Modifying Areal Interpolation Techniques for Analysis of Data on Food Assistance Benefits

Jerry Shannon and Francis Harvey

Abstract Analyses aimed at identifying food deserts—defined as areas with limited access to healthy food—have garnered much recent attention from the news media, policy makers, and non-profit groups. Much of this research relies on the proximity of large grocery stores as a measure of food access. These studies have been limited by poor data quality, boundary effects, and scale dependence. Drawing on data from the Supplemental Nutrition Assistance Program (SNAP, formerly known as food stamps), we suggest an alternative approach that incorporates the distribution and redemption of food assistance benefits in low-income neighborhoods. This data is publically available, but at the zip code level, limiting its usefulness for neighborhood analysis. We use a three-class areal interpolation method to develop three disaggregation techniques that increase the usability of this data. These utilize several external data sources to weight the distribution of this data, including the U.S. Census, U.S. Geological Survey satellite imagery, and existing cadastral data. Our analysis, focused on the Twin Cities metropolitan region for federal fiscal year 2010, thus allows for a more accurate depiction of how residents actually access the food system.

1 Introduction

Spatial analysis focused on the identification of "food deserts" has been the subject of increased research along with media and political attention in recent years, despite the fact that the concept is itself only a little more than a decade old (Clarke et al. 2004; Wrigley 2002). In 2008, the U.S. Congress passed legislation funding study of food deserts, defining them as "an area in the United States with limited access to

J. Shannon (✉) · F. Harvey
University of Minnesota, Minneapolis, MN, USA
e-mail: shann039@umn.edu

F. Harvey
e-mail: fharvey@umn.edu

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affordable and nutritious food, particularly such an area composed of predominantly lower income neighborhoods and communities" (USDA 2009, p. 1). Although the term "desert" suggests that these neighborhoods lack food of any kind, this definition does not frame the problem as a general absence of any food sources, or even the absence of healthy foods such as fruits and vegetables. Rather, as the above definition indicates, food deserts are low-income neighborhoods that lack affordable or accessible options for healthy food but a comparative abundance of highly processed, nutrient poor foods. Drawing from a broader framework of social ecological studies in public health, such neighborhoods are assumed to foster poor habits of food consumption among their residents and consequentially higher incidences of diet-related health problems such as heart disease or diabetes (Egger and Swinburn 1997; Stokols 1995; Swinburn et al. 1999).

The exact metrics used to measure food deserts have varied. A recent review of research in this area classified them using two broad categories: geographic studies and market-basket studies (Beaulac et al. 2009). Geographic studies have mainly measured food access through GIS-based analyses of distances to healthy and unhealthy food sources, frequently grocery stores and fast food restaurants respectively (Black et al. 2011; Hemphill et al. 2008; Zenk et al. 2005). While most geographic studies record the distribution of food sources throughout a given region, other researchers have prepared market-basket studies that focus on the quality of food offerings within each store (Block and Kouba 2007; Goldsberry et al. 2010; Hendrickson et al. 2006). Analyzing food prices and quality across neighborhoods helps with the identification of disparities in access to healthy foods. Despite their popularity, poor data quality, boundary effects, and scale dependence can limit these studies (Powell et al. 2011; Short et al. 2007). Since stores are often located along commercial corridors used as the boundaries of administrative units, boundary effects can be particularly problematic.

The research in this article attempts to address this last issue with current food desert research in two ways. First, by using data on actual food procurement by urban residents, we hope to avoid an over reliance on absolute measures of distance as proxies for food access. For this project, we use data from the Supplemental Nutrition Assistance Program (SNAP), also known as food stamps, the primary federal food assistance program in the United States. Data on both the distribution of SNAP benefits and their redemption at authorized food vendors is publically available, and it provides another method by which to analyze the types of stores utilized by neighborhood residents. Identification of neighborhoods with high net inward or outward flows of SNAP benefit dollars also provides another way to identify areas with low food accessibility. Second, we use areal interpolation to disaggregate this data and perform a fine scale neighborhood analysis. For this, we drew from techniques to develop three approaches to disaggregating this data. The finer scale data resolution that results from this approach significantly lessens the impact of boundary effects on data analysis and allows for a more robust, multi-scalar analysis of this data. While the results of this research are most immediately applicable to the U.S. context, this approach may serve as a broader model for the analyses of low food access.

2 Study Background

2.1 Background on the Supplemental Nutrition Assistance Program

Data on the distribution and redemption of federal food assistance provides insight on how food is procured in low-income neighborhoods. In 2010, SNAP provided assistance to over 36 million people throughout the United States (USDA 2011). In Minnesota, specifically the seven county Twin Cities Metropolitan Area, where this research is conducted, SNAP provides $29 million of benefits to approximately 270,000 individuals, and is accepted in just over 1,400 retail locations. Data on benefit distribution and redemption is publicly available through the United States Department of Agriculture (USDA) and individual state departments of public health.

