UNPACKING RURALITY

Evaluating the impact of rural community characteristics and the built environment on SNAP participation

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1 INTRODUCTION

A growing body of research has explored the impacts of the built environment on nutrition and health. The built environment—human-constructed aspects of the physical environment such as transportation infrastructure, land use and city design, and recreational facilities— has been shown to influence physical activity, nutrition, and rates of obesity (Ball, K. et. al., 2005; Gordon-Larsen et al., 2006; McKinnon et al., 2009; Sallis and Glanz, 2006; Simen-Kapeu et al., 2010). Many studies have focused specifically on the availability of retail outlets selling healthy food within a certain "accessible" geographic area as a significant determinant of healthy eating patterns (Burns et al., 2004, Hosler et al., 2006; Larson et al., 2009; Walker et al., 2010). However, few studies have applied similar measures to examine how participation in public assistance programs may be mediated by access.

Many of the earliest explorations of food environments and access arose out of the concept of a "food desert," a term first coined in the early 1990s (Cummins and Macintyre, 2002). The earliest definitions of food deserts specified these regions as urban areas with few food retailers, in which access to healthy, affordable food is highly limited (Cummins and MacIntyre, 2002; Hendrickson et al., 2006). The concept of food deserts has since been expanded beyond the purely urban context to more generally denote areas with poor access to food due to a general lack of food retailers or a lack of larger supermarkets that provide a wider selection of more affordable food (Shaw, 2006; Ver Ploeg et al., 2009). However, much of the newest and most innovative research regarding food access remains focused in urban areas, due to ease of measurement and availability of data, despite the great needs for further research in rural areas.

Rural areas and food access

Rural areas face special challenges in the realms of food access and health. Urban-rural health disparities in obesity prevalence and nutrition have been widely acknowledged in the recent literature (Guy, 1991; Larson et al., 2009; McKinnon et al., 2009; Simen-Kapeu et al., 2010). Simen-Kapeu et al. (2010) noted that both Canadian and U.S. studies have found higher obesity and overweight prevalence in children and youth living in rural environments (128). McKinnon et al. (2009), in a review of 137 articles addressing food environments, similarly find that rural populations face higher risks of obesity and also display greater sensitivities to environmental variables than non-rural populations, yet they found that few instruments have been developed to measure food environments in strictly rural contexts (S129).

A number of the studies in rural areas have focused solely on the availability and cost of food in area stores, reaching the same conclusion that food cost and availability are often compromised in rural areas (Burns et al., 2004; Guy, 1991; Hosler et al., 2006; Liese et al., 2007; McEntee and Agyeman, 2010; Yeager and Gatrell, 2014). Although studies of food availability across rural areas are important, few studies of the built environment in rural regions consider variations within rural communities, instead using rural as a monolithic identifier in opposition to urban communities (Boehmer et al., 2004; Burns et al., 2004; Hosler et al., 2006; Liese et al., 2007; Sharkey and Horel, 2008; Simen-Kapeu et al., 2010). The lack of exploration of intra-rural variation is problematic because knowing that an area is "rural" tells us very little of the context of the community—the needs of a family in a small, well-established farming town may have little in common with that of a family in a rather transient warm-winter haven along a freeway. This project begins to fill the existing gap in studies of the rural built environment and food access through the exploration of the impact of intra-rural cleavages and the built environment on participation in Supplemental Nutrition Assistance Program (SNAP).

SNAP participation in rural areas

This project follows several recent explorations of social conditions surrounding SNAP participation and health outcomes associated with program participation. Multiple studies have examined the impacts of SNAP participation on childhood and adult obesity, finding that SNAP participation is often related to high obesity and overweight prevalence across all age groups (Genser, 2009; Han et al., 2012; Leung et al., 2013; Leung and Villamor, 2011; Simmons et al., 2012; Vartanian and Houser, 2012). Very few studies have explored the impact of social and environmental factors on SNAP participation. Lacombe, Michieka, and Gebremedhin (2012) use Bayesian spatial econometric modeling to study the influence of key economic factors and immigration on SNAP participation in 417 Appalachian counties, finding that poverty and employment exert the largest influence on SNAP participation. Leftin, Eslami, and Strayer (2011), in a study of trends in SNAP participation by Mathematica Policy Research on behalf of the USDA, found that SNAP participation remains highest among households with children and individuals with the highest need and that participation rates were influenced by the economic downturn, changes in benefits, and increased outreach. However, neither of these studies considered the influence of additional social and community characteristics or the built environment on SNAP participation.

Addressing methodological challenges in studying rural areas

One of the continuing challenges of research into social and community characteristics in rural areas is data acquisition and the need to move data between varyingly-defined spatial units. Commonly-termed the “modifiable areal unit problem,” the arbitrary nature of the definitions of spatial units can confound statistical analysis (Openshaw, 1984). Mennis (2003) notes the inherent problems associated with the most commonly used small-area demographic datasets, such as the US Census, in that data are aggregated to arbitrary areal units such as blocks, block groups, and census tracts (31). The use of such units in geographic analysis assumes that the characteristics assigned to each unit are evenly distributed across the area of that unit, when the true distribution may be quite uneven due to both natural and built physical features such as lakes, mountain slopes, and patterns of land use (ibid.).

J.K. Wright (1936), an early 20th century cartographer, popularized a method of areal interpolation termed “dasymetric mapping.” In dasymetric mapping, physical characteristics of a geographic surface, such as land zoning and topographic terrain, are derived from ancillary datasets. These are then used to guide areal interpolation (conversion of spatial data from one set of units to another) to develop a continuous data surface that more accurately represents a population distribution than a choropleth map based on administrative areal units could (Eicher and Brewer, 2001; Mennis, 2003). Both Mennis (2003) and Eicher and Brewer (2001) found that use of dasymetric mapping, guided by ancillary land use data, to generate surfaces for socioeconomic and demographic variable distributions from the US Census produced highly accurate raster surfaces with finer detail than is often achieved through choropleth mapping. Dasymetric mapping approaches to area interpolations and remodeling of Census data have become widely used in geographic and urban planning literature, particularly since 2004 (Petrov, 2008; Wu et al., 2005). Shannon (2014) demonstrated the utility of a dasymetric approach to the specific study of SNAP benefit usage and food access.

This project uses these dasymetric mapping approaches and other quantitative methods to build upon prior research into the factors influencing SNAP participation through an exploration of the impact of rural community characteristics and retailer access on SNAP participation.

2 Research Objectives

There were two primary aims of this project. The first was to explore the relationship between theoretically-specified socio-geographical rural community characteristics and SNAP participation and how this relationship is mediated by access to SNAP-authorized retailers. Through the use of an exploratory technique, sequential canonical analysis, we attempted to identify factors that lead some communities to under-utilize SNAP.

The second aim was to develop a typology that could differentiate among rural areas based on these community characteristics. This approach follows from work done by Scholz and Herrmann (2010) on behalf of the European Union Rural Future Networks project to develop a typology of rural regions in Europe, and from geodemographic segmentation systems already used widely in commercial marketing (Spielman and Thill, 2008). Through the use of cluster analysis, we aimed to identify multiple discrete categories of rural communities that can be used to better understand the varying needs of different rural populations across a state.

By identifying socio-geographical indicators of SNAP utilization, and the communities where they cluster, we hope to be able to better develop and target outreach programs to rural communities with greatest need.

3 Methodology

3.1 Study Area

This study examines data for the rural population of the state of Arizona. For the purposes of this study, we define the rural population as any persons not living in a Census designated urban area. Urban areas, as defined by the US Census, are Census-designated places with populations greater than or equal to 50,000 (USDA, 2007). We have chosen to use the Census definition of rural and urban due to the limitations of county-based definitions to accurately capture the rural and urban populations of Arizona. Due to the large size of Arizona's counties, many counties are classed as metropolitan counties despite possessing sizable rural populations. For example, according to the 2010 US Census in Yavapai and Cochise counties, both classified as metropolitan by the USDA definition, approximately 35 percent of the population lives outside an urban cluster and 60 percent of the population live outside a cluster with a population of more than 50,000. Using the broader Census definition of rural allowed us to capture greater variability within rural areas in the state. Based on this definition of rural, our study looks at a population of approximately 1.3 million people that accounts for about 20 percent of the population of the state of Arizona.

We chose to study the rural population of the state of Arizona because of our team's extensive experience working in the state's rural communities through partnerships with many agencies and community organizations across the state. The extensive network our team has cultivated in the state of Arizona assisted in data acquisition and contextualization of results.

3.2 Data Sources

We drew data for this project from three existing datasets. Community demographic and socioeconomic data were obtained at the Census tract level from the 2010 US Decennial Census and the 2008-2012 American Community Survey (ACS) Five-Year Estimates. Select community health indicators were drawn from the Arizona Department of Health Services 2012 Primary Care Area Statistical Profiles. SNAP participation data were acquired from the Arizona Department of Economic Security, which administers SNAP benefits within the state of Arizona, by zip code.[1]

3.3 Data Processing

Spatial data are often collected and aggregated to a variety of geographic statistical units. In this study, the data obtained came at three different geographic unit scales: Census tract, zip codes, and Primary Care Areas (PCAs), a statistical unit created by the Arizona Department of Health Services. Holt, Lo, and Hodler (2004) suggest that dasymetric methods can be applied to re-aggregated geographic data between differing boundary definitions with a satisfactory level of accuracy. Following their approach, we used dasymetric mapping to generate raster data surfaces for the demographic and socioeconomic variables drawn from the 2010 Decennial US Census and the American Community Survey (ACS) 2008-2012 5 year-estimates as well as health variables from the Primary Care Area (PCA) Statistical Profiles and the 2012 SNAP enrollment dataset. All of these data surfaces were re-aggregated to the census tract level to ensure a consistent unit of analysis.

For the dasymetric mapping, a six-class model was created using land ownership data from the Bureau of Land Management, land cover data from the United States Geologic Service National Land Cover Dataset, and hydrologic, topographic, and infrastructure data from the Arizona State Land Department. The study area was classified into six land types: unpopulated, vegetated public land, vegetated private land, agricultural land, low-density developed land, and high-density developed land (see Table 1, page 13). We followed Mennis (2003) in developing population density fractions. A population density surface for each selected variable was created from the original source data at the geographic level provided (tract, zip code, or primary care area). The unpopulated land type was assigned a zero population density *a priori,* but density fractions for the other five land types were generated for each variable through the use of zonal statistics within each of Arizona's fifteen counties to determine the average variable population density within that zone by county. Following Mennis (2003), these average densities were converted to density fractions using overlay, raster calculator, and zonal statistics functions in ESRI ArcGIS. First, identity functions were used to create a composite geography of areal units of analysis (i.e., tracts, zip codes, PCAs), land class zones, and counties. For an area *t* of zone *k* in county *c* the population fraction (*d*) equals the average population density of that zone in county *c*

[1] We had initially planned to obtain health and nutritional outcomes from the 2012 Behavioral Risk Factor Surveillance Survey (BRFSS), obtained through the Arizona Department of Health Services. However, in the course of the research, the 2012 BRFSS was found to have insufficient coverage of Arizona's rural areas, precluding it from inclusion in our analysis. Unfortunately, 2014 data were not available in time to be processed for this report, and will be included in subsequent iterations of the models.

divided by the sum of all average population densities in county *c.* For that same area *t*, the area fraction (*g*) equals the portion of area *t* that falls into zone *k* divided by the total area *t* multiplied by the total number of zones. The population density fraction (*f*) for area *t* of zone *k* in county *c* equals the population fraction (*d*) multiplied by the area fraction (*g*) divided by the sum of the products of the population fractions multiplied by the area fractions for all areas within area *t*.

