CULTIVATING A LANDSCAPE FOR FOOD JUSTICE: AN EXPLORATORY STUDY OF COMMUNITY FOOD SECURITY MEASUREMENT TO INFORM COMMUNITY-BASED INTERVENTION STRATEGIES

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

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Dedicated to my loving and supportive parents,

David and Cindi,

and my amazing brother and sister,

Matthew and Sara

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CHAPTER 1

BACKGROUND

The current U.S. food production and distribution system has evolved through policy changes and incentives that were intended to provide adequate supplies to U.S. and worldwide food needs. The ‘green revolution’ food system now has evolved to pose a threat to the public health and natural environment. The ‘industrialized’ global food network that emerged in part as a response to worldwide malnutrition, relies heavily on technology and non-renewable energy inputs to produce, process, and distribute food (Story, Hamm, & Wallinga, 2009; Wallinga, 2009). Since the late 20th century, this unsustainable food system has contributed to the pollution of groundwater, soil, and air (McBeath & McBeath, 2009; Wallinga, 2009). Large-scale corporate farming practices have contributed to the loss of arable land in the U.S. (Hoff & Polack, 1993). The combined effects of climate change (Harvie, Mikkelsen, & Shak, 2009; Lang, 2009; McBeath & McBeath, 2009), an estimated U.S. population increase from 275 million people in 2000 to 335 million people in 2025 (Campbell, 1997), and a projected world population increase from six billion people in 2000 to eight billion people in 2030 (U.S. Census, 2010), are expected to exacerbate the burdens placed on water and other natural resources (Hamm, 2004; Lang, 2009). Global food demands, energy demands, and higher oil prices have contributed to rising food costs (Conceicao & Mendoza, 2009). Diminished purchasing power resulting from the economic recession and food price increases is likely to create shocks and perturbations within the food system (Conceicao & Mendoza, 2009; Needles Fletcher, 2008). The economic and environmental effects are likely to have the greatest impact on impoverished households and communities who are more likely to experience food hardships (Conceicao & Mendoza, 2009).

Problem Formulation

Communities may not be able to absorb the economic and environmental shocks resulting in an unequal distribution of affordable healthy foods and a strain on community resources (Paez, Mercardo, Farber, Morency, & Roorda, 2009). Rising food prices have the greatest effect on low-income households (Nord, Andrews, & Carlson, 2008; Rose, 1999). Low-income households have to make difficult food choices based on financial limitations, which may impact food consumption and nutritional intake (Lawrence & Baker, 2009; McGranahan, 2008). Rose's (1999) analysis of the National Health and Nutrition Examination Survey 13 (NHANES) and the Current Population Survey (CPS), found that people whose income was below the federal poverty level were more than 3.5 times as likely to have inadequate food intake. Between 2007 and 2008, household spending on monthly food expenditures rose by 6% (McGranahan, 2008). Families in the lowest income quintile and those participating in the Supplemental Nutrition Assistance Program (SNAP) are affected even more by fluctuating food prices since the distribution of SNAP dollars does not increase in response to food prices (Needles Fletcher, 2008; Rose, 1999). Emergency food assistance programs (e.g., food banks/pantries, soup kitchens) face challenges to meet the increase in food demands (Winne, 2008). Food banks that distribute food by truckloads to a network of food pantries also face difficulties absorbing the rising fuel costs (Needles Fletcher, 2008). Among the most vulnerable are the elderly poor, those who are living in rural areas

(Needles Fletcher, 2008), African Americans, Hispanics, and single-parent households (USDA, 2009a).

Prevalence of Food Insecurity

The USDA's (2009b) Economic Research Service and the U.S. Census Bureau developed the various versions of the Household Food Security Survey Module, which established four levels of food security (Table 1). The USDA food security definition emphasizes access to enough food at all times to meet the nutritional needs for physical health (Andrews, Nord, Bickel, & Carlson, 2000).

Table 1.

USDA Household Food Security Survey Module Food Security Categories

(USDA, 2009a)

High food security	No reported indications of food access problems or limitations.
Marginal food security	One or two reported indications-typically anxiety over food sufficiency or shortage of food in the house. There is little or no indication of changes in diet or food intake.
Low food security	Reports of reduced quality, variety, or desirability of diet. There is little or no indication of changes in diet or food intake.
Very low food security	Reports of multiple indications of disrupted eating patterns and reduced food intake.

In 2010, 14.5% of U.S. households (17.2 million) were characterized as low or very low food secure (USDA, 2011). Around 6.7 million U.S. households were classified as very low food secure (USDA, 2011). Since 2006, there has been a 3.5% decrease in the number of high food secure U.S. households (USDA, 2011). The number of very low food secure households has steadily increased from 2006-2008, but has remained between 5.35% and 5.72% since that time (Nord, Andrews, & Carlson, 2011). The highest prevalence was among African Americans (25.1%), single female-headed households (35.1%), single male-headed households (25.4%), and Hispanic households (26.2%) (USDA, 20011). Just over 40% of households with incomes below the 2010 federal poverty level (FPL), $22,050 for a family of four (U.S. Department of Health and Human Services, 2011), were food insecure (USDA, 2011).

Between 2006 and 2008, 15.8% of Missourians faced uncertain access to sufficient food to meet their health needs (Dawdy, et al., 2010). Very low food security, which was formerly called food insecurity with hunger (USDA, 2009b), and food insecurity rates have increased since the 2008 report. Very low food security has increased by more than 20% since 2003 (Dawdy, et al., 2010). Missouri has the 10th highest number of low or very low food secure households in the U.S. (Dawdy, et al., 2010). In 2008, 23.4% of Missouri households with children were food insecure. This equates to approximately 360,000 Missouri children living in food insecure households.

Conceptual Framework

The long-term threats that the food system poses on the public's health and the physical environment in combination with increasing poverty and food insecurity have led to questions about the ability of communities to sustain a nutritionally adequate food supply that is distributed equitably amongst all people (Winne, Joseph, & Fisher, 1997). Research has begun to move away from ways in which anti-hunger strategies impact food security to more complex models that incorporate community food security (CFS) strategies and values. Anti-hunger strategies meet the direct needs of individuals or households by providing food or transfer payments, while CFS models incorporate prevention strategies at the community level (Winne, et al., 1997). Anti-hunger programs provide emergency food assistance, distribute commodities, and reduce the societal costs associated with hunger. CFS models are long-term strategies developed through multi-disciplinary partnerships and community planning processes. CFS goals include building community assets, empowering individuals, and supporting local agriculture production to develop healthy food secure communities. These strategies are directed to geographically-bound areas where poverty levels are higher than average (Winne, et al., 1997).

Many CFS models have adopted a definition developed by Hamm and Bellows (2003). Their approach stresses self-sufficient communities in which all people have access to enough affordable healthy foods to live a quality life (Hamm & Bellows, 2003; Malhi et al., 2009). The American Dietetics Association (ADA) (2010) has endorsed CFS strategies that shift the emphasis from general caloric intake to the specific intake of vitamins, minerals, and other nutrients (Anderson, 1990; Campbell, 1991). Anderson (1990) and Campbell (1991) also address the need for food acquired in a socially acceptable manner. Socially acceptable acquisition strategies refer to traditional ways people access foods, such as "grocery stores, restaurants and government food assistance programs" (Campbell, 1991, p. 409). Campbell (1991) notes that some may view the reliance upon government assistance as socially unacceptable.

Lee and Greif's (2008) multi-dimensional food security framework components include consumption, quality, sources, and cost. This framework also addresses personal preferences, diverse food sources, and the frequency of meals. Cost is related to accessibility in terms of the strong relationship between income and food security.

CFS models stress that food production and distribution is conducted in a manner that is sustainable and reflects social justice principles (Hamm and Bellows, 2003). These models have also been called "green and fair" (Malhi et al., 2009). The Hamm and Bellows (2003) community food security definition will be used as a framework for this study because of its connection to sustainable development and ecological-social perspectives. CFS is a complex concept. Appendix 1 outlines many of the measures that researchers have included in CFS research. Not all will be used in this study.

Theoretical Framework

Anderson and Cook (1999) state that a common theoretical base for community food security needs to be established. They state the importance of linking hunger relief, community development, and sustainable agriculture with each other to further the research base (Anderson & Cook, 1999). This study uses a social-ecological systems framework that incorporates both sustainable development and social development theory as the basis for community food security. A social-ecological systems framework emphasizes the interactions between people and the natural and built environment, and recognizes that only appropriate use of natural resources, respect for the environment, and intentional long-term planning can secure future generations (Payne, 1995).