2.2 Obstacles to Analysis of SNAP Data

For this project, we obtained data on monthly SNAP benefit distribution and redemption for October 2009 through September 2010. However, two main obstacles to analysis quickly became apparent. First, while we were able to acquire data on benefit distribution and benefit redemption, these two datasets were held in different locations. Client and distribution data are managed by the Minnesota Department of Health, while vendor and benefit redemption data are held at the federal level by the U.S. Department of Agriculture. These two data sets follow different data models with the consequence that there is no clear way to link benefit distributions to clients' eventual redemptions at stores. Following data protection guidelines and to protect stores' exact sales numbers, the USDA releases data on benefit redemptions only for zip codes in which four or more retailers are present. Second, zip codes are the finest scale at which this data are offered (Fig. 1). While this scale may be sufficient for a broad analysis, it makes meaningful analysis at the neighborhood level difficult (Raper et al. 1992).

2.3 Areal Interpolation and Dasymetric Mapping

Areal interpolation offers a useful spatial analytical tool set to develop more detailed analysis of food deserts, as it allows for very small area estimation of food benefit distribution and redemption. Broadly speaking, areal interpolation refers to the reclassification of data from one set of areal units to another (Flowerdew and Green 1991; Goodchild and Anselin 1993; Goodchild and Lam 1980). Much recent work in this area has focused on the use of dasymetric mapping techniques While it has been in use for over a century, dasymetric maps have recently enjoyed greater usage among

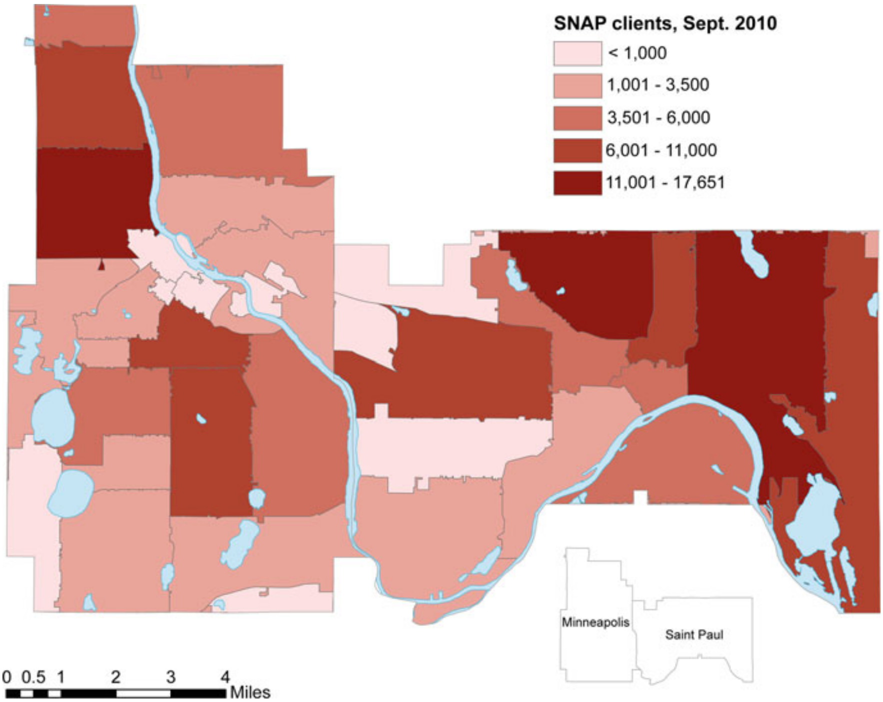

Fig. 1 Number of SNAP recipients per zip code in Minneapolis and St. Paul, September 2010

population geographers. In contrast to choropleth maps, which display variables as an uniform distribution within often politically determined areal units, an analysis using dasymetric maps highlights continuities of a given population variable over space. Thus, boundaries on dasymetric maps represent meaningful changes in the variable of interest, unlike choropleth maps, where boundaries are generally unrelated to these variables (Fotheringham and Rogerson 1993; O'Sullivan and Unwin 2002; Wright 1936). The distinction between areal interpolation and dasymetric mapping has, in practice, been somewhat fuzzy (Mennis 2009), and by seeking to develop small area estimations of food benefit utilization the approach outlined here borrows from both techniques.

Papers by Eicher and Brewer (2001) and Mennis (2003) recently have described several techniques by which datasets aggregated to political units, such as census data, might be transformed to a small area map. Both these papers advocate the use of land use classifications drawn from remotely sensed imagery to weigh the distribution of populations within pre-defined areal units, though the exact nature of the distributional method varies. Eicher and Brewer found that a limiting variable method, where land types are capped at a certain population density, produced the most accurate results. Eicher and Brewer found greater errors in the three-class method, which weights distribution of a demographic variable based on an underlying characteristic from an auxillary dataset such as land-use type. Mennis developed a modified version of the three-class method that addresses their concerns. Using classified land imagery and block-group level census data, this technique averages population densities in various land use types. These densities are then combined with area measurement to weight the distribution of that uniformly distributed block group data to a finer-scale raster distribution.