Raster data surfaces with a 30m pixel resolution were generated for all 30 input variables selected as well as their population denominators in addition to six outcome variables. All data were re-aggregated to the 2012 census tract level for analysis. Six census tracts containing several military bombing ranges and wildlife refuges with a total population of 0 were excluded from analysis. The total N for the study was 399 census tracts.

3.4 Variable Selection and Creation

Variable selection for our analysis was based on previous work around rural typology development, geodemographic segmentation, and socio-biogeographical analysis. Scholz and Hermann (2010) in their work on European rural typologies used primarily economic indicators. Spielman and Thill (2008) in their work on geodemographic segmentation used indicators having to do with population age and ethnicity, housing characteristics, and economic and educational attainment characteristics. Cabeza de Baca and Figueredo (2014) developed an integrated model of human ecology that takes into account both life history and social privilege paradigms in examining social outcomes. Their model draws on the idea that slow life history (indicated in our models by higher life expectancies, lower birth rates, and lower infant mortality) is an indicator of a more stable and predictable environment, which helps contribute to the development of human capital and associated positive social outcomes in communities.

We created ten indicators, from 30 selected input variables theoretically suggested by these approaches to be social and community factors likely to impact health-related outcomes, which could be mediated by access to food assistance. These variables were drawn from the American Community Survey and decennial Census and PCA statistical profiles, and included two derived access variables. Some were single items and some were composite indicators. The indicators included were **population density** (single item), **slow life history** (composite), **median age** (single item), **work engagement** (single item), **economic sector** (composite), **income equality** (composite), **linguistic isolation** (single item), **migration** (composite), **ethnicity** (composite), and **resource access** (composite) (see Table 2, page 14). As noted above, all indicators were at the 2012 census tract level, for an N of 399.

The two access variables making up resource access were generated using ESRI ArcGIS. The first, **distance to urban centers**, was a measure of driving time to the nearest urban area with a population greater than 50,000. The second was a measure of **driving time to the nearest SNAP-authorized retailer**. SNAP-authorized retailer locations were obtained from the USDA SNAP retail locator as of September 2013, and locations were validated using satellite imagery in Google Earth.

To create the access surfaces, a road network for all roads within the state of Arizona and a 50 mile buffer around the state was buffered by four meters and converted to a raster surface with values determined by the speed limits assigned to those roads. This road surface was converted to a cost surface by inverting those speed limits so that they represented minutes per mile traveled. This cost surface was then used to create a path distance surface using the ArcGIS Path Distance tool, which calculates the accumulated cost to traverse a surface given a set of origin points. The resulting two surfaces provided a continuous raster surface showing the estimated driving time to an urban center or to a SNAP retailer. This method of measuring access is limited as it does not account for traffic congestion, one-way streets, or other more complex navigational challenges, but for this analysis we felt it provided a sufficient measure of both retailer access and remoteness from a major urban center.

In addition to SNAP drive time, five other outcome variables were created for use in a series of multiple regressions examining the direct and indirect effect of social and community characteristics on SNAP enrollment (referred to below as the cascade analysis) (see Table 2, page 14). The first of these, **human capital**, was a composite factor capturing educational attainment, material wealth (e.g., home ownership, home value, vehicle ownership, etc.), and income. Because SNAP is a means-based assistance program, socioeconomic status should affect SNAP enrollment, and we wanted to control for this effect as a major causal factor. The distribution of human capital across the state is shown in Figure 1, page 16. The other four variables related to SNAP enrollment. Estimated **percentages of adults enrolled in SNAP and children enrolled in SNAP** were created by dividing the average monthly enrollment numbers for 2012 for adults and children by the census population numbers of children and adults. **SNAP enrollment differential variables for adults and children** were created by subtracting the percentage of adults and the percentage of children living at or below 200 percent of the poverty level from the estimated percentage enrolled in SNAP. These variables allowed us to assess SNAP enrollment relative to the low-income population. Preliminary analyses suggested that factors related to adult enrollment were likely to be different than those related to child enrollment. Because this study was conceived of as an initial examination of the feasibility and utility of these methodological approaches, for the purposes of interpretability, we opted to focus on child SNAP enrollment in our analyses

3.5 Data Analysis

We undertook a multi-phase analysis of the re-aggregated data with two primary goals: 1) to identify the relation of key rural characteristics with access to SNAP retailers and impact on SNAP participation, and 2) to develop a rural typology that captures the variations between communities with these key characteristics.

Our first phase involved the exploration of the influence of the chosen rural factors on retailer access and SNAP participation by structuring a pattern of regressions referred to as a *cascade model* in cognitive psychology (Demetriou, Christou, Spanoudis, & Platsidou, 2002). In a cascade model, a series of multiple regressions is performed in which the multiple criterion (outcome) variables are analyzed sequentially according to a hypothesized causal order.

Because these criterion variables are expected to causally influence each other (that is, the identified socio-geographic indicators are hypothesized to influence human capital in a community and human capital is likely to influence access, which is likely to influence nutrition assistance participation), they are entered sequentially into a system of multiple regression equations with each hierarchically prior criterion variable entered as the first predictor for the next. In this way, each successive criterion variable is predicted from an initial predictor variable, each time entering the immediately preceding criterion variable as the first predictor, then entering all the ordered predictors from the previous regression equation. Each successive regression enters all of the preceding criterion variables in reverse causal order, to statistically control for any indirect effects that might be transmitted through them.

Within this analytical scheme, the estimated effect of each predictor is limited to its direct effect on each of the successive criterion variables.

Analogous to a Sequential Canonical Analysis (SEQCA), this kind of cascade model has been proposed to serve as an exploratory form of path analysis (Figueredo & Gorsuch, 2007) where the exact model specification cannot be completely predicted by existing theory. Formal Structural Equation Modeling (SEM) would be unsuitable for the current study because SEM requires a complete model specification based on strong a priori theory, whereas this work, though theoretically based, is exploratory in nature. A cascade model therefore provides a theoretically-guided exploration rather than a formal and confirmatory test of a priori theory, which is very appropriate in the context of this early work.

The general schematic format for this system of multiple regressions for this study was:

$$Y(\text{HumanCapital}) = \beta_1 \text{ Socio-geographic (SG) Indicators}$$

$$Y(\text{Access}) = \beta_2 \, Y(\text{HumanCapital}) + \beta_1 \text{ SGIndicators}$$

$$Y(\text{SNAP Enrollment}) = \beta_3 \, Y(\text{Access}) + \beta_2 \, Y(\text{HumanCapital}) + \beta_1 \text{ SGIndicators}$$

$$Y(\text{SNAP Differential}) = \beta_4 \, Y(\text{SNAP Enrollment}) + \beta_3 \, Y(\text{Access}) + \beta_2 \, Y(\text{HumanCapital}) + \beta_1 \text{ SGIndicators}$$

We then used cluster analysis of the factors in the model to develop community clusters that served as the basis for our rural community typology. Our use of cluster analysis follows work done by Scholz and Herrmann (2010) on behalf of the European Union Rural Future Networks project that used k-means cluster analysis to develop a typology of rural development regions in the European Union. Similar techniques have long been used in marketing as a key component of geodemographic segmentation systems, which aim to develop discrete categories of consumers based on behavior, demographic, and lifestyle data by which small geographic areas can be classified (Spielman and Thill, 2008). We used k-means clustering, an unsupervised learning technique, to develop clusters of rural communities from which our typologies were drawn.

4 RESULTS

4.1 CASCADE ANALYSIS

We ran the cascade analysis with four outcome variables: human capital (Y1), mean drive time to a SNAP authorized retailer (Y2), estimated percent of children enrolled in SNAP (Y3), and child enrollment in SNAP relative to low-income status (Y4). The results, with each criterion variable statistically controlled in reverse order, are shown in Table 3 to Table 6, on pages 20-23 The overall pooled multivariate effect size for the model was large ($V=1.428$, $E=.6$, $F_{60,1532}=14.18$, $p<.001$).

In the first cascade, we predicted human capital from indicators selected to be likely to influence socioeconomic well-being in rural areas. Higher resource access (sR=.38), percent white (sR=.14), income equality (sR=.13), housing health (sR=.09), primary (sR=.16) or secondary (sR=.09) sector employment[2], work engagement (sR=.19), and higher median age of the census tract population (sR.10) were all

[2] Primary-sector employment includes agriculture and mining; secondary-sector employment includes manufacturing and construction; tertiary-sector employment includes the service industry.

associated with higher levels of human capital. Linguistic isolation (sR=-.42), percent Hispanic or Latino (sR=-.26), and percent non-Hispanic non-white (sR=-.25) were associated with lower levels of human capital. (The effect sizes presented are semi-partial correlations. See Table 3 for additional details. A schematic representation of the statistically significant direct effects are presented in Figure 5.)

In the second cascade, we predicted access (driving time) to SNAP retailers using the same indicators, controlling for their relation via human capital. Here, we found that human capital (sR=-.24) was significantly negatively correlated with mean drive time to a SNAP retailer (that is, tracts with higher human capital tended to have lower drive time to retailers). In addition to the indirect effects some variables had through human capital, resource access (sR=-.52), linguistic isolation (sR=-.21), percent Hispanic or Latino (sR=-.09), percent non-white non-Hispanic (sR=-.08), tertiary (sR=-.15)and secondary (sR=-.14) sector employment, work engagement (sR=-.09), and population density (sR=-.21) were also directly significantly negatively correlated with SNAP drive time. (See Table 4, page 21 for additional details. A schematic representation of the statistically significant direct effects are presented in Figure 6.)

In the third cascade, we predicted Census tract levels of child SNAP enrollment, based on estimates obtained via dasymetric mapping. Human capital (sR=-.53) was significantly negatively correlated with child SNAP enrollment (tracts with lower levels of human capital had a higher proportion of children enrolled in SNAP), but there was no statistically significant relationship between SNAP drive time and child SNAP enrollment. Even controlling for the effects through human capital, linguistic isolation (sR=.13), all employment sectors (primary sR=.20; secondary sR=.10; tertiary sR=.11), median age (sR=.09), and population density (sR=.41) were positively correlated with child SNAP enrollment. Resource access (sR=-.08), percent non-white, non-Hispanic (sR=-.11), and work engagement (sR=-.08) were negatively correlated with child SNAP enrollment. (See Table 5, page 22 for more details. A schematic representation of the statistically significant direct effects are presented in Figure 7.)

In the fourth cascade, child SNAP enrollment (sR=.67) had a positive relationship with relative child SNAP enrollment, meaning that as overall child enrollment increases, the gap between the percent of children that are low-income and the percent of children enrolled in SNAP decreases. Also, human capital (sR=.46) had a direct positive correlation, after partialling out the negative indirect effect through its relationship with child SNAP enrollment. However, SNAP drive time (sR=-.18) was significantly negatively correlated with relative child SNAP enrollment, suggesting that access to SNAP retailers does have a mediating role in SNAP enrollment. In communities with poor access to SNAP retailers (higher driving times to retailers), there are greater percentages of low income children who are not enrolled in SNAP, even though there is no direct relationship with child SNAP enrollment. Percent non-white non-Hispanic (sR=.08), income equality (sR=.14), work engagement (sR=.16), median age (sR=.12), and slow life history (sR=.07) were significantly positively correlated with parity in child SNAP enrollment, even after partialling out the effect through human capital and percent of SNAP enrollment where there was one. Linguistic isolation (sR=-.07), percent Hispanic or Latino (sR=-.05), percent white (sR=-.08), migration(sR=-.13), and primary-sector employment (sR=-.18) were significantly negatively correlated with relative child SNAP enrollment. (See Table 6, page 23 for more details. A schematic representation of the statistically significant direct effects are presented in Figure 8.)