CFS focuses on the interconnections among sustainable food systems, public health, and social justice within communities (Lang, 2009; Story, Hamm, & Wallinga, 2009). Contemporary community work in the UK is focused on encouraging communities to meet the population's needs through building social capital, encouraging civic responsibilities, strengthening the capacity through investment in human capital, and including all marginalized groups of society to have an active voice in the community (Callaghan & Colton, 2008; Henderson and Thomas, 2002). Social capital refers to interactions between people based on norms of reciprocity, trust, and shared values (Coleman, 1988; Putman, 2001). Human capital includes the education and training that are important for reciprocity (Bartel, 2000; Davenport, 1990; Oliver, 2001)

Midgley (1995) describes social development as a process of planned social change to promote the well-being of the population in conjunction with a dynamic process of economic development. Social development has been used in international work, particularly in the formerly colonized global South nations as a way to address human needs and improve societal well-being (Midgley, 2003). This planned change can be found in Hobhousian social liberalism theories that addresses human progress through economic progress (i.e., capitalism) in combination with social justice (Midgley, 2003; Seaman, 1978). The United Nations (1971) reaffirmed the idea that both economic and social development should be considered concomitantly in national planning processes (United Nations, 1971). Social development was popularized during a time when new independent nations were emerging and were planning for ways to secure economic and political freedom while simultaneously finding ways to address health, social, and economic needs (Midgley, 2003).

Social development emphasizes social equity between groups. Community participation from a diverse group of stakeholders aims at making structural changes to improve underlying economic and institutional problems. At the individualist level, people focus on their contributing behaviors to social problems and solutions (Midgley, 1993). Collectivist ideologies emphasize coalition-building and social cohesion between organizations. Populist ideologies used scalable community-based strategies (Midgley, 1993). Embedded in each system level are resources and linkages from a wide range of disciplines. Social developers evaluate processes in terms of systems that promote sustainable economic, environmental, and social justice interactions between the social and ecological environments.

CFS models fit well with the eight elements of social development. These include an emphasis on interdisciplinary works that is progressive, process-oriented, inclusive, and linked to economic development. The goal is to promote social welfare through a variety of intervention processes (Midgley, 1995). It extends systems theory to focus on community-level work addressing vulnerable populations (Payne, 1995) which is appropriate for the discussion of community food security strategies.

Sustainable development models recognize the existence of relationships between human and environmental problems that impact populations across geographic territories (Estes, 1993). Social-ecological interactions that impact the ability to sustain quality life include global population growth and environmental pollution and land degradation resulting from an increased use of natural resources (Ehrlich & Ehrlich, 1990). Lang (2009) describes the importance of considering the natural and built environment, the human relationships involved in the production, processing, and distribution of food, the shared cultural meanings of food, and the nutrition that food brings to sustain human life. Sustainable development planning requires decision-making to not rely solely on economic or market forces. It incorporates social, economic, and environmental goals (Leuenberger & Wakin, 2007).

Sustainable development goals seek to consider and balance the long-term impacts of social, economic, and political decisions through integrated strategies that consider the earth's natural resources (Estes, 1993; Leuenberger & Wakin, 2007; United Nations Development Programme [UNDP], 1994). The Intergovernmental Panel on Climate Change (IPCC) indicated that because food production would be affected by climate change, a sustainable model that encompasses environmental concerns, equitable access and distribution of resources, and social justice would be needed to ensure that communities could provide enough healthy food (Lang, 2009). A sustainable model would ensure that food was produced and distributed in a way that protected biodiversity, soil, and water (Lang, 2009). Furthermore, a sustainable model includes goals of social justice and equitable distribution of economic resources (Leuenberger & Wakin, 2007).

Story, Hamm, and Wallinga (2009) state that a sustainable food system is one that supplies the nutrition needs for all people in a community, while maintaining sustainable ecosystems and protection for all people within the food system. This process is markedly complex, as there are many interacting "inputs and outputs" impacting outcomes (Story, Hamm, & Wallinga, 2009, p. 223). Sustainable development perspectives are important in the context of "constantly changing conditions" that require "flexibility" within communities that have diverse cultural identities and values (Pettoello-Mantovani, 2005, p. 749). Although not every dimension of sustainability will be addressed in this study, several elements are parallel with CFS strategies and may be considered in the community-level model. Sustainable development dimensions most relevant to this study pertain to agricultural practices that emphasize respect for natural resources and economic practices that promote quality with the least amount of harm (Corson, 1994).

Purpose of the Study

Most food security measurement has been conducted at the individual and household level, but no adequate methods exist for community food security measurement (Hamm & Bellows, 2003). Community food security is a concept that cannot currently be observed or measured (Tchumtchoua & Lopez, 2005). Since CFS cannot be measured, practitioners and policy-makers may benefit from relative rankings of overall community food security and rankings for individual factors that are associated with community food security across several communities (Tchumtchoua & Lopez, 2005). Logit models have also been used to predict household food security based on local social and economic conditions (Bernell, Weber, & Edwards, 2006). Identifying whether local food production resources exist and are supported by the community is also important in order to better delineate the relationship with community food security (Cohen, 2002). Furthermore, a new way of estimating the percent of households that may be considered community food insecure allows a useful application for researchers, practitioners, and policy makers interested in understanding multiple variables related to the food environment.

Research Question

This study seeks to contribute to emerging knowledge of how community factors can predict or explain high rates of food insecurity. It extends research beyond income, wealth, and poverty indicators to account for the food system context in which food insecurity exists. The study will also include non-metropolitan areas, allow comparability between counties on several risk and protective factors, and identify vulnerable communities.

Previous research has focused on the household and community-level economic determinants related to food insecurity (Gunderson, Kreider, & Pepper, 2011; Nord, Andrews, & Carlson, 2008; Olson, Anderson, Kiss, Lawrence, & Seiling, 2004; Olson, Rauschenbach, Frongillo, & Kendall, 1997; Rose, 1999) Economists have provided evidence about the direct relationships between financial resources, budgetary constraints, and individual or household level food insecurity (Gunderson, et al., 2011). Higher rates of food security exist in lower income households, but poverty is not necessarily equivalent to food insecurity. Poor households can be food secure, while households above the poverty level may be food insecure (Gunderson, et al., 2011). Economists have looked at income over several years as a greater predictor of food insecurity than current income. Additional analyses have shown that liquid assets are a buffer to household food insecurity while unemployment can create financial stress and higher food insecurity (Gunderson, et al., 2011; Ribar & Hamrick, 2003).

The focus of economic determinants related to food insecurity suggest solutions like entitlement programs for income-qualified households and individuals (e.g., SNAP, National School Lunch Program) that provide transfer payments for the purpose of meeting immediate food needs. While evidence shows that these programs may decrease individual and household food insecurity (Gunderson, et al., 2011), the solutions may become problematic since they do not incorporate contextual environmental factors related to community food environments or incorporate sustainability. This is problematic in light of the increase in food insecurity since 2006 (USDA, 2011), rising food prices (McGranahan, 2008), and the loss in productive land for growing food due to population increases, pollution, and development (Hamm, 2007). This study seeks a better understanding of predictors of community food security beyond income and wealth distribution, which suggests solutions rooted in the sustainable community food security strategies.

Q1: What are the most important parts of a sustainable non-metropolitan food system that impact food security?

Q2: Which identified community-level risk and community-level protective factors are predictive of food security rates in non-metropolitan areas?

Q3: What significant differences in community-level risk and community-level protective factors exist between non-metropolitan areas and metropolitan areas?

Method of Inquiry

This study is intended to fill in the gaps in food security research by focusing on community-level factors in both metropolitan and non-metropolitan environments. Secondary data from the USDA Food Environment Atlas (n.d.) for 113 Missouri counties was analyzed. Since the county food security rates are not known, the dependent variable was modeled using a regression formula based on state-level data estimated at the county level. This "food uncertainty" variable is based on poverty, median household income, citizenship, age, race/ethnicity, unemployment, and female-headed households (Dawdy, et al., 2010). The University of Missouri Interdisciplinary Center for Food Security houses the data and provided the formula and support to obtain the most accurate estimates of food insecurity. A Principal Components Analysis was conducted to reduce the data to components used to predict community-level food security. Lopez, et. al's (2008) town-level assessment of food security in Connecticut included 38 indicators which mapped onto 11 factors. Similar indicators are used in this study, with some modifications based on the literature. Once components were determined they were added to a multiple regression model. Pervious research indicated factors related to accessibility, affordability, public food assistance, private food assistance, and local food production (Lopez, et al., 2008).