Applied research in a range of areas has drawn upon this approach (Langford 2006; Poulsen and Kennedy 2004). Satellite imagery is the most commonly used external dataset used for weighting. In the United States, preclassified land imagery from the National Land Cover Dataset (NLCD) from the U.S. Geological Survey simplifies this approach (Reibel and Agrawal 2007). Maantay et al. (2008) develop their own dasymetric mapping system based on cadastral data including residential area and number of units per residence. Other recent researchers have suggested alternative population estimation methods using automated classification or street network density (Langford 2006; Reibel and Bufalino 2005; Tapp 2010). However, each of these techniques is best suited for estimates of general population. As this study is focused particularly on the population of individuals receiving food assistance, a three-class method relying on a weighting variable from survey data was deemed most appropriate.

3 Methods

Our method adapted areal interpolation techniques to three different scenarios (outlined in Table 1). These involved a variety of areal units: polygons, points, and raster cells. To weight distribution of the data, we used both external datasets and averages of existing data. For data on benefit distribution, three external datasets were used to weight the disaggregation: (1) zoning classifications for the Twin Cities Metropolitan Area provided by a regional governmental council, (2) NLCD preclassified land use imagery, and (3) demographic data from the U.S. Census' American Community Survey (ACS) for the 5 year summary period 2005–2009, the most recent available at the time of this research. For benefit redemptions, USDA data on existing SNAP redemption patterns were used. Thus, while these three steps used similar methods, each required a specific adaptation of existing methods.

3.1 Benefit Distribution: From Zip Code to "Ziptracts"

Initial attempts to disaggregate this data directly to a density raster resulted in artificially sharp breaks at zip code boundaries, and so we developed a two stage process in which data is first disaggregated to the census tract level using ACS data and then further disaggregated to a 30 x 30 m grid using zoning and land use classifications.

Table 1 Three stages of disaggregation in our project

	Benefit distribution, point 1	Benefit distribution, point 2	Benefit redemptions
Data source	Minnesota Department of Health	Minnesota Department of Health	USDA
Initial resolution	Zip codes	"Ziptracts"	Zip codes
Ending resolution	"Ziptracts"	30×30 m raster	Points (store locations)
Population weighting variable	Density of SNAP households	Average density in existing data for 20 land use classes	SNAP redemption patterns by store type
Source of weighting areal units	U.S. Census	USGS preclassified land use imagery, regional zoning data	USDA
Data resolution	Census tracts	30×30m raster	N/A (weights are not spatial)
Area ratio utilized	Yes	Yes	No

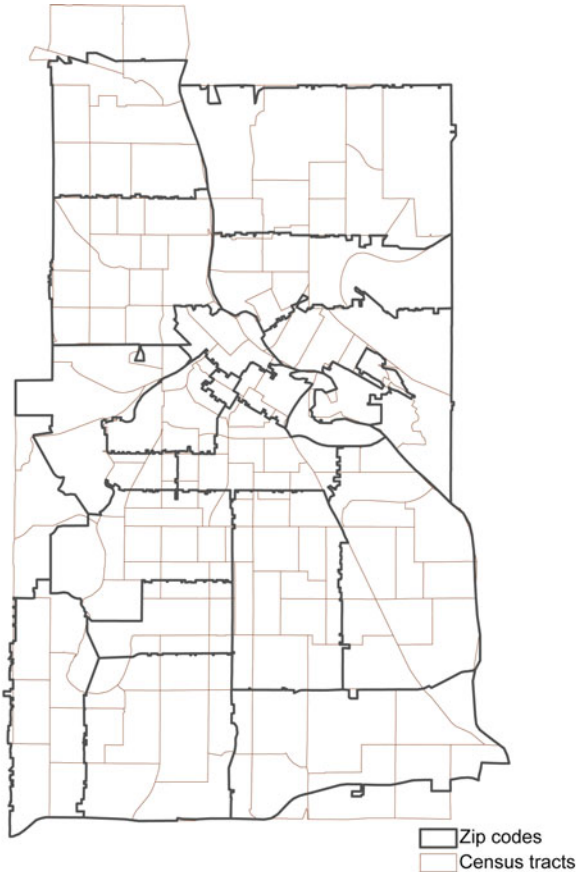

Fig. 2 Zip code and tract boundaries in Minneapolis

Zip codes and census tracts vary in size, though the former are generally much larger than the latter in high-density urban areas (Figs. 2, 3).

The steps of our analysis can be done in most GIS software packages. Prior to the first stage of this process, both the zip code and tract layers were clipped so that they only included land zoned for permanent residential use. We calculate food stamp utilization, reported by households in the ACS, as a density based on the clipped area of each census tract (per km^2). Finally in the analysis we create a set of unique polygons that share the same zip code and tract identifiers (Fig. 4). To distinguish them, the new polygons of this layer were referred to as "ziptracts."