4.2 CLUSTERING

To increase interpretability of this data in order to make these results more easily actionable, we used k-means clustering to create a typology of rural communities in Arizona based on our input variables and our human capital factor. Because k-means clustering is an unsupervised learning method that does not produce an outcome measure of fit or error, it is left to the experimenter to choose appropriate clusters. As such, we ran multiple cluster analyses with differing allowed numbers of clusters, and chose an eight-cluster set that was both interpretable and that had face validity with those working in these rural communities in Arizona.

The clusters were named based on their relative levels of the variables included, and on other characteristics of the areas (see Figure 10, page 25).

Ag/Mining/Forestry: This cluster encompassed areas of the state known for mining and agriculture. It had the highest primary-sector employment and lowest tertiary-sector employment as well as low population density.

Border City: This cluster encompassed the smallest tracts at the center of towns straddling the US-Mexico border. It was characterized by high population density, high linguistic isolation, high migration, high Hispanic population, and low housing capital.

Border Periphery: This cluster encompassed the tracts surrounding the border cities. It was characterized by high migration, high Hispanic population, high primary-sector employment, and high linguistic isolation.

Mixed Migrant: This cluster encompassed tracts widely spread across Arizona. It was the most ethnically diverse cluster, with high migration and high primary- and secondary-sector employment as well.

Suburb/Historically Mormon: This cluster encompassed many of the tracts closest to major cities in Arizona as well as a number of areas that were historically founded by Mormon settlers. This cluster possessed the highest resource access, the highest income equality, the highest work engagement, highest human capital, and the lowest primary-sector employment.

Retirees: This cluster encompassed the belt across central Arizona known for its snowbird population as well as some of the major retirement destinations in the state. It had the highest median age, highest white population and the slowest life history, while also being characterized by high human capital and low work engagement.

Scenic: This cluster encompassed much of northern Arizona, including many popular locations for vacation homes. It was characterized by high median age, the highest housing capital, high work engagement, high secondary-sector employment, and a high proportion of white residents.

Tribal: This cluster encompassed the majority of the reservation lands within Arizona. It possessed the highest non-white and non-Hispanic population with low migration, low median age, fast life history, and low income equality.

The means and standard deviations of the four outcome variables by cluster are shown in Table 8, ordered by percentage of child SNAP enrollment relative to child low income. As might be expected, the clusters with the highest mean human capital (Retiree, Scenic and Mormon/Suburb), have the lowest proportion of child SNAP enrollment. Four clusters have a greater than 10 percent disparity between enrollment and low income: Tribal, Mixed Migrant, Border Periphery, and the Ag/Mining and Forestry tracts. The clusters with the two highest drive times to SNAP retailers are represented (Tribal & Ag/Mining/Forestry), as is the cluster with the lowest human capital (Tribal). In spite of its low ranking on human capital, and high levels of SNAP enrollment, the mean Border City relative SNAP enrollment was high, suggesting that a relatively high proportion of low-income children are enrolled in SNAP.

MANCOVA results showed a statistically significant effect of cluster on the SNAP indicators ($\Lambda = .480$, $F(35,1630) = 8.89$, $p<.01$)

Looking at each of the criterion variables separately (in ANOVAs), there were significant differences by cluster on each of the four measures, though the variance explained by cluster for relative child SNAP enrollment is less than 10 percent (see Table 8, Page 26).

5 Discussion

The objectives of this study were to explore factors that are related to SNAP enrollment in rural areas, and to attempt to aggregate those factors in ways that differentiated among rural areas and are actionable.

Our analyses show that the variables we have identified as likely to have an influence on SNAP enrollment, and ultimately on health outcomes, had explanatory power and are interrelated in theoretically interesting ways. The cascade models show that there are complicated relationships among many of the variables that predict whether low income children in any particular rural area are likely to be enrolled in SNAP.

For instance, population density is typically used as a measure of rurality, and as a proxy for a number of facets of rurality such as economic development or resource access. We have shown that using a direct measure of remoteness, such as driving time to an urban center and length of work commute, has a strong direct relation to the level of human capital in an area, and through indirect effects, a stronger relation to relative SNAP enrollment, than population density, per se. However, population density does predict both drive time to SNAP retailer and estimated child SNAP enrollment even when accounting for remoteness and other predictors of human capital. Considering both remoteness and density captures a more nuanced sense of what is important about rurality.

Although access to a SNAP retailer does not directly predict a higher proportion of children enrolled in SNAP within a community, the driving distance to a SNAP retailer does predict that a relatively lower proportion of low-income children will be enrolled in SNAP. This demonstrates that access may be a significant factor in mediating SNAP enrollment. Enrollment and educational outreach efforts should include awareness by staff of the likely drive time to SNAP retailers in a community.

About 14 percent of the variance in relative SNAP enrollment was predicted by the direct effect of indicators that had originally been hypothesized to be likely to show an effect on SNAP enrollment only indirectly, through human capital. For instance, primary-sector employment (mining, forestry, agriculture) has a direct negative effect on relative SNAP enrollment for children, over and above economic sector effects on human capital, drive time to SNAP retailer and estimated child SNAP enrollment. Ethnicity also had direct effects even after effects through the previous criterion variables and linguistic isolation have been partialled out. As our previous work has suggested (Walsh, Katz & Sechrest, 2002; Walsh, et al., 2000), ethnicity is not itself a causal factor, but represents, and often can be accounted for by better measuring, the many facets that underlie it. Efforts to better understand and measure the meaning of ethnicity in rural areas could be fruitful in better targeting SNAP outreach.

Two of our indicators did not have an indirect effect at all but *only* showed a significant direct effect on relative SNAP enrollment: our migration indicator (which captured both international and intra-national migration) and our slow life history variable (which captured fertility and mortality, theoretically related to harsher environments). These indicators had an effect even after controlling for human capital, access to SNAP retailers and estimated child SNAP enrollment, suggesting unique effects of these factors that would be worth exploring through additional qualitative and quantitative work. It may be that migration effects reflect both eligibility and informational barriers to enrollment. Slow life history is theoretically related to higher levels of parental effort to provide resources for their children (e.g. Cabeza de Baca et al., 2012), which is consistent with the findings here.

Overall, the results of the cascade model help to illustrate how important it is to consider multivariate models that account for many of the variables affecting relative SNAP enrollment simultaneously, rather than relying on bivariate descriptions of relationships. Unfortunately, as we described in the introduction, efforts to develop multivariate models in rural areas are stymied by the challenge of including data from varyingly-defined spatial units. Dasymetric mapping allowed us to produce a consistent level of analysis (Census tract) for each of these variables and so to include more sociogeographic variables than are typically available. We believe that this is a promising approach for more refined rural analysis. As the amount of intra-county variability shown in our maps demonstrates, this type of small area analysis is likely to result in a better understanding of rural populations and their needs than is the more typical county-level analyses, especially in western areas where the geographic size of counties can be vast.

As our ANOVAs showed, we were able to use cluster analysis to capture the variability of rural areas across the indicator variables. The eight clusters were able to account for a statistically significant proportion of the variance in each of our criterion variables, ranging from 47 percent of the variance in Human Capital down to 8 percent of the variance in Relative Child SNAP Enrollment. The four clusters lowest on Relative Child SNAP Enrollment (the Tribal, Mixed Migrant, Border Periphery, and Ag/Mining/Forestry) were more than 10 percent lower than the others. Better outreach or other interventions in these particular areas might increase the proportions of low-income children enrolled in SNAP. The relatively low enrollment of low-income children in SNAP in Tribal clusters may be a feature of an alternative food assistance option for people residing on Indian reservations: the Food Distribution Program on Indian Reservations (FDPIR). The FDIR was established, in part, as a recognition of the barrier to benefit use that the long distances to SNAP (then food stamp) retailers placed on reservation residents (Finegold, et al., 2009). Although eligibility requirements are similar, households cannot participate in both FDPIR and SNAP in the same month. A report comparing FDPIR and SNAP (Finegold, et al., 2009) found that the size of the benefit that would be received by participants was typically larger with SNAP, but that program staff and participants reported that ease of enrollment and cultural compatibility favored FDPIR.

Importantly, we have begun to use the typology which the clusters form to engage with Cooperative Extension agents and staff in thinking about the counties they work in. We have been met with excitement about this approach, and have been given feedback that this way of considering and documenting variability is more meaningful to those working in rural areas.

5.1 Limitations and Future Directions

Although this work was theoretically driven, it is exploratory in nature, and uses methodologically innovative approaches that will need confirmation through various other studies. Therefore, even though this study is a good starting point for unpacking rurality as it relates to SNAP usage, it is only a beginning.

In particular, we want to avoid reifying the typology we have developed so far, but rather refine it by developing targeted model comparisons and conducting sensitivity analyses. In order to do so, we intend to continue to engage with stakeholders around the face validity and utility of the typology, and to solicit their input for variables to include that would better capture and differentiate among the areas they work in. Qualitative data from program participants would be helpful in better understanding some of the barriers to enrollment and redemption in different areas, which would allow us to further refine our variable selection. As a step towards developing a more robust typology, it would be useful to go beyond k-means clustering and to incorporate methods of multivariate aggregation that allow for assessing goodness of fit, such as latent class analyses. Because a useful typology should capture variation across a number of related phenomena, as we continue to develop the typology, we will explore its relationship with other variables, including enrollment and use of other social benefit programs (such as WIC) and health outcomes.

Although we have used enrollment estimates in the current model, it would be useful to extend the model to include redemption data. We would anticipate that SNAP retailer access would have even a stronger effect on SNAP redemption. In the current model, we have treated all SNAP retailer types as equivalent. (Types of SNAP retailers include supermarkets, small grocery stores, convenience stores, farmers markets, and others.) In the future, we would like to use these techniques to explore the influence of SNAP retailer types and changes in SNAP retailer access, enrollment and redemption over time. It would also validate the influence of SNAP retailer access on SNAP enrollment by conducting intervention studies that improve access to SNAP benefit redemption in areas identified as having limited access. It is also important to recognize the limitations of secondary data when exploring barriers to SNAP enrollment. The integration of qualitative data gathered from SNAP enrollees could greatly enhance our understanding of the role that physical access plays in SNAP enrollment and participation.

The primary benefit of the approaches we have laid out is in the utility they offer to stakeholders in rural areas. Having a concrete way to better understand and describe the variability in rural areas would aid in stronger advocacy for the differing needs across rural populations. Although these techniques do not fully account for the rich variation in culture and experience in rural communities, these methods go beyond the standard way of presenting rural as a monolithic identifier that can mask the great diversity of needs and assets in rural America.