Connection to Social Work

Food Security as a Human Right

The United Nations approaches food security from a human rights-based perspective. This means that social and economic determinants must be addressed in a holistic manner. The public must participate in community food security decisions in order to hold the government accountable for meeting the needs of secure access to an adequate variety of quality food (Chilton and Rose, 2009). In 1948, The United Nations adopted the Universal Declaration of Human Rights, Article 25, which describes the minimum standard of living. The United Nations (Ziegler, 2002) working definition of "right to food" is:

> "The right to have regular, permanent and unrestricted access, either directly or by means of financial purchases, to quantitatively and qualitatively adequate and sufficient food corresponding to the cultural traditions of the people to which the consumer belongs, and which ensure a physical and mental, individual and collective, fulfilling and dignified life free of fear." (p. 11)

Social workers are responsible for meeting basic human needs, empowering vulnerable populations, addressing individual and societal well-being, and targeting the contextual environmental in which humans and social problems exist (National Association of Social Workers [NASW], 2008). The Code of Ethics is the backbone of the profession and provides social workers with guidance regarding ethics and decisions. Ethically, social workers are compelled to pursue social welfare in communities in order to help people meet their basic needs (NASW 6.01, 2008). Equally important is the call to seek equitable access to resources, support social justice, prevent exploitation, and increase opportunities for oppressed populations (NASW 6.04, 2008).

Two social work core values include service and social justice. Together, they are meant to encourage social workers to devote time to larger social problems and challenge injustices and oppressive systems (NASW, 2008). In many ways, the current food system lends itself to an unjust distribution of resources. Knowledge of the food system and working within the food system are keys to social change in the context of food security.

Food Insecurity as a Public Health Concern

Food insecurity is a public health and social problem associated with poor health, child cognitive and emotional development deficiencies, and adult depression (Adams, Gummer-Strawn, and Chavez, 2003; Alaimo, Olson, & Frongillo, 2001; Casey, Goolsby, & Berkowitz, et al., 2004; Chilton, & Booth, 2007; Cook, Frank, & Berkowitz, et al., 2004; Siefert, Heflin, Corcoran, & Williams, 2001). Research shows connections amongst food security, obesity, and chronic health problems (Adams, Gummer-Strawn, & Chavez, 2003; Dietz, 1995; Hamelin, Habicht, & Beaudry, 1999; Tarasuk & Beaton, 1999; Wilde & Peterman, 2006). Marsh (2004) reports that people living in low income neighborhoods are more at risk for obesity than people living in wealthy neighborhoods, and that the impact of social inequalities needs to be researched more in-depth to determine what factors of poverty are significantly associated with obesity. Lack of access to affordable nutrient-rich foods contributes to poor dietary intake and malnourishment. This is exacerbated by health care costs. In the U.S., 15% of the population has no health insurance coverage and many are underinsured (DeNavas-Walt, Proctor, & Smith, 2009).

Persons who are classified as overweight or obese have higher rates of diabetes, depression, anxiety, atherosclerosis, hypertension, limited mobility, work impairment, low self esteem, and discrimination, all of which contribute to over $147 billion annually in medical costs (Finkelstein, Trogdon, Cohen, & Dietz, 2009; Hesketh, Wake, & Waters, 2004; Houston et al., 2009; Petry, Barry, Pietrzak, & Wagner, 2008; Rodbard, Grandy, & Shield Study Group, 2009).

Significance of Study

Food security is an important social work issue that has roots dating back to the Settlement House Movement. Nobel Peace Prize winner Jane Addams, who was a pioneer of social work and the settlement house movement, housed an emergency food program at Hull House in Chicago, Illinois. Recently, the Hull House Museum has started a program called, Re-thinking Soup, in which community members are invited to discuss food justice issues (Lee, 2011). Their food security framework recognizes the linkages among "women's rights, labor, poverty, and other social causes" (Lee, 2011, p. 75). People share a meal made from local ingredients and a gathering of people interested in farming, health, economics, cooking, and activism discuss the interplay of the globalized food production and distribution system in the context of practices and policies. The modern Hull House started an urban garden and acknowledges the role sustainable food production can play in the community's health and well-being (Lee, 2011). Acknowledging that food insecurity is a cross-cutting issue within areas like health care settings, child welfare, school social work, and recognizing the role social workers may play in policy decisions concerning SNAP, Supplemental Nutrition Program for Women, Infants, and Children (WIC), and other public and private programs is important.

This study seeks to add to knowledge about community food security. This study will fill in the gaps of studies that limit measurement of food security to socio-demographic variables related to race, poverty, income, and wealth. It seeks to explore ways in which sustainable food systems may have an impact on communities in terms of their ability to provide healthy, affordable food to all people. Lastly, the study will include many non-metropolitan areas, which extends the research beyond the heavily urban-based literature.

CHAPTER 2

REVIEW OF THE LITERATURE

One of the challenges to conducting research related to food security and community food security is the broad-based roots that spread across multiple disciplines. Researchers from perspectives ranging from agricultural economics to sociology, public health, and sustainable agriculture have studied a vast number of issues that are relevant to this study. Chapter 2 provides a thorough review of the literature, beginning with a discussion about why food security may be studied in the context of the existing complex food system. The discussion then shifts to the most prevalent food security literature based on poverty and socio-demographic indicators.

As research has moved towards identifying variables related to food environments, disparities in cost and availability of quality healthy food have been studied. The concept of "food deserts" is defined and followed by research related to accessibility and availability of food stores and healthy foods. This leads to a further description of studies conducted in the nutrition and public health sectors.

It is also important to understand the policies and programs designed to decrease household and individual level food insecurity. Select public and private food assistance are outlined and research related to their relationship to food security and health are include.

Lastly, the discussion ends with a focus on identified community food security strategies related to food production. The relationship between sustainable food systems and environmental issues is included because of the link to social development, sustainable development, and community food security.

The Complex Food System and its Relationships to Food Security

Community-based food systems are tools for improving community-wide health by improving access to affordable healthy produce while considering the long-term viability of resources (Hamm, 2009). "Locally integrated" (Hamm, 2009, p. 244) food systems allow more opportunities for communication among consumers and producers that may help retain knowledge of food production and sustain geographically-based agricultural systems through sharing of growing strategies (Hamm, 2009). Sustainability is important to understanding the need for re-developing food systems at local and regional levels, while existing in the context of a globalized food system (Hamm, 2009; Lang, 2009). Sustainability includes environmental protection, social justice, and equitable distribution of resources (Lang, 2009). Hamm's (2009) conceptual model of interconnected health across systems level starts with healthy soil for healthy plants provided to people that create opportunities for healthy families and communities.

A food systems approach to food insecurity emphasizes sustainability, community food justice (Story, Hamm, & Wallinga, 2009), and public health that can impact community economic development, land preservation, and nutrition (Story, et al., 2009). Re-localizing food systems is a way to improve overall access to healthy food in communities, while protecting the land and people involved in producing and distributing food (Story, et al., 2009). The food system is complex with many processes, people, and institutions. Improving community food security is no easy task. Story, et al. (2009) states that by considering the complex interactions of the entire system, health, agriculture, and rural development, food access will be improved over time. Food should be considered from the farm to the plate and indirect long-term costs associated with health and the natural environment needs to be included in improved food systems (Lang, 2009).

CFS strategies value interdisciplinary community efforts that address issues of equitable access to healthy foods. These connections have been described as effective public health promotion tools that may impact obesity, economic development tools, and as methods for addressing food insecurity at the local level. While CFS does not seek to revamp the globalized food system, the strategies are intended to improve local and regional systems since much concern about oil prices, climate change, mono-cropping, mass industrialized farms, and pollution have the potential to unintentionally harm people's food and health (Harvie, et al., 2009; Wallinga, 2009). Localizing food systems may not only improve access, but may build wealth through development of food networks that will eventually be sustainable and income producing (Herrera, Khanna, & Davis, 2009).