Following the guidelines outlined in Mennis (2003), a population fraction and area ratio are created for each zip tract. The population fraction is based on the ACS household density, normalized against all tracts within a given zip code. In a hypothetical zip code A containing tracts 1, 2, and 3, the population fraction would be represented in this way:

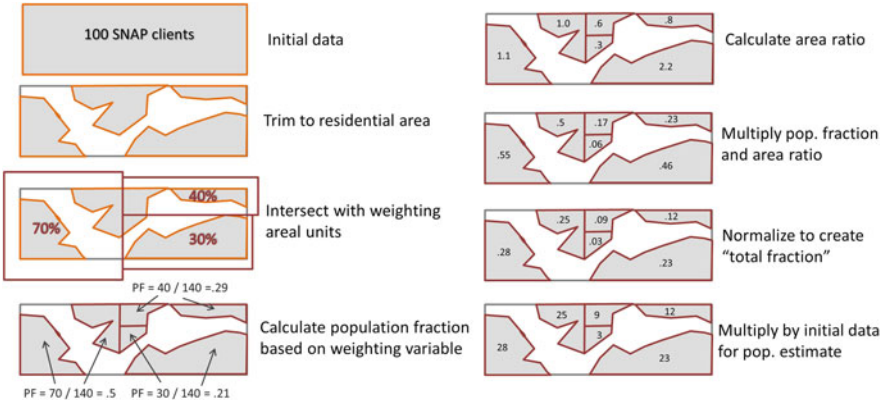

Fig. 3 Overview of approach used to disaggregate to "ziptracts"

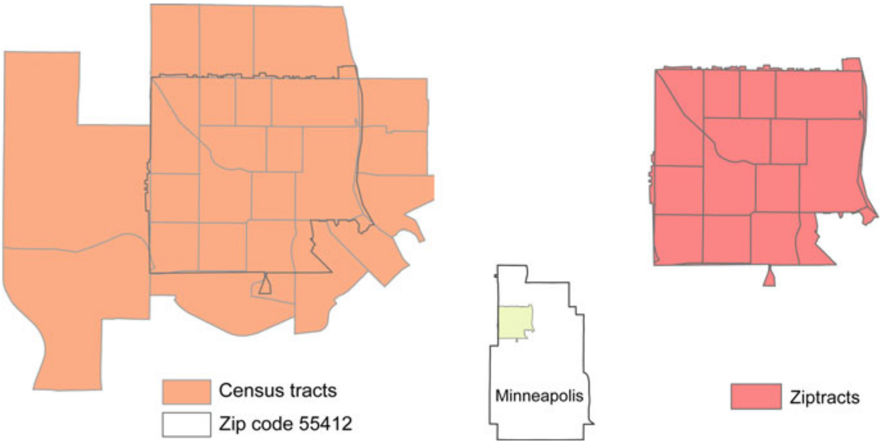

Fig. 4 Census tracts and the boundary of zip code 55412 (*left*) and results of intersecting these two boundaries (*right*)

$$\mathrm{pf}_{\mathrm{A1}} = \frac{\mathrm{den}_1}{(\mathrm{den}_1 + \mathrm{den}_2 + \mathrm{den}_3)}$$

In this case, $\mathrm{pf}_{\mathrm{A1}}$ refers to the population fraction for the ziptract for zip code A and tract 1, den_1 refers to the weighting variable (rate or density from the ACS) for tract 1, and den_2 and den_3 refer to the weighting variables for tracts 2 and 3.

The area ratio adjusts for the unequal areas of each tract within a zip code. It compares the actual proportion of a tract's area in a zip code to its expected proportion if all areas were equal. If a zip code contained three tracts, for example, that expected proportion would be 0.33 for each tract (see Mennis (2003), for further explanation). The area ratio in this instance would be greater than 1 for tracts taking up more than one-third of a zip code's total area or less than one for those smaller than a third of the zip code's area. Using the hypothetical example given above, the area ratio can be written:

$$\mathrm{ar}_{\mathrm{A1}} = \left(\frac{\mathrm{area}_{\mathrm{A1}}}{\mathrm{area}_{\mathrm{A}}}\right) \Big/ \left(\frac{1}{\#\mathrm{tracts}_{\mathrm{A}}}\right)$$

Here, $\mathrm{ar}_{\mathrm{A1}}$ refers to the area ratio for the ziptract for zip code A and tract 1, $\mathrm{area}_{\mathrm{A1}}$ is the area of that ziptract, $\mathrm{area}_{\mathrm{A}}$ is the total area of that zip code, and $\#\mathrm{tracts}_{\mathrm{A}}$ is the total number of tracts in zip code A.

Once computed, the population fraction and area ratios are multiplied together and then again normalized to determine a total fraction for each ziptract. The calculation would be written in this way:

$$\mathrm{tf}_{\mathrm{A1}} = \frac{(\mathrm{pf}_{\mathrm{A1}} \times \mathrm{ar}_{\mathrm{A1}})}{((\mathrm{pf}_{\mathrm{A1}} \times \mathrm{ar}_{\mathrm{A1}}) + (\mathrm{pf}_{\mathrm{A2}} \times \mathrm{ar}_{\mathrm{A2}}) + (\mathrm{pf}_{\mathrm{A3}} \times \mathrm{ar}_{\mathrm{A3}}))}$$

Here, $\mathrm{tf}_{\mathrm{A1}}$ refers to the total fraction for the ziptract for zip code A and tract 1, $\mathrm{pf}_{\mathrm{A1}}$ is the population fraction and area ratios for the tracts 1, 2, and 3 are listed as above. Once calculated, the recorded population of SNAP clients for the zip code in the benefit distribution data is multiplied by this total fraction to determine the estimated number of clients living within the ziptract.