6 TABLES AND FIGURES

Table 1. Six-Class Dasymetric Zone Classification

Dasymetric Zone	Description
Unpopulated	Land areas within 4 meters of a body of water, within 2 meters of a road or highway, with a slope of greater than 30 degrees, falling within the footprint of airports, golf courses, or parks, or classified as barren
Vegetated Public Land	Publicly owned land (state or federal) classified as covered by forest, shrubs, or grasses
Vegetated Private Land	Privately owned land classified as covered by forest, shrubs, or grasses
Agricultural Land	Private or publicly owned land classed as agricultural
Low Density Developed Land	Private or publicly owned developed at low density
Mid-High Density Developed Land	Private or publicly owned developed at medium or high density

Table 2. Factors Used in Analysis

Type	Variable Used in Analysis	Operationalization	Source
Input	Population Density	Total population per square kilometer	U.S. Census 2010
	Slow Life History	Composite factor of birth rate per 1,000 population, fertility rate per 1,000 females ages 15-44, teen birth rate per 1,000 females ages 14-19, percent premature mortality	ADHS PCA Profiles
	Median Age	Median age	ACS 2008-2012
	Work Engagement	Percent of population ages 16 and over in the labor force	ACS 2008-2012
	Economic Sector	Three composite factors of the percent of population ages 16 and over employed in the following economic sectors: PRIMARY (Mining, agriculture, forestry, hunting), SECONDARY (Construction, manufacturing), TERTIARY (Service, retail, management, scientific, administration)	ACS 2008-2012
	Housing Health	Composite factor of the reverse coded mean of non-seasonal vacancy rate and median year built.	ACS 2008-2012
	Income Equality	Reverse-coded Gini coefficient, which measures the degree of inequality in the income distribution within the census tract.	ACS 2008-2012
	Linguistic Isolation	Percent of households in which no one over the age of 14 speaks English "very well"	ACS 2008-2012
	Migration	Composite factor of the percent of the population that is foreign born, percent reporting non-citizenship, percent that lived in a different city or town one year ago	ACS 2008-2012
	Ethnicity	Three composite factors of the percent of the population that is non-Hispanic white (WHITE), Hispanic or Latino (HL), or non-white non-Hispanic (OTHER)	ACS 2008-2012
	Resource Access	Composite factor of mean drive time to urban center and percent of the population that commutes an hour or more to work by private vehicle	Derived; ACS 2008-2012
	Human Capital	Composite factor of median household income, education attainment (ordinal), employment rate, percent of population above the poverty line, median home value, homeownership rate, percent of homes that are not overcrowded, percent of homes with phone service, percent of households with access to a vehicle	ACS 2008-2012

Type	Variable Used in Analysis	Operationalization	Source
Outcome	Access to SNAP Retailer	Population-weighted mean drive time to a SNAP retailer	Derived
	Estimated SNAP Enrollment	Estimated percent of total population enrolled in SNAP	AZ DES
	Estimated Child SNAP Enrollment	Estimated percent of children enrolled in SNAP	AZ DES
	SNAP-Poverty Differential	Difference between percent of total population enrolled in SNAP and percent of total population that is low-income	AZ DES and ACS 2008-2012
	Child SNAP-Poverty Differential	Difference between percent of children enrolled in SNAP and percent of children that are low-income	AZ DES and ACS 2008-2012