Chilton and Rose (2009) acknowledge the contradictory, "morally reprehensible" (p.1203) nature of food insecurity in the United States, where food production is so great that surplus commodities exist. Neff, Palmer, McKenzie, and Lawrence (2009) describe the need to move beyond individual-level interventions to macro interventions. This model emphasizes the need to address "food systems" and "social disparities" that "constrain and affect the choices" people make (Neff, et al., 2009, p. 284). This model also recognizes that low-income communities are often impacted by "health threats associated with food production and processing methods" (Neff, et al., 2009, p. 284). Issues related to limited access to healthy foods, disparities in prices of food, unequal distribution of wealth, policy changes impacting public food assistance programs, economic shifts impacting private food assistance programs, and limited community resources have been viewed as potential risks for ensuring the greatest amount of food secure households.

Poverty and Demographic Indicators

Poverty is the greatest predictor of food insecurity (Nord, Andrews, & Carlson, 2008). Rose (1999) analyzed data from the National Health and Nutrition Examination Survey 13 (NHANES) and the Current Population Survey (CPS). Findings indicated that people whose income was below the Federal Poverty Level (FPL) were more than 3.5 times as likely to be food insufficient as those with incomes above the FPL (Rose, 1999). Social workers are concerned with poverty rate increases and economic disparities that have far-reaching community implications. Rose's (1999) study must be considered since over 13% of the population (39.8 million people) was at or below the FPL in 2008, representing the highest poverty rate since 1959 (DeNavas-Walt, Proctor, & Smith, 2009). Poverty rates for members of the African American and Hispanic populations were 23.2% and 24.7% respectively. Other subsets of the populations at risk for food insecurity due to their poverty rates include single parent households (Olson, et al., 1997; Rose, 1999). Over 37% of single female-headed households and 27.6% of single male-headed households were food insecure in 2008 (USDA, 2009a). Kaiser, et al.'s (2003) study showed that females in Latino households that had lower education were more likely to be food insecure.

Gross and Rosenberger's (2005) ethnographic study of a rural Oregon county revealed the complexities of measuring income and wealth of low-income households. First, differences existed between the FPL and living wages. In their study, the living wage was $2000 higher than the FPL. While most of their sample lived below the FPL, several above the FPL were food insecure. Many of their informants had multiple income sources, such as jobs, retirement, Social Security, disability, and SNAP (Gross & Rosenberger, 2005). Other expenses such as after-school care and health care debt were burdensome to many families. Many households sought assistance from social networks to assist with childcare, carpooling, food sharing, and cash assistance to help meet their needs (Gross & Rosenberger, 2005).

Olson, et al. (2004) surveyed 316 low-income families living in rural counties in 14 states in the U.S. While only 5% of their sample had incomes above 185% of the FPL, almost 65% of this group was food insecure. Persons with less than a high school education who were not Caucasian were more likely to be food insecure. Other predictors included persons who had difficulties paying for medical expenses and persons who paid rent for housing (Olson, et al., 2004).

Rose (1999) found that nearly one-half of food insecure households are living above the poverty line. Merely looking at income did not accurately reflect expenditures, such as health care, housing, and food (Rose, 1999). Mezzo and macro level factors related to food insecurity also existed. Rose (1999) showed that economic impacts due to job loss, low or nonexistent Food Stamp benefits (now SNAP), and household composition were related to higher levels of food insufficiency in his national secondary data analysis. Holben and the American Dietetic Association (2006) cited a 2004 U.S. Conference of Mayors report that social causes such as unemployment, underemployment, reduced public benefits, high housing costs, and health problems may be factors related to food insecurity. Conversely, studies have consistently linked home ownership to increased protection from food insecurity (Rose, 1999).

Lopez, et al., (2008) identified seven indicators of town-level income and wealth including measures related to assets (housing), property values per capita, and property tax rates. Income measures included median household income, income per capita, and town-level income distribution (Lopez, et al., 2008). Olson, et al., (1997) found significant relationships between food security and personal savings, owning a home, economic security, and income-earning potential in a rural New York county. Gross and Rosenberger (2005) showed that housing, health care, transportation, utilities, child care, and debt impacted the financial stability of many households in Oregon. While food spending may be flexible, costs like rent and utilities must be paid monthly in order to prevent the risk of homelessness. Informants with health crises, debt problems, and reduced incomes due to death or divorce of a partner/spouse were at the greatest risk of food insecurity (Gross & Rosenberger, 2005).

Lopez, et al., (2008) defined poverty as a category predicting community food security. This factor included the number of renter-occupied housing units per capita, the proportion of children living in poverty, the proportion of the community with income levels below the FPL, and the ratio of unemployed persons to those in the labor force.

Taponga, Suter, Nord, and Leachman (2004) analyzed state-level food security. Persons paying more than 50% of their monthly income for rent and households moving within the last year were significantly predictive of both low food security and very low food security (Taponga, et al., 2004). Very low food insecurity was highest during times when unemployment was highest during the three-year period data was collected. Poverty rates significantly predicted low food security (Taponga, et al., 2004). Although the percentage of ethnic/racial minorities was not a significant predictor of food insecurity in Taponga, et al. (2004), Grussing (2007) noted that interpretation should include interactions between race/ethnicity and poverty.

Bernell, Weber, and Edwards' (2006) multilevel analysis of food insecurity in Oregon considered the distribution of state level food security in the local context of social and economic conditions via a secondary data analysis of the 2000 Oregon Population Survey. Social supports were included as a way to account for household food provisioning strategies (i.e., sharing food with neighbors) that may mitigate food insecurity. Social support was defined by the percentage of households living in rural areas, the percentage of households affiliated with a religious institution, and the percentage of households that had moved within the past five years. Economic opportunity was defined as county unemployment rates and county wages. These represented the community's economic status. Housing affordability was also used as a surrogate for nonfood prices. Counties in the top 25% of Oregon's rent distribution were labeled as "rent" (Bernell, et al., 2006, p. 201). Their results supported the hypothesis that county-level factors, in addition to household and individual variables, influenced food insecurity rates. In their sample, moving from an urban environment to a rural environment reduced the likelihood of food insecurity. Bernell, et al. (2006) suggested that rural communities might have unique social support systems and resources available to decrease community food insecurity rates. Low-income persons in counties where the median rent was the highest in the state were more likely to be food insecure. African American households, persons with disabilities, and single-parent households were more likely to be food insecure. Adults older than 65 years of age and adults with a college degree were significantly less likely to be food insecure.

Martin, Rogers, Cook, and Joseph (2004) also looked at whether social capital was associated with household food security while controlling for household-level socio-demographic variables. Their systematic random sample yielded 330 households (55% response rate) in Hartford, Connecticut that had incomes less than 185% of the FPL that responded to face-to-face surveys completed in homes. The survey instrument included the 18-Item USDA Food Security Module, demographics, and seven items on a four-response Likert Scale measuring social capital. Participants were given $5 as an incentive and responded to questions about the length of the time they have lived in their home, in Hartford, and whether they were involved in any civic organizations, clubs, or religious groups. Martin, et al. (2004) found that higher household social capital reduced the odds of household hunger when household socio-demographics were controlled. No socio-demographic indicators significantly predicted hunger when social capital was included. Martin, et al. (2004) also found that community-level social capital significantly decreased odds of hunger. Households who participated in local organizations or had an elderly person living with them had significantly higher social capital scores on their four-point scale. Their cross-sectional study was not able to determine whether food security was more likely because of social capital, whether social capital was higher because households were food secure, or whether other factors may have contributed to social capital and food security (Martin, et al., 2004).

Edwards, Weber, and Bernell (2007) studied factors impacting state-level hunger rates across the U.S. Hunger was measured using the April 1995 Current Population Survey Food Security Supplement which included the USDA Food Security Module.

Predictors included household income divided by the U.S. FPL for each household size, adult unemployment, full-time employment for 12 months, household structure, and home ownership. Renting households, single-mother households, and limited income were related to food insecurity. Households with unemployed or partially employed adults experienced higher rates of hunger across the U.S. (Edwards, Weber, & Bernell, 2007).

Food Deserts

Food access relates to both affordability of foods and accessibility of food stores. These are connected through community food environments. The term "food deserts" has often been used to describe areas in which food may be unavailable or expensive (Cummins & MacIntyre, 2002). Food desert literature emerged from the UK (McEntee, 2009). Food deserts are often in geographically disadvantaged regions with limited food supplies (Guy and David, 2004) or inadequate retail choices (McEntee, 2009). Other common issues are high numbers of persons living in poverty and poor nutrition (Guy and David, 2004). Food desert literature connects availability of foods with affordability of foods, emphasizing healthier foods are often harder to find in low-income communities and cost more than wealthier communities (Wrigley, 2002).