3.2 Benefit Distribution: From Ziptract to Raster Cell

Once our benefit distribution data is disaggregated to the ziptract scale, we use zoning and land use classification data to create a density raster. The zoning data contain five residential classifications (farmstead, single family detached, single family attached, multifamily, and manufactured housing). This data is converted from vector to a 30×30 m raster so that both datasets have the same formatting and resolution. We clip the land cover layer to match the extent of the zoning data, resulting in four classifications (open land, urban-light use, urban-medium use, and urban-heavy use). We then combine these two rasters to create a new layer containing 20 distinct classifications (farmstead-open land, farmstead-light use, etc.). These datasets are complementary: an area on the urban fringe zoned single family detached has a very different density than the same zoning category in the urban core.

Since no population variable could be used to weight data at this scale, we then calculate our own density weights based on our ziptract data. The density of SNAP participants was calculated for each ziptract by dividing our estimated count by the ziptract's area. Using the ArcGIS zonal statistics tool, we then determined the average density of each of our 20 classifications. These densities then became the weights for our disaggregation. Similar to the first stage, these weights were normalized by dividing them by the sum of weights for all classes within a zip tract. For example, in zip tract B containing land use classes 10, 20, and 30, the population fraction for land use 10 would be calculated as

$$\mathrm{pf}_{\mathrm{B}10} = \frac{\mathrm{w}_{\mathrm{B}10}}{(\mathrm{w}_{\mathrm{B}10} + \mathrm{w}_{20} + \mathrm{w}_{30})}$$

where $\mathrm{pf}_{\mathrm{B}10}$ is the population fraction for class 10, $\mathrm{w}_{\mathrm{B}10}$ is the calculated weight for class 10, and $\mathrm{w}_{\mathrm{B}20}$ and $\mathrm{w}_{\mathrm{B}30}$ are the weights for classes 20 and 30.

Zonal statistics were again used to sum the area of each classification within ziptracts and to calculate the ziptracts total area. The area ratio was calculated as in step 1 of our research:

$$\mathrm{ar}_{\mathrm{B}10} = \left(\frac{\mathrm{area}_{\mathrm{B}10}}{\mathrm{area}_{\mathrm{B}}}\right) \Big/ \left(\frac{1}{\#\mathrm{classes}_{\mathrm{B}}}\right)$$

Where $\mathrm{ar}_{\mathrm{B}10}$ is the area ratio of class 10 in ziptract B, $\mathrm{area}_{\mathrm{B}10}$ is the area of class 10 in ziptract B, $\mathrm{area}_{\mathrm{B}}$ is the total area of ziptract B, and $\#\mathrm{classes}_{\mathrm{B}}$ is the number of classes present in ziptract B.

The "total fraction" is also calculated as in the previous stage. The estimated ziptract population was multiplied by this fraction to determine the population of each class within each zip tract. Assuming a equal dispersion, this population was then distributed within each class by dividing it by the number of cells, which is found by dividing the total class area by the cell size.

3.3 Benefit Redemption

Data on SNAP benefit redemption is also aggregated by zip code. Unlike the benefit distribution data described above, redemption data is disaggregated to discrete points. This method of moving from polygons to points was simpler, as no area weighting was needed. Following data privacy restrictions, the data set we obtained from the USDA excludes zip codes that contained 3 or less eligible locations, largely on the urban fringe or affluent neighborhoods (Names and addresses of SNAP eligible vendors are available as a downloadable spreadsheet at a USDA website (http://www.snapretailerlocator.com)). For this analysis we use a geocoded list of vendors for federal fiscal year 2010, the period of this study. We code these stores based on categories adapted from USDA's own reporting. National rates of redemption at these various store types are available, and we used these rates to weight our disaggregation (USDA 2009, p. 62). For example, in 2008, 47 % of food stamp benefits were redeemed at supermarkets, meaning that supermarkets in our scheme received a raw weighting of 0.47.

Our method of disaggregation here is similar to the population fraction described above. For each zip code, we summed the number of stores in each classification. These weights are then normalized by dividing the weight of each store by the sum of weights for all stores within a zip code. This normalized weight is then multiplied

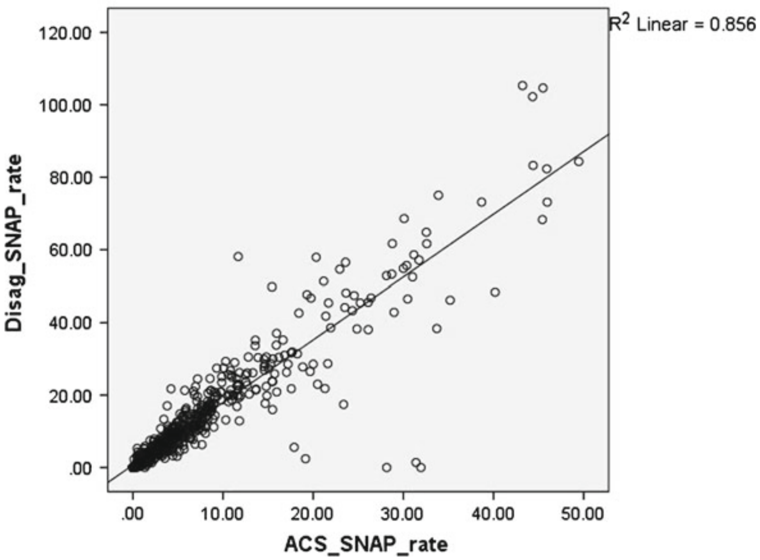

Fig. 5 Disaggregated SNAP rates for tracts measured against the reported ACS household SNAP rate