Figure 1. Human Capital Factor

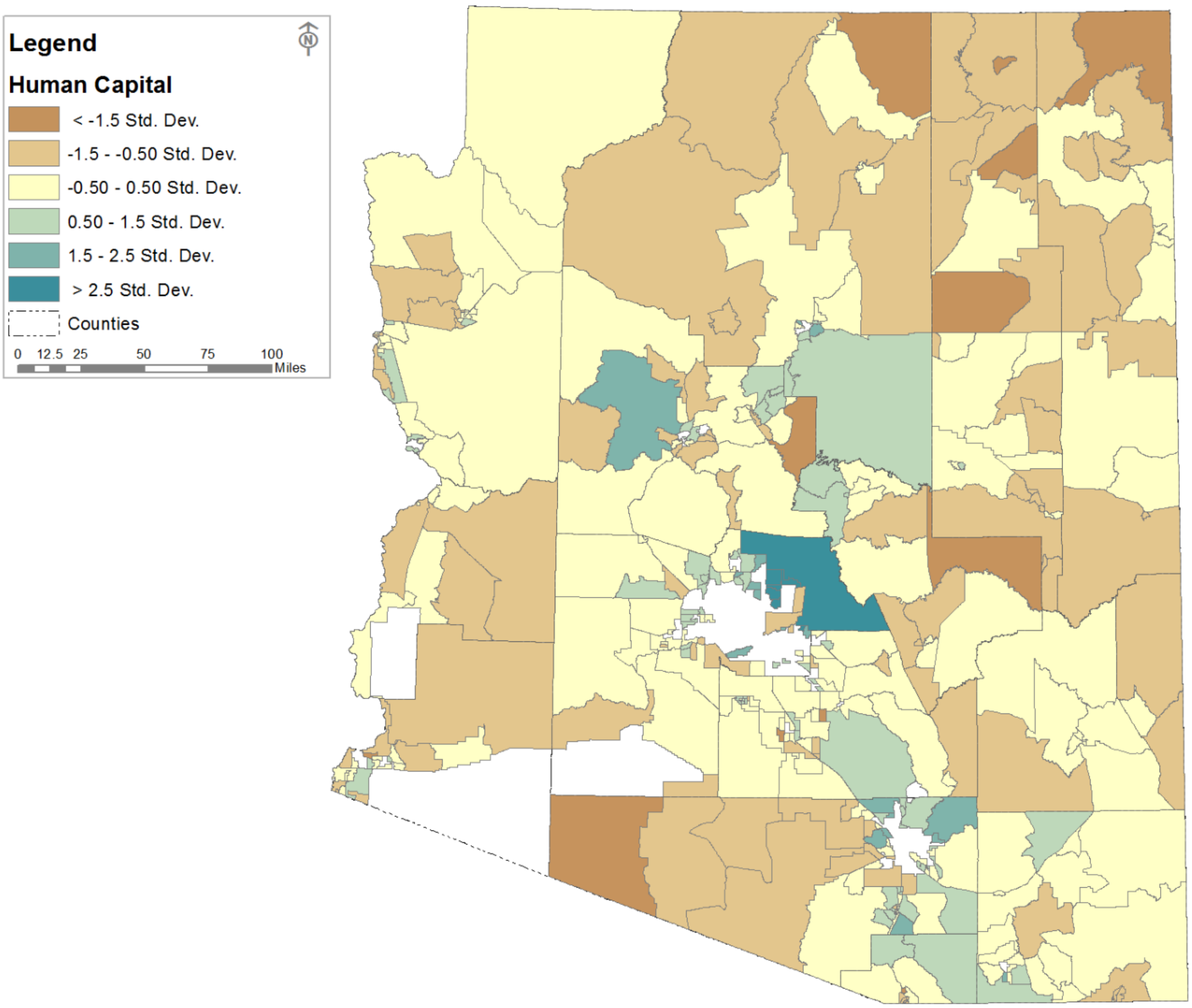

Figure 2. Population-Weighted Mean Drive Time to a SNAP retailer

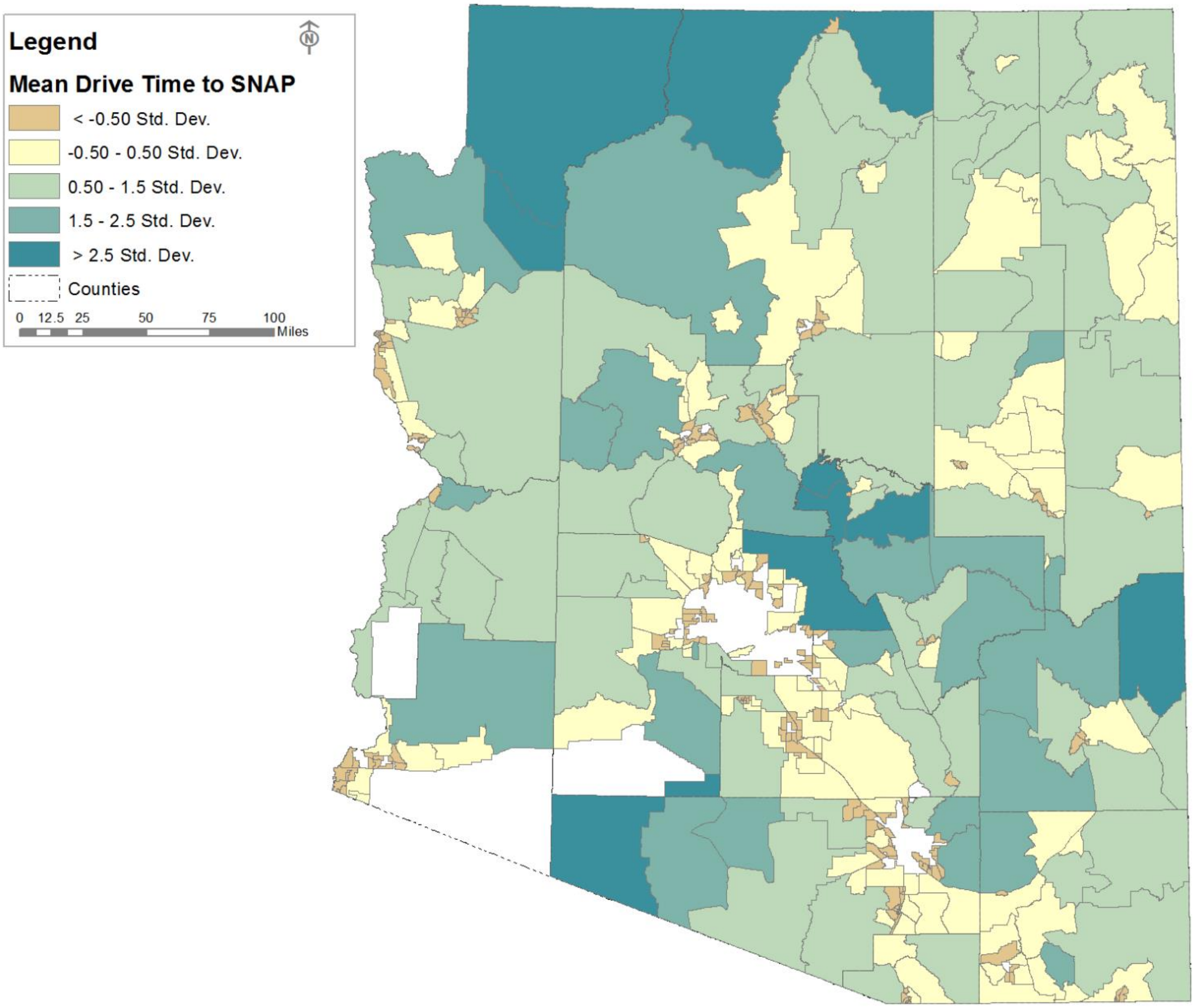

Figure 3. Estimated Percent of Children Enrolled in SNAP

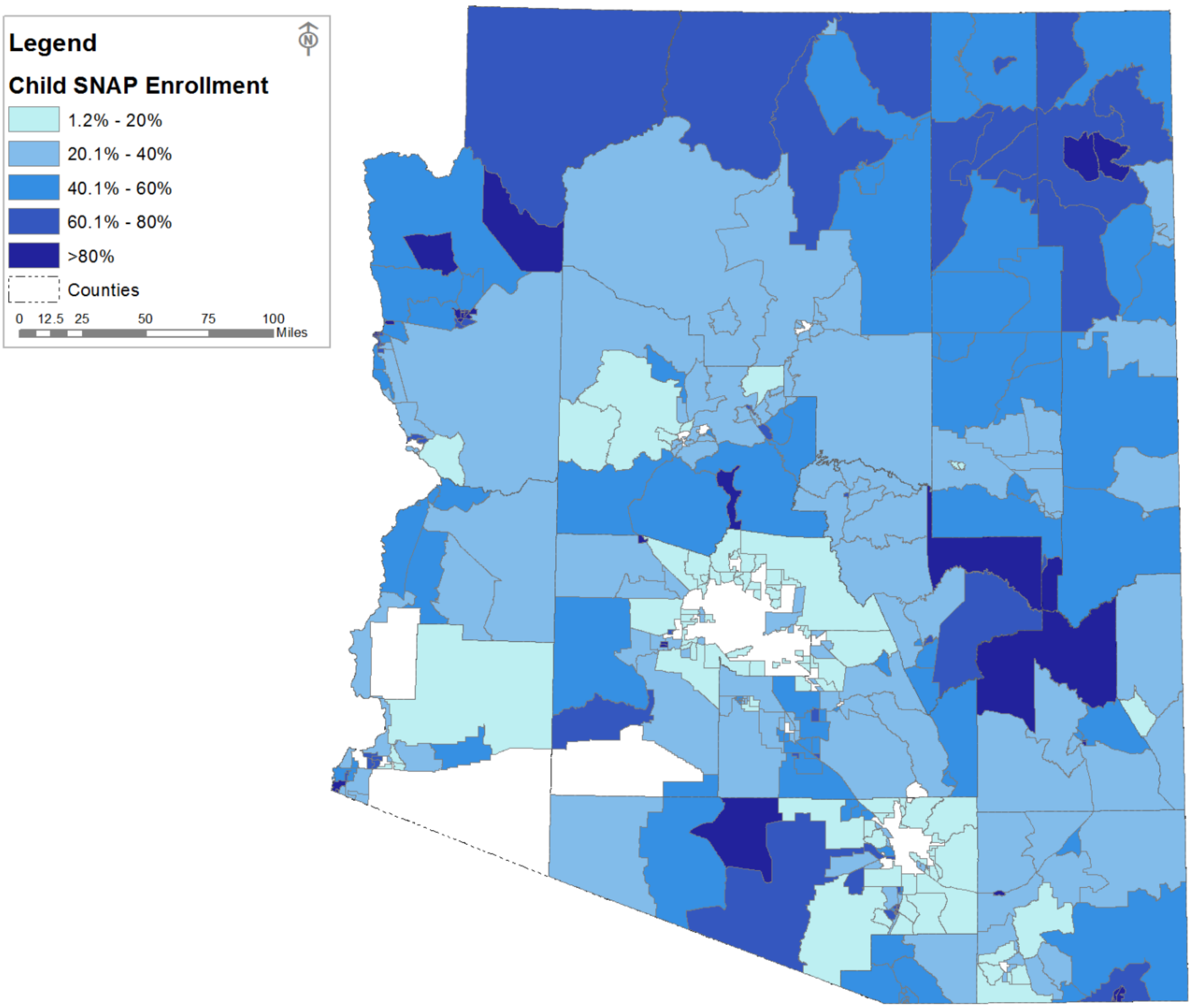

Figure 4.SNAP-Poverty Differential for Children (0-17)

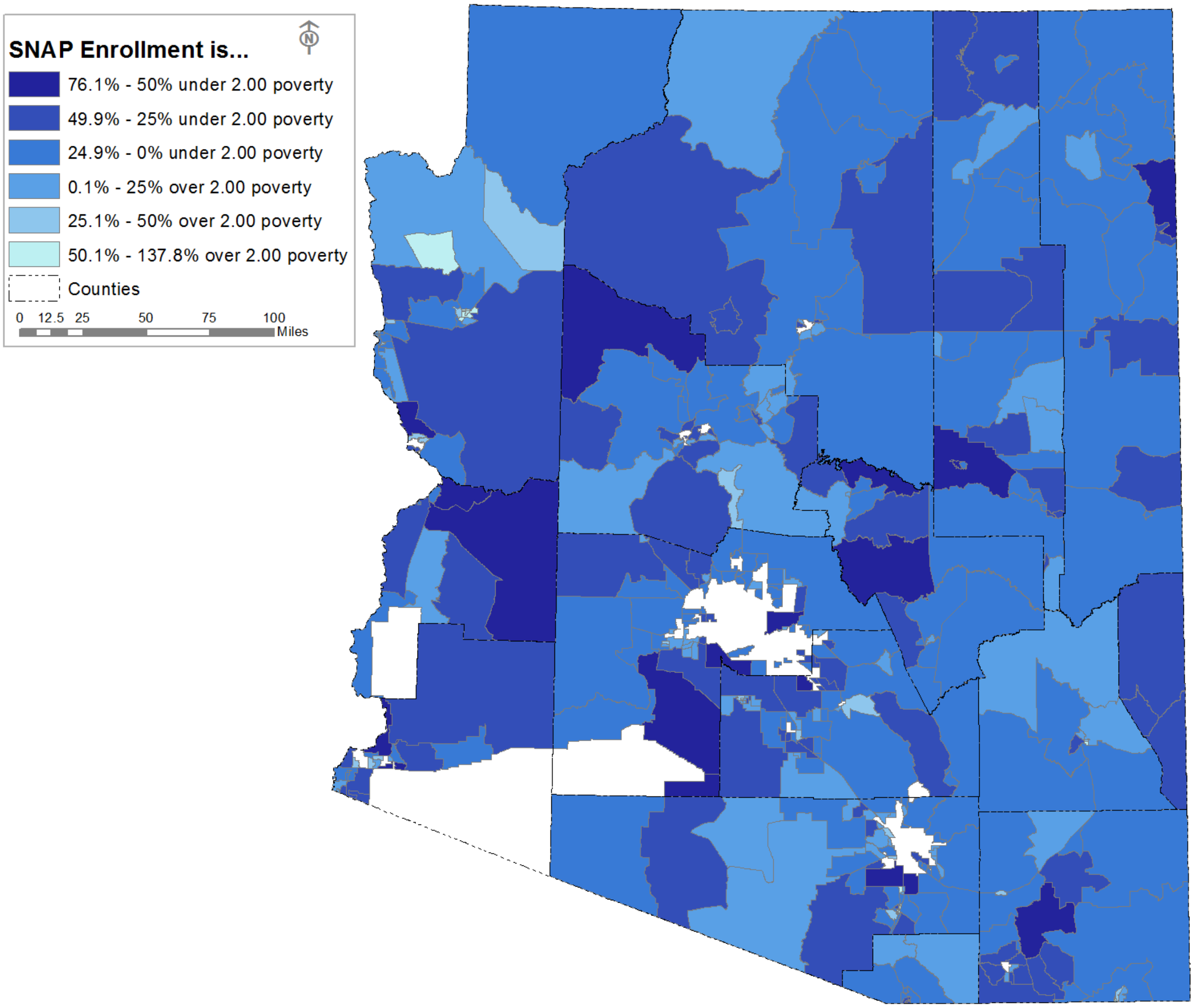

Table 3. Cascade Analysis Results: Y1, Human Capital

Criterion Variable	Prior Criterion Variables	Predictor Variables	Effect size	F-ratio	DF	*p*
Human Capital		Population Density	-0.05	2.56	(1,383)	0.11
		Slow Life History	-0.03	.80	(1,383)	0.37
		Median Age	0.10*	9.76	(1,383)	0.002
		Work Engagement	0.19*	32.73	(1,383)	<0.0001
		Economic Sector	0.18*	9.88	(3,383)	<0.0001
		Primary	0.16*	22.10	(1,383)	<0.0001
		Secondary	0.09*	7.52	(1,383)	0.006
		Tertiary	0.00	.01	(1,383)	0.92
		Housing Health	0.09*	7.27	(1,383)	0.007
		Income Equality	0.13*	16.42	(1,383)	<0.0001
		Migration	0.01	.19	(1,383)	0.66
		Ethnicity	0.39*	45.96	(3,383)	<0.0001
		White	0.14*	18.54	(1,383)	<0.0001
		Hispanic/Latino	-0.26*	62.11	(1,383)	<0.0001
		Other	-0.25*	57.24	(1,383)	<0.0001
		Linguistic Isolation	-0.42*	165.30	(1,383)	<0.0001
		Resource Access	0.38*	132.68	(1,383)	<0.0001

Note: N=399. Where numerator df=1, the effect size is the semipartial correlation (*sR*); where numerator df>1, the effect size is the multiple correlation (R), or, for the overall model, the eta/trace correlation (E).
*p<.05

Figure 5. Cascade Analysis Direct Effects: Y1, Human Capital

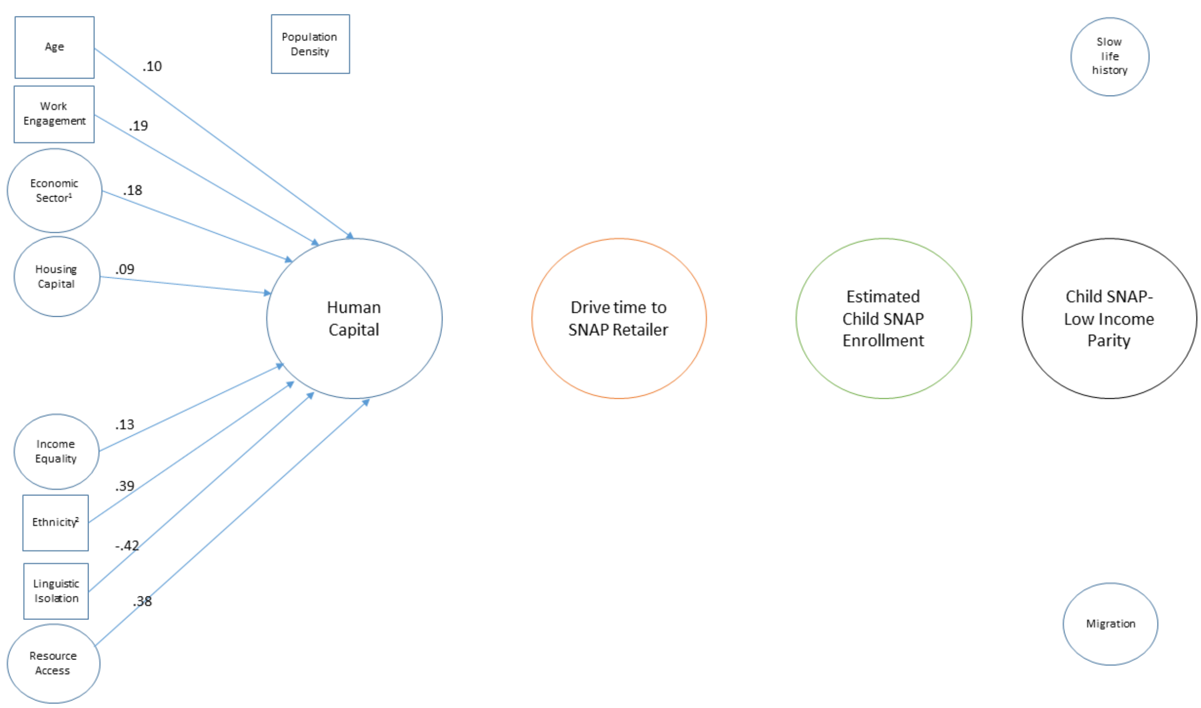

Table 4. Cascade Analysis Results: Y2, SNAP Drive Time

Criterion Variable	Prior Criterion Variables	Predictor Variables	Effect size	F-Ratio	DF	p
SNAP Drive Time	Human Capital		-0.24*	43.07	(1,382)	<0.0001
		Population Density	-0.21*	31.37	(1,382)	<0.0001
		Slow Life History	0.03	0.66	(1,382)	0.42
		Median Age	0.04	1.00	(1,382)	0.32
		Work Engagement	-0.09*	6.33	(1,382)	0.01
		Economic Sector	0.20*	10.19	(3,382)	<0.0001
		Primary	0.01	0.08	(1,382)	0.78
		Secondary	-0.14*	14.49	(1,382)	0.0002
		Tertiary	-0.15*	15.99	(1,382)	<0.0001
		Housing Health	-0.03	0.64	(1,382)	0.42
		Income Equality	0.00	0.02	(1,382)	0.90
		Migration	-0.04	1.05	(1,382)	0.31
		Ethnicity	0.13*	3.90	(3,382)	0.009
		White	0.04	1.50	(1,382)	0.22
		Hispanic/Latino	-0.09*	5.86	(1,382)	0.02
		Other	-0.08*	4.36	(1,382)	0.04
		Linguistic Isolation	-0.21*	33.94	(1,382)	<0.0001
		Resource Access	-0.52*	200.68	(1,382)	<0.0001