Wright Morton and Blanchard (2010) found commonalities among identified food desert communities. Generally, these communities had a higher percentage of persons without a GED or high school diploma, higher poverty rates, lower median incomes, large older populations, more people living outside of city centers, and higher ratio of small food stores and convenience stores per capita.

In the past, food deserts were identified according to proximity to the nearest supermarket, the number of supermarkets within a .62 mile radius, and the variety of foods offered (Apparicio, et al., 2007). Ver Ploeg, et al.'s (2009) report to Congress provided a methodology and definition of food deserts in the U.S. This was developed, in part, as a reliable way to assess food deserts across the U.S. that could be evaluated for federal funding related to grocery store accessibility and obesity. This new U.S. food desert definition relates to income and access to grocery stores. Ver Ploeg, et al.'s (2009) report used 1-km grids in their definition, but it has since been changed to Census tracts for easier identification and use (USDA, n.d.) The USDA states that food deserts existed in Census tracts with a poverty rate greater or equal to 20% or the median income less than or equal to 80% of the area median income. In rural areas, food deserts are defined by 33% of the population or 500 people that live more than 10 miles from a large grocery store or a supermarket. In urban areas, the distance is 1 mile (Ver Ploeg, et al., 2009, USDA, n.d.a.).

Affordability

Much food security literature has been concerned with the affordability of food for low-income families. This includes the actual price of food and associated opportunity costs for food that is unaffordable. Low-income households often have to make choices about how to spend their money that may impact the amount available for food expenditures. Gross and Rosenberger (2005) found that tradeoffs were often made between food and housing, transportation, utilities, health care, child care, or medicine each month.

Low-income families have less money to spend and often purchase high-calorie, low-nutrient foods (Kozikowki and Williamson, 2009). These diets have contributed to poor nutrition, cardiovascular problems, diabetes, and child development issues. Children, low-income persons, and lower educated persons consumed the lowest amounts of fruits and vegetables (Putnam, Allshouse, & Kantor, 2002; Johnson, Taylor, & Hampel, 2000). According to the Consumer Price Index (CPI), fresh fruits and vegetables prices have increased by 118%, compared to a 20% increase for carbonated soft drinks, a 35% increase for fats and oils, and a 46% increase for sugar and sweets (Putnam, et al., 2002). Due to agricultural policies and the technologically advanced food system, commodities like sugars and fats are added to food products, which can be sold at low prices. Low-income households spending less than $25 per person each week (Putnam, et al., 2002) may consider the economics of food choices as a determinant of their dietary intake. According to Guthrie, Frazao, Andrews, and Smallwood's study (2007), demand for fruits and vegetables was more responsive to lower prices than other foods. A 10% decrease in the price of fruits or vegetables translated into a 6-7% increase in fruit and vegetable purchases.

Drewnowski and Specter (2004) studied the inverse relationship of energy density of food and costs in relation to consumer behaviors in low-income neighborhoods. Drenowski (2007) calculated that every dollar spent needs to be the equivalent of 300 kilocalories (kcal) to yield a daily caloric intake of 2500 kcals each day. Higher-energy dense diets of processed foods made with sugars and fats will easily garner 300-500 kcal per dollar. Drewnowski and Specter (2004) found that purchasing more of these foods may be perceived as a better way to stretch limited incomes for low income households since fruits and vegetables do not yield the same high calories per dollar.

The relationship among actual prices, perceptions of prices, and fruit and vegetable consumption has been of interest to researchers particularly from the field of nutrition. Cassady, Jetter, & Culp (2007) surveyed 25 supermarkets in heterogeneous census tracts in Los Angeles, California and Sacramento, California during three time periods. They compared the prices of specific produce items between the USDA Thrifty Food Plan (TFP) and the 2005 Dietary Guidelines, determined differences among food stores within economically diverse neighborhoods, and accounted for any variance due to seasonal price differences. The TFP is one of four plans developed by the USDA to show which nutritious foods can be bought with different amounts of money. The TFP is the basis for SNAP allotments (USDA, 2007). Trained researchers recorded the lowest prices per unit of food items. During the three time periods, the cost of one serving of fruits, vegetables, or legumes ranged from $0.07 (orange vegetables) to $0.24 (legumes). While the TFP basket cost significantly less in low- and very low-income stores, there were vast differences among the 10 low-income stores (Cassady, et al., 2007). Families receiving an annual SNAP allotment of around $3888 needed to allocate 43% of their SNAP budget to fruits and vegetables to meet the Dietary Guidelines (Cassady, et al., 2007). Lower income families spending around $2000 on food for home would have to use up 70% of their food budget to afford the fruit and vegetable market basket (Cassady, et al., 2007). Cassady, et al. (2007) concluded that it is not the price per serving of produce that is a barrier to consumption of produce by low-income people, but the servings recommended by the USDA.

While most food security research concerning the built environment has been conducted in urban and suburban markets, researchers have started to study rural food environments. Liese, Wris, Pluto, Smith, and Lawson (2007) collected data on the availability and costs of food at 77 stores (10% grocery, 16% supermarkets, 74% convenience) in a rural South Carolina county with a population of less than 100,000. Price differences were significant between supermarkets and convenience stores. They found a $0.54 difference in the price of nonfat milk and $0.58 for high fiber bread (Liese, et al., 2007). Except for milk, healthier versions of food items were more expensive than the less healthy versions in all store types (Liese, et al., 2007). Wright Morton and Blanchard (2007) compared costs of 149 items in four rural counties in Iowa with less than five grocery stores and no supercenter. They found that supercenters sold canned vegetables, cereals, meats, breads, and frozen juices at lower prices than smaller retailers, but were priced higher on eight of 13 fresh vegetables. Seventy-five percent of households (75%; N=1500) shopped at food stores in their counties and most lived 20 miles from a supercenter (Wright Morton & Blanchard, 2007).

Food prices at stores in urban communities, rural communities, and adjacent neighborhoods were compared to the TFP's market basket price (MBP) (Hendrickson, Smith, & Eikenberry, 2006). Between 11% and 52% of the food items were more expensive in the four stores than the TFP MBP (Hendrickson, et al., 2006). Focus groups identified cost as one barrier to purchasing fruits and vegetables. Between zero and four of the 19 foods were less expensive than the MBP in the urban and rural stores. Hendrickson, et al. (2006) found that supermarkets in adjacent neighborhoods had a significantly greater selection of fruits and vegetables than the two urban stores.

Chung and Myers (1999) compared prices of food in 55 stores in the Minneapolis-St. Paul area to the USDA TFP MBP. Chain store prices were between 10 and 40% less than convenience or grocery stores with the exception of certain types of fruit, baby formula, and produce. Dry goods accounted for the largest price disparity. Inner city store prices were about 2% higher than their counterparts in different locations. Certain commodities offset each other. Quality, nutritional value, and availability were not included in the equation (Chung & Myers, 1999). Their major finding was that low-income households paid more for food because they shopped at small grocery stores and convenience stores, rather than chain supermarkets (Chung & Myers, 1999). Perspectives from consumers concerning decisions about their food store preference were not included. Additionally, opportunity costs such as transportation costs or the time needed to travel and shop at stores for low-income households were not included in the overall costs.

Short, Guthman, and Raskin (2007) conducted research in five San Francisco and Oakland neighborhoods between 2004 and 2005. They specifically focused on the role that small-scale markets played in meeting the community's food needs. Each neighborhood was racially and ethnically diverse, representing African American, Latino, Asian, and Caucasian sub-populations. Between 26% and nearly 53% of people in the sample neighborhoods were living at or below 200% FPL. They compared food prices to the TFP and low cost MBP's to determine affordability using price surveys and previously collected survey data. A Latin American food basket was created for the Mission neighborhood. Unlike previous studies, Short, et al. (2007) found that food prices at small retailers was affordable. Food prices were below the low-cost food plans and below neighboring chain stores. Short, et al. (2007) showed that only one store had a complete basket that was more expensive that the prices of the national chain. Many of the stores were in neighborhoods with high concentrations of Latinos. Furthermore, they described how stores were often family-owned and had smaller profit margins than their supermarket counterparts. Short, et al. (2007) stated that costs might be lower by virtue of low-rent buildings and employing family members.