by benefit redemption amount for the zip code, with the result being an estimate redemption amount for that particular store. For store 1 in zip code A, which also contains stores 2, 3, and 4, this would be written

$$\mathrm{red}_{A1} = \mathrm{red}_A \times \frac{\mathrm{rw}_{A1}}{(\mathrm{rw}_{\mathrm{A1}} + \mathrm{rw}_{\mathrm{A2}} + \mathrm{rw}_{\mathrm{A3}} + \mathrm{rw}_{\mathrm{A4}})}$$

where $\mathrm{red}_{\mathrm{A1}}$ is the estimated redemptions at store 1 in zip code A, $\mathrm{red}_{\mathrm{A}}$ is the total redemption dollars in zip code A, and $\mathrm{rw}_{\mathrm{A1}}$, $\mathrm{rw}_{\mathrm{A2}}$, $\mathrm{rw}_{\mathrm{A3}}$, and $\mathrm{rw}_{\mathrm{A4}}$ are the raw weights assigned to stores 1, 2, 3, and 4 respectively.

4 Results

4.1 Disaggregation of Benefit Distribution Figures

To assess the effectiveness of this method, we reaggregate ziptracts back to the tract level, summing their estimated population of SNAP clients. Using total population from the 2010 Census, we create a ratio of SNAP clients to the general population and plotted this rate against the household participation rate in the ACS data. We expected to find a strong overall correspondence between these variables, which this analysis confirmed (Fig. 5). There were a handful of upper and lower outliers. The

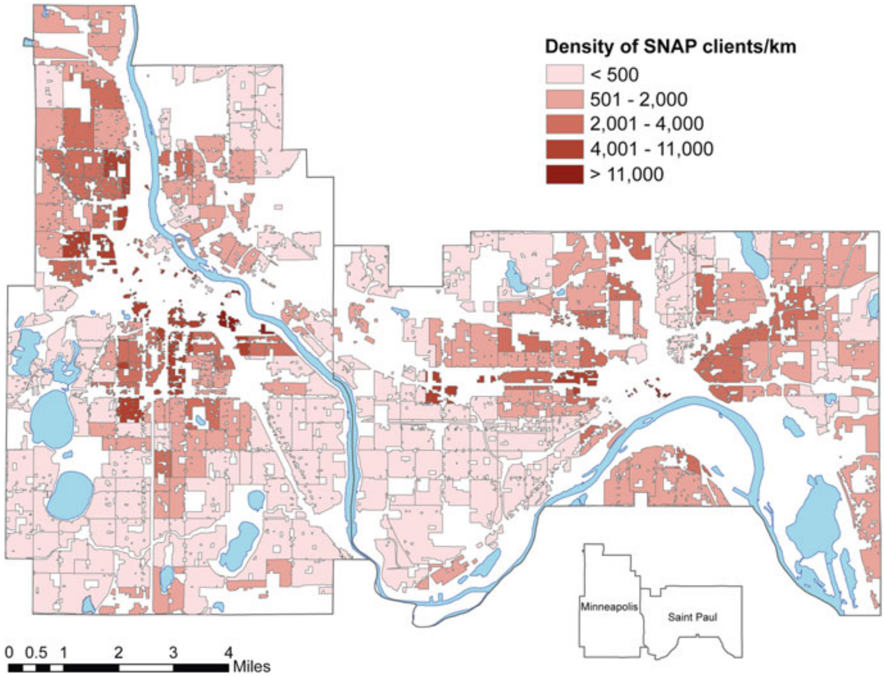

Fig. 6 Modeled density of SNAP clients per ziptract (residential areas only), September 2010

latter were explained by our data on actual SNAP participation, which in the case of lower outliers were lower than ACS estimates. The former are concentrated in three zip codes with high SNAP participation overall. They are potentially addressed through bounding the upper limit of the disaggregation, and the use of this technique will be incorporated in future research. It is also worth noting that SNAP participation numbers were significantly higher than ACS rates ($\beta = 1.73$). This factor may reflect undercounting or the effects of the economic recession, which began in 2008, as the difference between household and individual counts alone is unlikely to explain the difference.

This weighting also was more effective than just disaggregation based on area. Comparing Figs. 1 and 6, in the northwest quadrant of Minneapolis, there is much more internal heterogeneity than the zip code data alone would indicate. The east/west gradient of this data is particularly visible and there is relatively little remaining effect from the zip code boundaries in the choropleth map.

The full disaggregation using zoning and land use classifications provides further detail, with differences in estimation within census tracts clearly visible, though tract boundaries still had a significant effect (Fig. 7). In the southern section of Minneapolis, for example, the gradient from high to low values was smoothed significantly (Fig. 8).