Note: N=399. Where numerator df=1, the effect size is the semipartial correlation (*sR*); where numerator df>1, the effect size is the multiple correlation (R), or, for the overall model, the eta/trace correlation (E).
*p<.05

Figure 6. Cascade Analysis Direct Effects: Y2, SNAP Drive Time

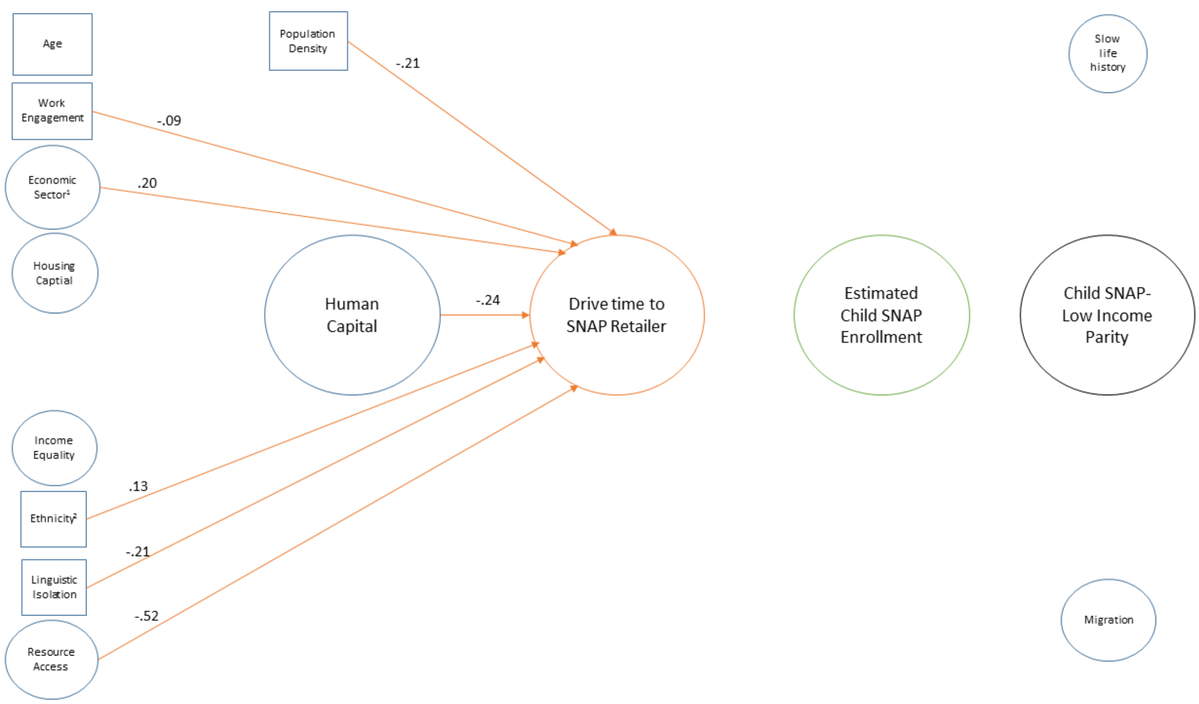

Table 5. Cascade Analysis Results: Y3, Child SNAP Enrollment

Criterion Variables	Prior Criterion Variables	Predictor Variables	Effect Size	F-Ratio	DF	p
Child SNAP Enrollment	SNAP Drive Time		-0.04	1.73	(1, 381)	0.19
	Human Capital		-0.53*	251.67	(1,381)	<0.0001
		Population Density	0.41*	147.65	(1, 381)	<0.0001
		Slow Life History	-0.01	0.15	(1, 381)	0.70
		Median Age	0.09*	6.42	(1, 381)	0.01
		Work Engagement	-0.08*	5.59	(1, 381)	0.02
		Economic Sector	0.25*	17.83	(3, 381)	<0.0001
		Primary	0.20*	33.79	(1, 381)	<0.0001
		Secondary	0.10*	9.32	(1, 381)	0.002
		Tertiary	0.11*	10.38	(1, 381)	0.001
		Housing Health	0.04	1.59	(1, 381)	0.21
		Income Equality	-0.04	1.43	(1, 381)	0.23
		Migration	-0.04	1.44	(1, 381)	0.23
		Ethnicity	0.12*	4.06	(3, 381)	0.007
		White	0.02	0.40	(1, 381)	0.53
		Hispanic/Latino	0.02	0.26	(1, 381)	0.61
		Other	-0.11*	11.52	(1, 381)	0.0008
		Linguistic Isolation	0.13*	14.44	(1, 381)	0.0002
		Resource Access	-0.08*	5.59	(1, 381)	0.02

Note: N=399. Where numerator df=1, the effect size is the semipartial correlation (*sR*); where numerator df>1, the effect size is the multiple correlation (R), or, for the overall model, the eta/trace correlation (E).
*p<.05

Figure 7. Cascade Analysis Direct Effects: Y3 Child SNAP Enrollment

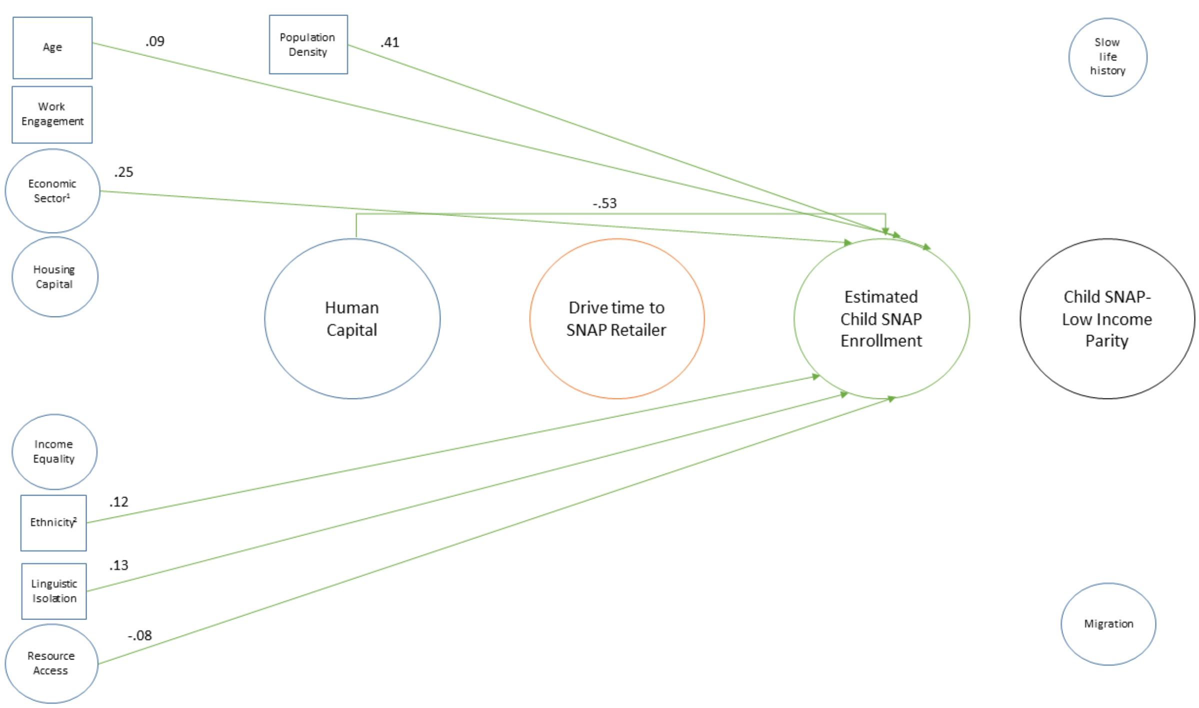

Table 6. Cascade Analysis Results: Y4, Relative Child SNAP Enrollment

Criterion Variables	Prior Criterion Variables	Predictor Variables	Effect Size	F-Ratio	DF	p
Relative Child SNAP Enrollment	Child SNAP Enrollment		0.67*	955.75	(1, 380)	<0.0001
	SNAP Drive Time		-0.18*	69.64	(1, 380)	<0.0001
	Human Capital		0.46*	444.74	(1, 380)	<0.0001
		Population Density	0.03	2.34	(1, 380)	0.13
		Slow Life History	0.07*	9.59	(1, 380)	0.002
		Median Age	0.12*	28.76	(1, 380)	<0.0001
		Work Engagement	0.16*	54.82	(1, 380)	<0.0001
		Economic Sector	0.18*	22.72	(3, 380)	<0.0001
		Primary	-0.18*	68.01	(1, 380)	<0.0001
		Secondary	0.01	0.14	(1, 380)	0.71
		Tertiary	0.00	0.00	(1, 380)	0.90
		Housing Health	0.04	2.84	(1, 380)	0.09
		Income Equality	0.14*	41.57	(1, 380)	<0.0001
		Migration	-0.13*	38.43	(1, 380)	<0.0001
		Ethnicity	0.12*	10.88	(3, 380)	<0.0001
		White	-0.08*	14.33	(1, 380)	0.0002
		Hispanic/Latino	-0.05*	4.68	(1, 380)	0.03
		Other	0.08*	13.62	(1, 380)	0.0003
		Linguistic Isolation	-0.07*	9.27	(1, 380)	0.002
		Resource Access	0.01	0.23	(1, 380)	0.63

Note: N=399. Where numerator df=1, the effect size is the semipartial correlation (*sR*); where numerator df>1, the effect size is the multiple correlation (R), or, for the overall model, the eta/trace correlation (E).
*p<.05

