	6.26
3	Tract Level	0.239	5.45
M2: Number of Supermarkets within 1 km (3280 feet)			
1	Block to Tract	0.672	15.14
2	Block Group to Tract	0.393	8.88
3	Tract Level	0.292	6.62
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)			
1	Block to Tract	0.483	10.91
2	Block Group to Tract	0.436	9.84
3	Tract Level	0.409	9.24
M3B: Average Distance to Three Closest Supermarkets			
1	Block to Tract	0.484	10.92
2	Block Group to Tract	0.437	9.88
3	Tract Level	0.410	9.28

*All z scores significant at the .0001 level or higher.

Table 13. Descriptives Statistics for Census Tract Food Access Measures by Measure and Methodological Variant (n=243)

Access Measure and Variant		Mean	Std Dev	Median	Minimum	Maximum
M1: Distance to Nearest Supermarket (feet)						
3	Tract Level - Euclidean Distance	3,651	122,804	3,418	265	16,625
5	Tract Level - Street Network Distance	5,023	167,397	4,653	43	21,335
M2: Number of Supermarkets within 1 km (3280 feet)						
3	Tract Level - Euclidean Distance	0.41	47.3	0.00	0.00	5.00
5	Tract Level - Street Network Distance	0.29	40.9	0.00	0.00	5.00
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)						
3	Tract Level - Euclidean Distance	5,513	130,876	5,318	1,027	19,596
5	Tract Level - Street Network Distance	7,478	183,066	7,200	1,548	25,470
M3B: Average Distance to Three Closest Supermarkets						
3	Tract Level - Euclidean Distance	5,431	133,261	5,254	1,027	19,596
5	Tract Level - Street Network Distance	7,473	182,962	7,161	1,548	25,470

Table 14. Spearman Rank Correlations between Tract Level Measures with Euclidean and Street Network Distances by Type of Food Access Measure (n=243)

Access Measure	Rank Correlation
M1: Distance to Nearest Supermarket (feet)	0.93
M2: Number of Supermarkets within 1 km (3280 feet)	0.81
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)	0.89
M3B: Average Distance to Three Closest Supermarkets	0.91

* All coefficients significant at the .001 or higher

Table 15. Moran's I Measure of Spatial Autocorrelation for Food Access Measures by Measure and Methodological Variant (n=243)

Access Measure and Variant	Moran's I	z*
M1: Distance to Nearest Supermarket (feet)		
3 Tract Level - Euclidean Distance	0.239	5.45
5 Tract Level - Street Network Distance	0.269	6.11
M2: Number of Supermarkets within 1 km (3280 feet)		
3 Tract Level - Euclidean Distance	0.292	6.62
5 Tract Level - Street Network Distance	0.320	7.27
M3A: Average Distance to Three Closest Supermarkets (Different Parent Companies)		
3 Tract Level - Euclidean Distance	0.409	9.24
5 Tract Level - Street Network Distance	0.444	10.03
M3B: Average Distance to Three Closest Supermarkets		
3 Tract Level - Euclidean Distance	0.410	9.28
5 Tract Level - Street Network Distance	0.449	10.13

*All z scores significant at the .0001 level or higher.

Table 16. OLS Regression Estimates
Dependent Variable: Food Access Measures Computed with Network Analyst Distances
(standard errors in parantheses)

	Food Access Measure			
	M1	**M2**	**M3A**	**M3B**
Intercept	899.2 ***	-0.009	1421.6 ***	1454.7 ***
	(213.3)	(.056)	(327.8)	(309.3)
Food access measured with Euclidean distance	1.26 ***	0.499 ***	1.24 ***	1.23 ***
	(.043)	(.055)	(.049)	(.046)
Population density of residential tract	-0.04	0.000005	-0.062	-0.066
	(.028)	(.000009)	(0.042)	(.040)
Food access x population density	-0.00002 *	0.00002 ***	-0.00002 *	-0.00001
	(.0001)	(.000006)	(.000009)	(.000009)
R-squared	0.892	0.748	0.860	0.873
N	243	243	243	243