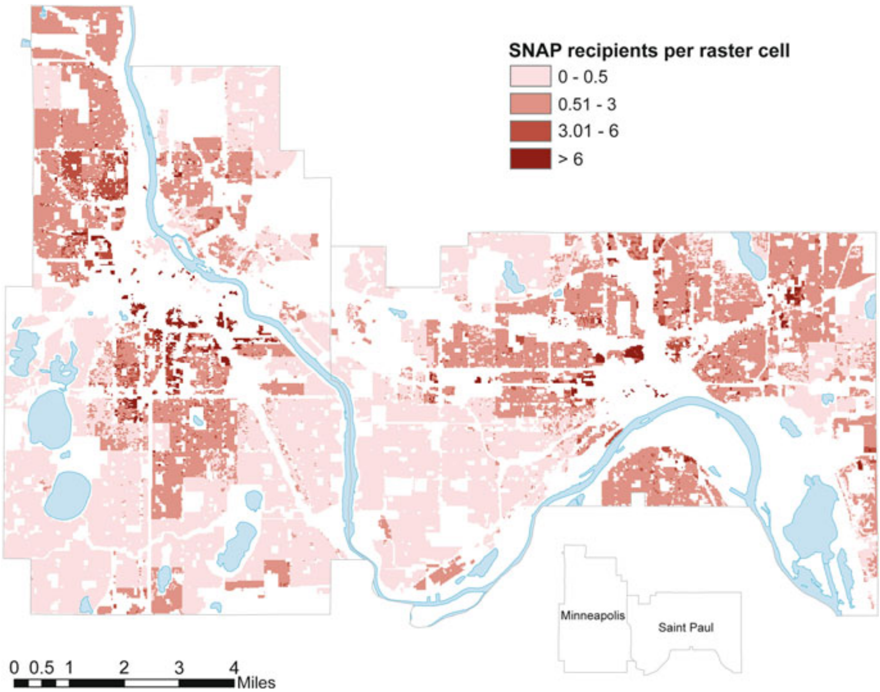

Fig. 7 Modeled density raster of SNAP clients, Sept. 2010

4.2 Disaggregation of Benefit Redemption

Disaggregating store information provides estimated benefit redemption at 1,352 stores in the Twin Cities metro area. Examining the distribution of these stores their placement along major roadways becomes apparent (Figs. 9 and 10). This highlights the potential boundary effects of analysis on zip code data and the improved usability of this dataset. By far, the largest source of redemption dollars in the Twin Cities is supermarkets (65 % of total redemptions), which is unsurprising as it was weighted most heavily in our disaggregation (Fig. 9). Convenience and corner stores represent nearly half of total stores, though they account for only 23 % of total redemptions. This is higher than national redemption rates, and further testing of this procedure might further refine this technique to better match the national sample.

5 Conclusions and Future Research

Areal interpolation provides a useful way to facilitate analysis of data on food shopping practices in low-income neighborhoods. By adapting these methods to a two-stage process for benefit distribution and using a similar procedure to estimate

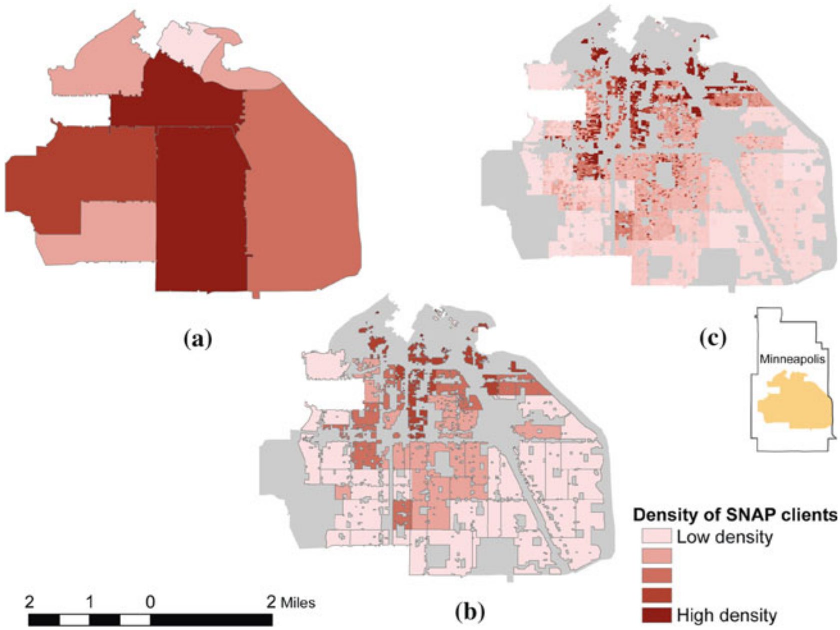

Fig. 8 Results of the two stage process of disaggregation with zip codes (**a**), ziptracts (**b**), and raster (**c**)