Figure 8. Cascade Analysis Direct Effects: Y4, Relative Child SNAP Enrollment

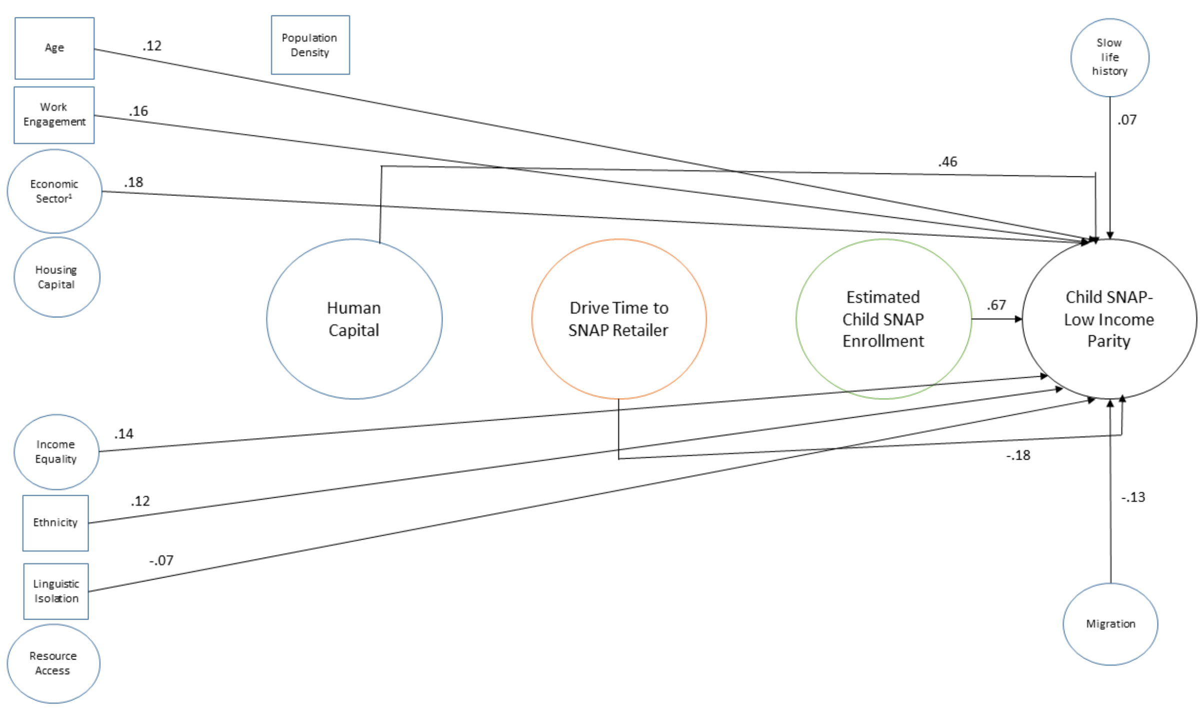

Figure 9.Total Cascade Analysis Effects

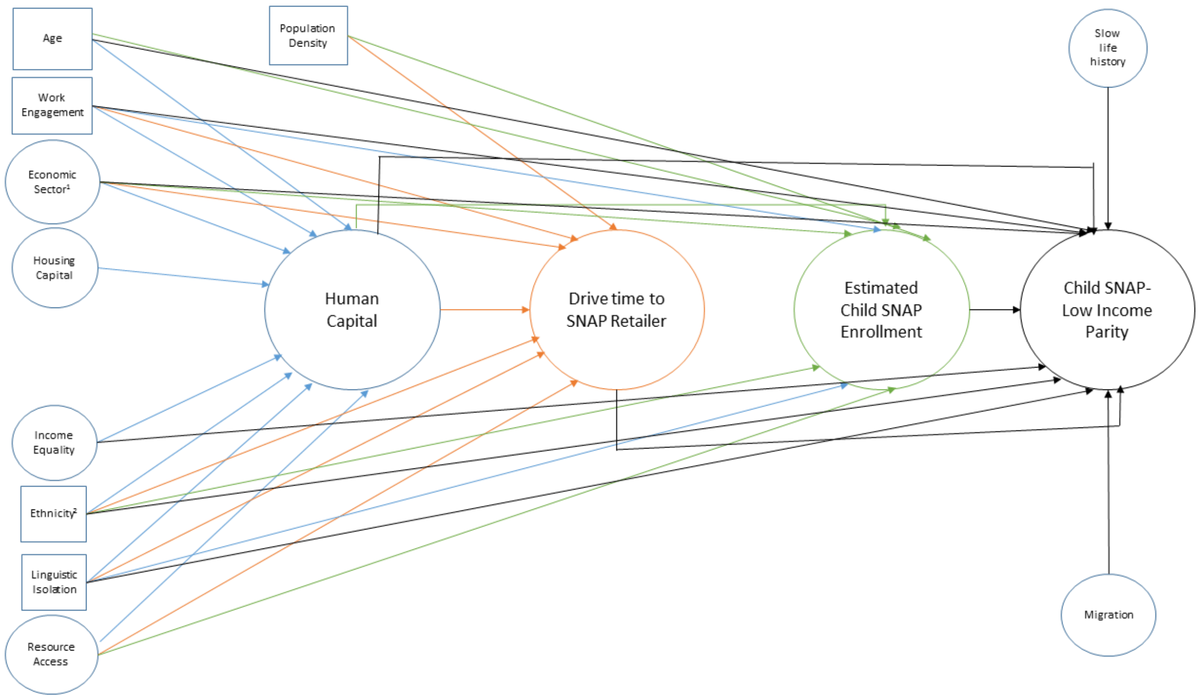

Figure 10. Arizona Rural Clusters

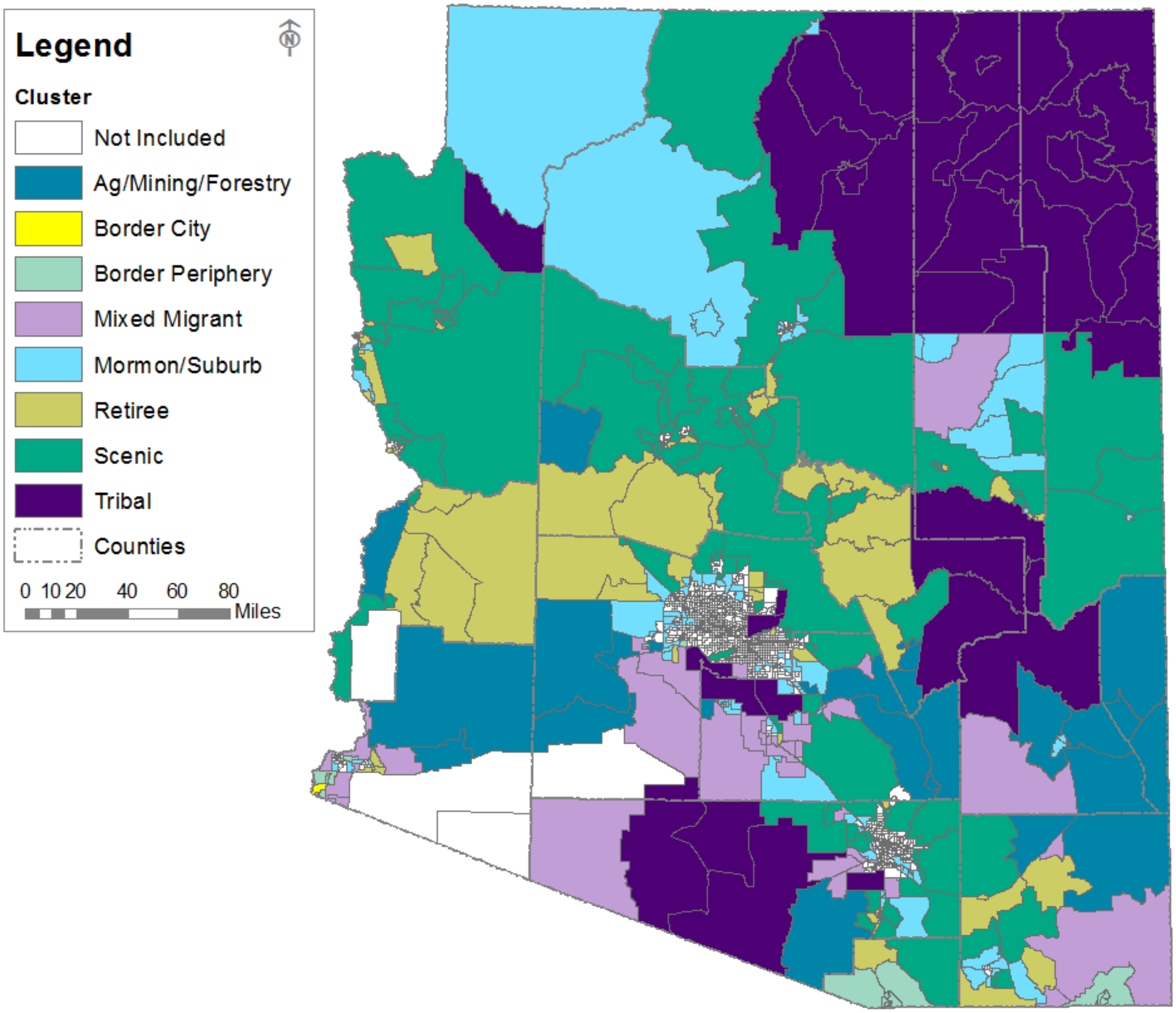

Table 7. Cluster Descriptions

CLUSTER	KEY CHARACTERISTICS
Ag, Mining, Forestry	Highest Primary-sector Employment, Low Population Density, Lowest Tertiary-sector Employment
Border City	High Population Density, Highest Linguistic Isolation, Highest Migration, Highest Hispanic Population, Low Housing Capital
Border Periphery	High Migration, High Hispanic population, High Primary-sector Employment, High Linguistic Isolation
Mixed Migrant	High Migration, Most Ethnically Diverse, High Primary-sector Employment, High Secondary-sector Employment
Suburb/Historically Mormon	Highest Resource Access, Highest Income Equality, Highest Work Engagement, Lowest Primary-sector Employment
Retirees	Highest Median Age, Low Work Engagement, Slowest Life History, Highest White Population, High Human Capital
Scenic	High Median Age, Highest Housing Capital, High Work Engagement, High Secondary-sector Employment, High White Population
Tribal	Low Median Age, Fast Life History, Low Income Equality, Low Migration, Highest non-white and non-Hispanic population

Table 8. Outcome Variables by Cluster

		HUMAN CAPITAL		SNAP DRIVE TIME		SNAP ENROLLMENT (CHILD)		RELATIVE SNAP ENROLLMENT (CHILD)	
Cluster	*N*	*MEAN*	*SD*	*MEAN*	*SD*	*MEAN*	*SD*	*MEAN*	*SD*
Tribal	**45**	**0.179**	**0.102**	**0.275**	**0.170**	**0.580**	**0.199**	**-0.196**	**0.216**
Mixed Migrant	**39**	**0.358**	**0.098**	**0.127**	**0.182**	**0.427**	**0.165**	**-0.194**	**0.243**
Border Periphery	**16**	**0.300**	**0.078**	**0.055**	**0.072**	**0.583**	**0.212**	**-0.130**	**0.224**
Ag/Mining/Forestry	**28**	**0.424**	**0.081**	**0.222**	**0.170**	**0.380**	**0.198**	**-0.124**	**0.251**
Retiree	60	0.498	0.142	0.126	0.146	0.425	0.353	-0.086	0.367
Scenic	104	0.493	0.139	0.139	0.153	0.357	0.356	-0.066	0.314
Mormon/Suburb	100	0.489	0.107	0.057	0.096	0.331	0.235	-0.060	0.218
Border City	7	0.220	0.062	0.007	0.011	1.207	0.622	0.396	0.671

7 REFERENCES

Abarca, J., & Ramachandran, S. (2005). Using community indicators to assess nutrition in Arizona-Mexico border communities. *Preventing Chronic Disease*, *2*(1), A06.

Alwitt, L. F., & Donley, T. D. (1997). Retail stores in poor urban neighborhoods. The Journal of Consumer Affairs, 31(1), 139-164.

Bader, M. D. M., Purciel, M., Yousefzadeh, P., & Neckerman, K. M. (2010). Disparities in neighborhood food environments: implications of measurement strategies. *Economic Geography*, *86*(4), 409–30.

Bartfeld, J., Dunifon, R., & Chandran, R. (2005). *State-Level predictors of food insecurity and hunger among households with children*.