Zenk, et al. (2009) did not find an association between observed prices of fruits and vegetables and satisfaction with the availability of fresh produce in three Detroit neighborhoods. The researchers warned that their study may have yielded different results because their research did not look at specific supermarket prices. Instead, they considered neighborhood food environments that included several types of food stores.

An Alabama study used discrete choice analysis to look at how price, demographic variables, income, and parental Body Mass Index (BMI) explained the presence or absence of fruits and vegetables in 1355 Birmingham homes with children (Ard, et al., 2007). The USDA's average cost per serving of produce was inversely related to the proportion of homes that had particular food items available (Ard, et al., 2007). For each $0.10-unit increase in cost, the odds of homes having the food item decreased by 23%. Produce that cost more than $0.30 per serving more than the average was the primary predictor of availability (Ard, et al., 2007). Statistically significant differences in the availability of certain types of foods existed between African American and Caucasian households. Several of the food items found more in African American homes cost more than that the median cost. The interaction between race and cost was significant; Caucasians were more impacted by cost increases (Ard, et al., 2007). The study was based on self-report, and did not include perceived costs, preparation costs, and storage costs. Canned, frozen, dried, and fresh fruits and vegetables were included together (Ard, et al., 2007), which limited the study to addressing quantity, not quality. Another limitation was using national data to estimate costs, which may vary depending on regional differences.

Over 250 Latino families participating in WIC, Head Start, and other community agencies participated in a cross-sectional survey between February and May 2001 in six California counties (Kaiser, et al., 2003). The survey included a 141-food item inventory and the 18-item USDA Food Security Module. Households that reported less supplies of grains, meats, vegetables, fruits, snack foods, and dairy were correlated with higher levels of food insecurity during the past three months and the last 12 months (Kaiser, et al., 2003).

Various researchers have used quasi-experimental designs and experimental control group designs to examine whether improving access to produce encourages purchasing and consumption behaviors. Much of this has been done within the context of the SNAP and WIC subsidies. The underlying assumption is that subsidies earmarked for fruits and vegetables frees up food budgets since produce tends to be costlier per serving than other foods.

Kropf, Holben, Holcomb, Jr., and Anderson (2007) conducted a cross-sectional study of Ohio WIC recipients who received $18 per growing season and found that those who received Farmers' Market Nutrition Program (FMNP) benefits had significantly higher intakes of vegetables than those who did not have FMNP benefits. The program allowed WIC vouchers to be used for purchasing fresh produce at farmers' markets. The WIC FMNP Program Impact Report (National Association of Farmers' Markets, 2003) indicated that 73% of the 24,800 surveyed across 30 U.S. programs reported increased vegetable consumption compared to the previous growing season without FMNP benefits. The report stated that 54% spent additional money at the farmers' market, and 73% planned to continue shopping at the farmers' market after their vouchers ran out (National Association of Farmers' Markets, 2003). Findings were limited to self-report and potential social desirability biases. Further research, although costly, could include documentation of receipts, records of purchases, and quantities of different types of food consumed.

Postpartum WIC clients in Los Angeles, California participated in a non-equivalent experimental control group study designed to determine whether a fruit and vegetable subsidy increased their dietary intake of fruits and vegetables (Herman, Harrison, Afifi, & Jenks, 2008). They were assigned to a control group, a farmers' market intervention group, or a supermarket intervention group. The control group received $13 each month for diapers. The intervention groups each received $10 each week for six months. Measurements were taken six times at each of the intervention sites and four times with the control group. Those who received the targeted subsidy increased their intake of fruits and vegetables during the study and sustained it six months following the intervention. Eating more fruits and vegetables at the baseline measurement, speaking Spanish, and participating in the intervention groups explained 14% of the variance in fruit and vegetable consumption at the six-month follow-up interview (Herman, et al., 2008). No statistically significant differences were found between the two intervention sites, although participants consumed more fruits and vegetables at the farmers' market sites than the supermarket sites. Herman, et al. (2008) did not systematically collect qualitative data but reported that participants often cited the quality of produce to be a factor. Those at the farmers' market sites reported fresher produce, better quality, and general satisfaction with the interactive nature of the farmers' markets (Herman, et al., 2008).

A United Kingdom (UK) study of 680 low-income adults addressed consumers' attitudes and behaviors concerning purchasing and consuming fruits and vegetables (Dibsdall, Lambert, Bobbin, & Frewer, 2003). They mailed questionnaires to 3000 low-income housing units and had a 23% response rate. The questionnaire included demographic variables, self-reported fruit and vegetable intake as a measure of their perception of their diet, and 30 attitudinal and behavioral items on a seven-point Likert Scale. They used a multivariate analysis of variance (MANOVA) to see whether the availability of fresh, frozen, and canned fruits and vegetables at food stores, perception of diet and health, affordability, willingness to change behavior, desire to eat organic fruits and vegetables, and mode of transportation impacted fruit and vegetable consumption (Dibsdall, et al., 2003). In terms of affordability, they found that only one-third of respondents believed that having a low income prevented them from having a healthy diet. Of this group, only 27% felt they did not eat healthy. Unemployed persons or persons on sick leave were most prone to think that lack of money was the main reason for their unhealthy diets. Dibsdall, et al.'s (2003) study revealed that 75% of the respondents felt fruits and vegetables were affordable, but 50% perceived price as a barrier to purchasing more fruits and vegetables.

Accessibility

Affordability may be related to the community food environment. This includes the places people purchase food and the disparities in availability of different types of food. Wrigley (2002) describes this as social exclusion. McEntee's (2009) review of social exclusion concepts in food desert articles identified the roots of this term in British cities that were experiencing pockets of poverty and increasing disparities in health. This was linked to limited access to fresh fruits and vegetables and overall dietary intake (Wrigley, 2002). McEntee's (2009) food access conceptual diagram depicted four levels of food choices that impacted adequate food access. The model considered whether a person desired to have a healthful diet, whether a person had acquired enough knowledge to make informed decisions about healthy eating, whether purchasing healthful foods was within the person's financial means, and whether those food choices were physically available (McEntee, 2009).

Eisenhauer (2001) states that people generally purchase food within two miles of where they live, so access to food stores is important for people with limited transportation or physical mobility issues. Other important factors like food store amenities, store hours, and whether stores are accessed through public transportation have not generally been included, but may be barriers for low-income households.

Lopez, at al (2008) combined transportation access indicators with access to SNAP offices and WIC offices. The USDA (n.d.a.) Food Environment Atlas identifies food access as transportation and distance to stores. This includes the number and percentage of households without cars living more than one mile from a food store, the number and percentage of low-income households who live more than one mile from a food store, the number and percentage of households without a car living more than 10 miles from a food store, and the number and percentage of low-income households living more than 10 miles from a food store. Gross & Rosenberger (2005) found that the cost of purchasing, insuring, and maintaining a vehicle, and the cost of gas may also be burdensome to low-income households.

Accessibility can be viewed in terms of the "sum contributions of all food retail in a neighborhood" (Short, et al., 2007, p. 356). Apparicio, Cloutier, and Shearmur (2007) defined their components of accessibility as proximity to the nearest supermarket, the number of supermarkets within a targeted range of 1000 meters, and the variety of food and differences in prices available.

Caraher, Dixon, Lang, and Car-Hill (1998) analyzed the UK Health Education Survey results finding that lower income households were less likely to have personal transportation and that food decisions were often determined by what could be transported by foot or by public transportation. A study of Appalachian Ohio households with children attending Head Start showed a significant relationship between lack of reliable transportation and food insecurity with hunger (Holben, McClincy, Holcomb, Kelly, Dean, & Walker, 2004). Holben, et al. (2004) suggested that lack of reliable transportation might be an indicator of limited income.

Wright Morton and Blanchard (2007) identified 803 low-access U.S. counties where at least half of the population lived more than 10 miles from a large supermarket or supercenter. Around half of those counties were labeled as food deserts, defined here as having all residents living further than 10 miles from a supermarket where prices are relatively lower. Wright Morton and Blanchard (2007) noted that over 97% are in rural areas with 10,000 people or less.