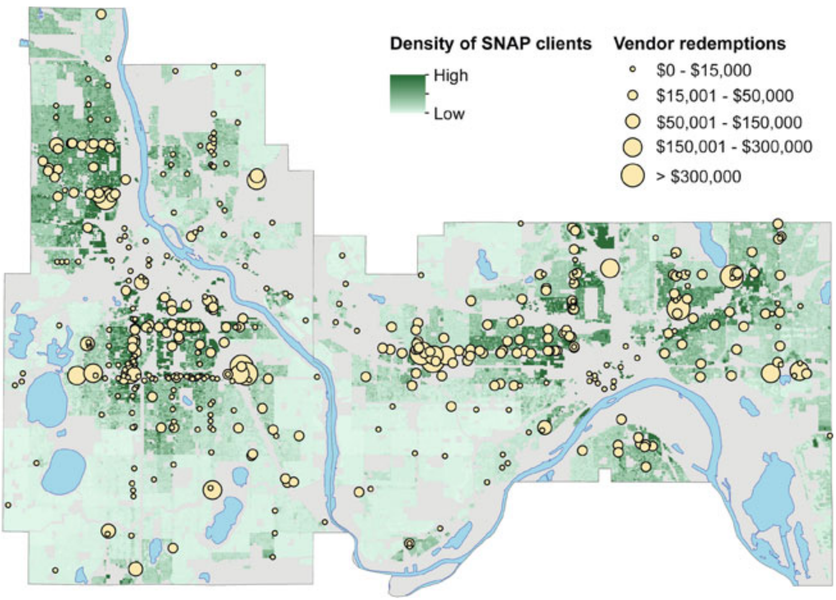

Fig. 9 Graduated symbol map of the modeled density of SNAP clients and estimated benefit redemptions in Minneapolis and St. Paul, Sept. 2010

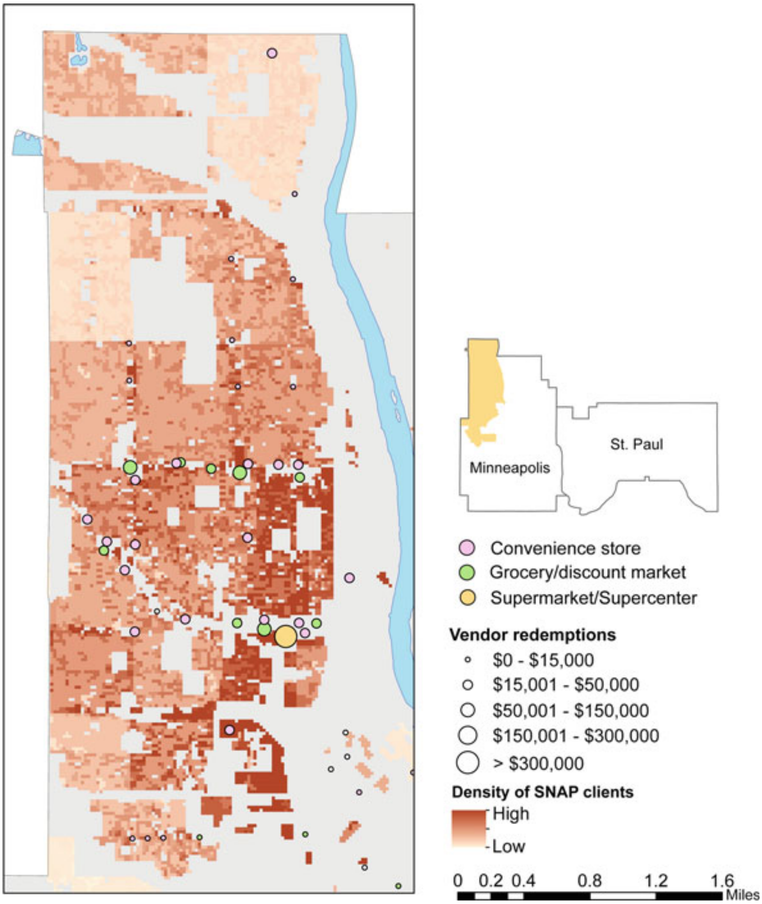

Fig. 10 Modeled density of SNAP clients and benefit redemptions by store in north Minneapolis, Sept. 2010

redemptions at individual store locations, we can begin a neighborhood-level analysis, which avoids the scalar and boundary effects of zip code data. Ground truthing the accuracy of these estimates could be a main task of future research.

Nonetheless, the initial results of our analysis have shown that the use of areal interpolation techniques in this context can contribute significantly to research on issues of neighborhood influences on food access. By producing fine scale data on the usage of food assistance programs, this method can shed light on a number of areas: the profile of food benefit distribution and usage in varying low-income neighborhoods, the relationship between food stamp usage and other measures of disparity such as poverty rate, and the effects of distance to various food outlets on household shopping patterns. More specifically, future research will aggregate benefit disbursement and redemption through checkerboard grids of decreasing size to analyze the scale at which poor access to food sources (measured as net outflows of food assistance) becomes noticeable. This data may also better demonstrate the role of small and mid-sized markets in providing access to food in low-income neighborhoods. This is particularly helpful as these stores are most common in dense urban areas and not often included in food desert measures. In sum, we find this a promising technique to advance knowledge of food deserts and their consequences.

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