Bertrand, L., Thérien, F., & Cloutier, M. (2008). Measuring and mapping disparities in access to fresh fruits and vegetables in Montréal. Canadian Journal of Public Health / Revue Canadienne De Sante'e Publique, 99(1), 6-11.

Boehmer, T. K., Lovegreen, S. L., Haire-Joshu, D., & Brownson, R. C. (2006). What constitutes an obesogenic environment in rural communities? *American Journal of Health Promotion*, *20*(6), 411–21.

Burns, C. M., Gibbon, P., Boak, R., Baudinette, S., & Dunbar, J. A. (2004). Food cost and availability in a rural setting in Australia. *Rural and Remote Health*, *4*(311).

Cabeza de Baca, T., Figueredo, A.J., & Ellis, B.J. (2012). An evolutionary analysis of variation in parental effort: Determinants and assessment. Parenting: Science and Practice, 12, 94-104).

Cummins, S., & Macintyre, S. (2002). "Food deserts"--evidence and assumption in health policy making. *BMJ (Clinical Research Ed.)*, *325*(7361), 436–8.

Eicher, C. L., & Brewer, C. A. (2001). Dasymetric Mapping and Areal Interpolation: Implementation and Evaluation. *Cartography and Geographic Information Science*, *28*(2), 125–138.

Demetriou, A., Christou, C., Spanoudis, G., Platsidou, M., Fischer, K. W., & Dawson, T. L. (2002). The development of mental processing: Efficiency, working memory, and thinking. *Monographs – Society for Research in Child Development, 67*(268), ALL.

Figueredo, A. J., & Gorsuch, R. L. (2007). Assortative mating in the jewel wasp. 2: Sequential canonical analysis as an exploratory form of path analysis. Journal of the Arizona-Nevada Academy of Science, 39(2), 59-64.

Finegold, K., Pindus, N., Levy, D., Tannehill, T. & Hillabrant, W. (2009). *Tribal Food Assistance: A Comparison of the Food Distribution Program on Indian Reservations (FDPIR) and the Supplemental Nutrition Assistance Program (SNAP)*. Washington, D.C: The Urban Institute.

Genser, J. L. (2009). Diet Quality of Americans by SNAP (Food Stamp) Participation Status. *Journal of Nutrition Education and Behavior*, *41*(4S), 2157.

Gordon-Larsen, P., Nelson, M. C., Page, P., & Popkin, B. (2006). Inequality in the built environment underlies key health disparities in physical activity and obesity. *Pediatrics*, *117*(2), 417–424.

Guy, C. M. (1991). Urban and rural contrasts in food prices and availability—a case study in wales. *Journal of Rural Studies*, *7*(3), 311–325.

Han, E., Powell, L. M., & Isgor, Z. (2012). Supplemental nutrition assistance program and body weight outcomes: the role of economic contextual factors. *Social Science & Medicine (1982)*, *74*(12), 1874–81.

Holt, J. B., Lo, C. P., & Hodler, T. W. (2004). Dasymetric estimation of population density and areal interpolation of census data. Cartography and Geographic Information Science, 31(2), 103-121.

Hosler, A. S., Varadarajulu, D., Ronsani, A. E., Fredrick, B. L., & Fisher, B. D. (2006). Low-fat milk and high-fiber bread availability in food stores in urban and rural communities. *Journal of Public Health Management and Practice : JPHMP*, *12*(6), 556–62.

Jackson, R. J. (2003). The impact of the built environment on health: an emerging field. *American Journal of Public Health*, *93*(9), 1382–4.

Kaufman, P. R. (1999). Rural Poor Have Less Access to Supermarkets, Large Grocery Stores. *Rural Development Perspectives*, *13*(3), 19–26.

Lacombe, D. J., Michieka, N. M., & Gebremedhin, T. (2012). A Bayesian Spatial Econometric Analysis of SNAP Participation Rates in Appalachia. *The Journal of Regional Analysis & Policy*, *42*(3), 198–209.

Larsen, K., & 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), 16-16.

Larson, N. I., Story, M. T., & Nelson, M. C. (2009). Neighborhood environments: disparities in access to healthy foods in the U.S. *American Journal of Preventive Medicine*, *36*(1), 74–81.

Lefttin, J., Eslami, E., & Strayer, M. (2011). *Trends in Supplemental Nutrition Assistance Program participation rates: Fiscal year 2002 to fiscal year 2009* (pp. 1–65). Washington, D.C.

Leung, C. W., Blumenthal, S. J., Hoffnagle, E. E., Jensen, H. H., Foerster, S. B., Nestle, M., … Willett, W. C. (2013). Associations of food stamp participation with dietary quality and obesity in children. *Pediatrics*, *131*(3), 463–72. doi:10.1542/peds.2012-0889

Leung, C. W., & Villamor, E. (2011). Is participation in food and income assistance programmes associated with obesity in California adults? Results from a state-wide survey. *Public Health Nutrition*, *14*(4), 645–52. doi:10.1017/S1368980010002090

Li, C., Balluz, L. S., Ford, E. S., Okoro, C. a, Zhao, G., & Pierannunzi, C. (2012). A comparison of prevalence estimates for selected health indicators and chronic diseases or conditions from the Behavioral Risk Factor Surveillance System, the National Health Interview Survey, and the National Health and Nutrition Examination Survey, 2007-2008. *Preventive Medicine*, *54*(6), 381–7.

Liese, A. D., Weis, K. E., Pluto, D., Smith, E., & Lawson, A. (2007). Food store types, availability, and cost of foods in a rural environment. *Journal of the American Dietetic Association*, *107*(11), 1916–23.

Lois, B., Morton, W., & Blanchard, T. C. (2007). Starved for Access: Life in Rural America's Food Deserts, *1*(4), 1–10.

Lwin, K. K., & Murayama, Y. (2010). Development of GIS Tool for Dasymetric Mapping. *International Journal of Geoinformatics*, *6*(1), 11–18.

Lytle, L. A. (2009). Measuring the food environment: state of the science. *American Journal of Preventive Medicine*, *36*(4 Suppl), S134–44.

Macintyre, S., Ellaway, A., & Cummins, S. (2002). Place effects on health: how can we conceptualise, operationalise and measure them? *Social Science & Medicine*, *55*(1), 125–139.

McEntee, J., & Agyeman, J. (2010). Towards the development of a GIS method for identifying rural food deserts: Geographic access in vermont, USA. Applied Geography, 30(1), 165-176.

McKinnon, R., Reedy, J., Morrissette, M. a, Lytle, L. a, & Yaroch, A. L. (2009). Measures of the food environment: a compilation of the literature, 1990-2007. *American Journal of Preventive Medicine*, *36*(4 Suppl), S124–33.

Mennis, J. (2003). Generating Surface Models of Population Using Dasymetric Mapping*. *The Professional Geographer*, *55*(1), 31–42.

Nelson, D. E., Powell-Griner, E., Town, M., & Kovar, M. G. (2003). A comparison of national estimates from the National Health Interview Survey and the Behavioral Risk Factor Surveillance System. *American Journal of Public Health*, *93*(8), 1335–41.

Oliveira, V. (2014). *Food Assistance Landscape: FY 2013 Annual Report*, EIB-120. U.S. Department of Agriculture, Economic Research Services.

Openshaw, S. (1984). Ecological fallacies and the analysis of areal census data. Environment & Planning A, 16(1), 17

Pearce, J., Witten, K., & Bartie, P. (2006). Neighbourhoods and health: A GIS approach to measuring community resource accessibility. Journal of Epidemiology and Community Health (1979-), 60(5), 389-395.

Pierannunzi, C., Hu, S. S., & Balluz, L. (2013). A systematic review of publications assessing reliability and validity of the Behavioral Risk Factor Surveillance System (BRFSS), 2004-2011. *BMC Medical Research Methodology*, *13*(49).

Powell, L. M., Slater, S., Mirtcheva, D., Bao, Y., & Chaloupka, F. J. (2007). Food store availability and neighborhood characteristics in the United States. *Preventive Medicine*, *44*(3), 189–95.

Rose, D., & Richards, R. (2004). Food store access and household fruit and vegetable use among participants in the US Food Stamp Program. *Public Health Nutrition*, *7*(8), 1081–8.

Sallis, J. E., & Glanz, K. (2006). The role of built environments in physical activity, eating, and obesity in childhood. *The Future of Children*, *16*(1), 89–108.

Scholz, J., & Herrmann, S. (2010). *Rural regions in Europe. A new typology showing diversity of European rural regions*. European Union FP 7 RUFUS (Rural Future Networks Project).

Sharkey, J. R. (2009). Measuring potential access to food stores and food-service places in rural areas in the U.S. *American Journal of Preventive Medicine*, *36*(4 Suppl), S151–5.

Sharkey, J. R., & Horel, S. (2008). Neighborhood socioeconomic deprivation and minority composition are associated with better potential spatial access to the ground-truthed food environment in a large rural area. *The Journal of Nutrition*, *138*(3), 620–7. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/18287376

Shaw, H. J. (2014). Food deserts: Towards the development of a classification. *Geografiska Annaler. Series B, Human Geography*, *88*(2), 231–247.

Simen-Kapeu, A., Kuhle, S., & Veugelers, P. J. (2010). Geographic Differences in Childhood Overweight, Physical Activity, Nutrition and Neighbourhood Facilities: Implications for Prevention. *Canadian Journal of Public Health*, *101*(2), ALL.

Simmons, S., Alexander, J. L., Ewing, H., & Whetzel, S. (2012). SNAP Participation in Preschool-Aged Children and Prevalence of Overweight. *Journal of School Health*, *82*(12), 548–553.

Srinivasan, S., O'Fallon, L. R., & Dearry, A. (2003). Creating healthy communities, healthy homes, healthy people: initiating a research agenda on the built environment and public health. *American Journal of Public Health*, *93*(9), 1446–50.

USDA (2007). Arizona rural definitions maps. Retrieved from http://www.ers.usda.gov/data-products/rural-definitions.aspx

Vartanian, T. P., & Houser, L. (2012). The effects of childhood SNAP use and neighborhood conditions on adult body mass index. *Demography*, *49*(3), 1127–54. doi:10.1007/s13524-012-0115-y

Ver Ploeg, M., Breneman, V., Farrigan, T., Hamrick, K., Hopkins, D., Kaufman, P., Kim, S. (2009). *Access to Affordable and Nutritious Food : Measuring and Understanding Food Deserts and Their Consequences- Report to Congress* (pp. 1–150). U.S. Department of Agriculture, Economic Research Services.

Ver Ploeg, M., Dutko, P., & Breneman, V. (2015). Measuring food access and food deserts for policy purposes. Applied Economic Perspectives and Policy, 37(2), 205-225

Walker, R. E., Keane, C. R., & Burke, J. G. (2010). Disparities and access to healthy food in the United States: A review of food deserts literature. *Health & Place*, *16*(5), 876–84.

Walsh, M., Katz, M., Sechrest, L. (2002). Unpacking cultural factors in adaptation to Type II diabetes mellitus. *Medical Care*, 40(1 Supp), 129-139.

Walsh, M., Smith, R., Morales, A. & Sechrest, L. (2000*). Ecocultural Research: A Mental Health Researcher's Guide to the Study of Race, Ethnicity, and Culture*. Human Services Research Institute: Cambridge, MA.

Wang, M. C., Gonzalez, A. A., Ritchie, L. D., & Winkleby, M. A. (2006). The neighborhood food environment : sources of historical data on retail food stores. International Journal of Behavioral Nutrition and Physical Activity, 3(15), 1–5