Urban populations often face the problem of access to traditionally lower-priced supermarkets that are often located in the suburbs. Transportation problems limit access for low-income households who then rely on the prolific convenience stores, liquor stores, and fast food establishments for their dietary needs (Drewnoski & Specter, 2004; Morland, Wing, Diez-Roux, & Poole, 2002; Nayga & Winberg, 1999; Winne, 2008). The rural poor have also been found to have difficulties accessing affordable transportation (Garasky, Wright Morton, Greder, 2004; Moreland, Wing, Roux, & Poole, 2002). Freedman (2008) addressed the accessibility of supermarkets in a Nashville study, showing that 70% of people purchased their food at convenience stores and 24% at local stores.

Chung and Myers (1999) studied distribution patterns of 526 urban and suburban stores in the Minneapolis-St. Paul metropolitan area. Around 22% of supermarket chains and nearly 50% of nonchains were located in the inner city area. Nearly 90% of the chain stores were located in areas with less than 10% of the population living below the poverty level. About 40% of nonchain stores were in areas with more than 10% living below the poverty level. The same pattern emerged when comparing store revenues. Food stores earning over $10 million dollars annually were mostly located in the areas with the least amount of poverty (Chung & Myers, 1999). No control variables, such as land use and development policies, were included. There was also no data concerning where people shopped or how far they traveled to purchase food. While affordability was a barrier to purchasing foods, the lack of lower-priced supermarkets in poor neighborhoods was the main reason low-income households were paying more for their groceries (Chung & Myers, 1999).

Short, et al. (2007) used GIS-mapping and direct observation to show that food providers varied greatly between five San Francisco and Oakland neighborhoods. Only one neighborhood had no supermarkets or small grocery stores and was described as having food access problems. Other neighborhoods often had small grocery stores, while supermarkets tended to exist along the periphery and were not accessible by foot. Some areas had main commercial streets where food stores were populated, while other main streets merely housed abandoned shops and liquor stores. Several stores sold food that catered to the historical ethnic and cultural foods of the population (Short, et al., 2007).

Apparicio, et al. (2007) used GIS-mapping and hierarchical cluster analysis to identify Montreal food deserts based on their defined components of accessibility: proximity to the nearest supermarket, the number of supermarkets within a targeted range of 1000 meters, and the variety of food and differences in prices available. They operationalized "variety" as the mean distance to three of the closest chain supermarkets (Apparicio, et al., 2007). This is a limitation to the study, since conceptually, distance to a chain supermarket does not directly measure the prices and types of foods available. It may act as a surrogate, but the definition appears limited. Apparicio, et al. (2007) used a social deprivation index based on five accepted common categories related to poverty to identify low-income areas of census tracts. The overall sum of variables took into account the percentage of low-income people in relationship to the total population, the percentage of single-parent households, the percentage of adults with less than a high school diploma, and the percentage of immigrants who arrived between 1996 and 2001. While the number of supermarkets decreased outside of the city center, accessibility in peripheral areas was associated with close proximity to a single supermarket. Apparacio, et al. (2007) found that accessibility was related more to the existence of a variety of stores clustered in neighborhoods in the central city Census tracts. Their findings showed that low-income populations clustered in urban areas actually had better access to food stores. Their limited measures of accessibility are based on geographic distances. Apparcio, et al. (2007) noted that "social and cultural norms, physical disability, economic assets" (p. 10) and knowledge about food preparation may be additional non-geographic barriers to food access.

Paez, et al. (2010) used GIS-mapping and spatial expansion methods to assess accessibility deprivation in Montreal. They studied distances traveled to retail and fast food stores, controlling for socioeconomic and demographic variables. Using Montreal's Business Point Data and travel survey, they obtained information about how and where people travelled. Paez, et al. (2010) mapped 4711 retail food establishments and 543 fast food points. Paez, et al. (2010) found that living in the central urban environment was associated with increased access to food services since 10-18% of the food opportunities exist in the city center. This was consistent with Apparacio, et al.'s (2007) findings. Vehicle ownership was associated with improved food access for low-income urban dwellers that tended to travel further purchase food (Apparacio, et al., 2007). The major limitation of the data used was that people do not necessarily travel to food stores and fast food restaurants from their home. They may start from various other coordinates, which is not accounted for in their spatial analysis of distances traveled variable.

Donkin, Dowler, Stevenson, and Turner (1999) studied food access in lower income London neighborhoods. They recorded the availability of 50 common food items (e.g., soda, candy) and 71 healthy foods. They found that food stores were generally within 207 meters of households and considered easily accessible. However, when the types of foods available at the stores are considered, the mean increased to 277 meters for food stores with healthier food available. The mean distance households would have to travel to purchase healthier foods at affordable prices was 323 meters. While the majority of common food items were prevalent in every food store, less than one-third of the food stores had healthy foods available (Donkin et al., 1999).

Several studies have identified complex racial, ethnic, geographic, and socioeconomic predictors of food store accessibility with major discrepancies. Sharkey and Horel (2008) examined 219 food stores in six rural central Texas counties (101 census block groups) using ground-truthing and camera-based GPS, directories, and USDA data. The distance to the nearest supermarket, grocery store, or discount store decreased in areas with higher population density, more ethnically and racially diverse individuals, and lower socioeconomic statuses (Sharkey and Horel, 2008). Moore, Roux, Nettleton, and Jacobs (2008) analyzed secondary data from a multi-ethnic atherosclerosis study in North Carolina, Maryland, and New York. Participants lived in areas with high densities of supermarkets, as defined by Standard Industrial Classification (SIC) codes and having more than 50 employees (Moore, et al., 2008). Moore and Diez-Roux (2006) studied the relationship among income, race and the types of stores available in those same 685 census tracts. Predominately white census tracts had more supermarkets and half as many small grocery stores as African American or racially mixed census tracts. Census tracts in which the median income was less than $25,000 annually had half as many supermarkets as wealthier tracts, but four times the number of grocery stores (Moore and Diez-Roux, 2006).

Galvez, et al.'s (2007) findings were different from other studies. They identified

219 food stores within 165 census blocks in East Harlem, New York. Galvez, et al. (2007) found that 76% of predominately African American blocks, 15% of primarily Latino blocks, and 40% of racially mixed blocks had no food stores. Latino blocks were more likely to have convenience and specialty stores than racially mixed blocks. African American blocks were less likely to have convenience stores than racially mixed blocks (Galvez, et al., 2007). Horowitz, Colson, Herbert, and Lancaster (2004) compared the more affluent and predominately Caucasian Upper East Side area of New York City to East Harlem. East Harlem stores were generally smaller, defined as having one register (Horowitz, et al., 2004). The study areas had complex relationships between race, population density, and socioeconomic status. It is hard to determine whether confounding political, geographical, or policy-oriented variables impacted where food stores are located.

Limited availability of fresh produce and healthy eating options has been found to be common in low-income neighborhoods. Liese, et al. (2007) found the majority of food items assessed in their food surveys were found in supermarkets, while half were found in grocery stores, and none or few of the items were sold at convenience stores. Convenience stores were more likely to sell less healthy versions of food items (i.e., whole milk and no skim milk, low-fiber bread and no high fiber bread). Fresh produce was only available in 28% of all stores (Liese, et al., 2007). Freedman (2008) found that 75% of urban Nashville convenience stores and 85% of urban Nashville local markets did not sell fresh fruit. None of the convenience stores and 25% of local markets sold fresh vegetables (Freedman, 2008). Hendrickson, Smith, and Eikenberry (2006) compared urban stores to supermarkets in adjacent neighborhoods. They found differences in the varieties of fruits and vegetables available. Urban stores averaged selling 10 vegetables and five fruits, whereas their counterparts averaged 61 vegetable and 36 fruit varieties (Hendrickson, et al., 2006).

Households within local food environments with limited food store options may be at greater risk for poor diets. Moore, et al. (2008) measured the impact of local food environments on diet using the Alternate Healthy Eating Index (AHEI) and the Fats and Processed Meats (FPM) scale. They found that people living in communities without supermarkets were 25-46% less likely to have a healthy diet then people who had greater access to food stores (Moore, et al., 2008).

Availability of fruits and vegetables may be a factor in consumers' decisions about where they purchase food (Dibsdall, et al., 2003). In their UK study, attitudes about availability differed between single and married families. Over 88% felt the store had a wide variety of fresh produce, and 57.6% felt there were many food shops from which to choose. Attitudes about availability differed significantly between those reporting between low and high fruit and vegetable consumers. Low-income consumers were more likely to feel that the type of stores and food items available in the stores limited them (Dibdall, et al., 2003).

Zenk, et al. (2009) hypothesized that satisfaction of the availability of fruits and vegetables was associated with multilevel factors. Zenk, et al. (2009) analyzed individual-level data from a 2002-2003 survey conducted in three Detroit neighborhoods, neighborhood-level data from a 2002 food store audit, the 2000 Census, and a 2002 mapping of various types of food stores were analyzed. They looked at how neighborhood poverty rates, individual socioeconomic statuses, and individual observations concerning the distance and availability of supermarkets, grocery stores, convenience stores, and liquor stores impacted overall satisfaction of the availability of fresh produce (Zenk, et al., 2009). They also addressed whether a variety of affordable, high quality fresh fruits and vegetables was observed in the neighborhoods. Their racially diverse “stratified proportional probability sample” (Zenk, et al., 2009, p. 50) included 919 adults older than 25 who lived “within 146 census blocks and 69 census block groups” (Zenk, et al., 2009, p. 50). While poverty rates of the immediate neighborhood and surrounding neighborhoods were not associated with satisfaction, lower satisfaction was reported in neighborhoods with higher concentrations of African American residents. Controlling for poverty and racial composition, Zenk, et al. (2009) found that residents traveling longer distances to supermarkets were statistically more likely to be unsatisfied with the availability of fresh produce in their neighborhoods. The presence of convenience stores, small grocery stores, and higher concentrations of liquor stores in neighborhoods was associated with decreased satisfaction of fresh produce availability for persons whose highest education was high school (Zenk, et al., 2009).

While much food access research has been conducted in urban environments, Garasky, Wright Morton, and Greder (2004) studied perceptions of food access in 597 rural (n=60), suburban (n=60), and urban (n=477) Iowa food pantry users. Participants from four Iowa counties responded to questionnaires that addressed household food security, access to food stores and community food resources, participation in food programs, and various socio-demographic variables. Garasky, et al. (2004) found that 50% of rural food pantry clients perceived that their community did not have enough grocery stores. This was statistically significant and a more likely viewpoint that those in urban populations (22%) and suburban populations (13%). Suburban participants reported the highest level of affordability in their community. Around 38% of urban and rural populations believed that stores in their communities lacked affordable healthy foods (Garasky, et al., 2004). When compared to other subgroups, urban participants believed food stores were in unsafe areas, although it was not a major concern (Grasky, et al., 2004). The average travel time was between nine and 13 minutes. Grasky, et al. (2004) sated that nearly 40% of both suburban and rural participants reported that lack of affordable transportation was a concern for them. The distribution of surveys that were completed and the subsequent sample sizes varied by subpopulation. There was no indication of whether this study was generalizable to populations who regular use food pantries or other low-income populations.

Nutrition and Health

The link between food insecurity and nutrition has been researched, in terms of overconsumption of unhealthy foods and under-consumption of nutrient-dense foods. Dietz (1995) is recognized as the first person who addressed the paradox of high prevalence of hunger and obesity in poor populations, positing in a single case study of a low-income overweight patient that weight gain is either caused by a biological adaptive response to periods of food insecurity or increased fat consumption to prevent hunger. At the time, large cross sectional studies had not been conducted.

The connections between dietary quality, nutritional quality, and food security are complex. Research has shown that the intake of nutrient-dense fruits and vegetables is associated with reduced risk of a variety of diseases, many of which are associated with obesity (VanDuyn & Pivonka, 2000). Some of these chronic diseases relate to obesity

(Finkelstein, et al., 2009; Hesketh, et al., 2004; Houston et al., 2009; Petry, et al., 2008; Rodbard, et al., 2009). Research relating food insecurity and obesity has shown contradictory results, dependent upon the measurement tools used and which demographic variables were controlled (Tarasuk and Beaton, 1999; Hamelin, Habicht, & Beaudry, 1999; Adams, Grummer-Strawn, & Chavez, 2003).

Radimer, Olson, Greene, Campbell, and Habicht (1992) determined that food coping strategies for low-income households included dietary modifications in terms of nutritional quality and amount of food consumed. Adults often skipped meals or altered their diets to ensure the optimum food security level for their children (Radimer, et al., 1992). McIntyre, Glanville, Raine, Fayle, Anderson, and Battaglia (2003) conducted a survey with over 140 low-income single mothers who had at least two children between the ages of zero and 14. McIntyre, et al. (2003) compared the daily self-reported dietary intake of the mothers and their children. The mothers' intakes were generally worse than their children and widened near the end of the month when money presumably ran out (McIntrye, et al., 2003).

Kozikowki and Williamson (2009) described how low-income families have less money to spend and often purchase high-calorie, low-nutrient foods, which have contributed to health problems related to poor nutrition, cardiovascular problems, diabetes, and developmental issues in children. Several studies cite evidence that those who consumed the lowest amounts of fruits and vegetables included children, low-income persons, and lower educated persons (Putnam, Allshouse, & Kanrot, 2002; Johnson, Taylor, & Hampel, 2000).

Raedeke's (2007) study of 1314 food pantry clients revealed a significant relationship between food insecurity and fresh or frozen fruit and vegetable intake. Nearly 75% of the pantry clients who reported their height and weight, were overweight or obese using the Body Mass Index (BMI) measure. Raedeke (2007) found that food insecurity was predictive of diabetes, high cholesterol, and high blood pressure.

Adams, Gummer-Strawn, and Chavez (2003) used data from the 1998 and 1999 California Women's Health Survey. They found that obesity was more prevalent in food insecure women (31%) then food secure women (16.2%), with a greater risk for non-white women.

Wilde and Peterman (2006) conducted multivariate analyses of longitudinal data about food security and weight from the National Health and Nutritional Examination Survey between 1999 and 2001. They found that women who were marginally or low food secure were significantly more likely to be obese and gain weight, when compared with women classified as food secure. The same phenomenon was seen in men, but to a lesser magnitude.

Seligman, Laraia, and Kushel's (2010) secondary data analysis of 5094 low-income adults from the NHANES (1999-2004) showed that food insecurity was associated with self-reported hypertension, but not diabetes. They controlled for socio-demographic differences of age, gender, income, and education. The link to cardiovascular disease was also significant, suggesting the need for policies directed at increasing opportunities to purchase quality foods that may be unaffordable for low-income households (Seligman, et al., 2010).

Public Food Assistance Programs

SNAP

SNAP is a federally administered program through the USDA Food and Nutrition Service (FNS) that is operated at the state level. Household with incomes below 130% of the Federal Poverty level may be eligible for the minimum benefit of $14-$16 per month (USDA FNS, 2009). SNAP dollars are used to purchase food (Trenkamp & Wiseman, 2007). In 2008, the program shifted from paper coupons (Food Stamps) to the electronic benefit transfer system (EBT). The name change also reemphasized the intention of the USDA to promote health and nutrition (Tolma & Garner, 2007). According to the USDA FNS (2011), 43 million participants obtained the SNAP benefits in 2010. The average benefit was $101 for individuals per month and $227 per household in 2008 (USDA FNS, 2011). The federal government paid 100% of costs, which amounted to $64,443,157,056 in FY2010. This is a 29% increase from FY2009 (USDA FNS, 2010a).

Lombe, Yu, and Nebbitt (2009) studied the relationships among socio-demographic variables, SNAP use, and informal food assistance. Data from households below 185% of the FPL who responded to both the 2003 Current Population Survey (CPS) and the 2003 December Food Security Supplement were analyzed. Over 32,800 households were included in the sample with a subset of 7,987 female-headed households. Household food security was analyzed using the 18-item USDA Food Security Module. Participation in SNAP was a dichotomous nominal variable. Informal assistance included participation in Meals on Wheels, food pantries, and community meal programs. SNAP use was correlated with informal food assistance and a number of socio-demographic variables (non-white, younger age, low income, low educational attainment). After controlling for the socio-demographic variables in the multiple regression analysis, both types of food assistance were positively related to household food security. This model explained 22% of variance. Greater household use of informal private assistance programs weakened the relationship between food security and SNAP use. Similar results occurred for female-headed households (Lombe, et al., 2009).

Rhode Island families between 100 and 130% of the FPL with at least one child under six years old (N=418) participated in telephone surveys that addressed food insecurity, income, expenditures, child well-being, demographics, and participation in SNAP (Gorman, Horton, & Houser, 2006). Participants received a $10 supermarket gift card. Gorman, et al. (2006) found that single-parent households, larger households with more children, and lower income households were the greatest predictors of SNAP use. Over half of the participants not receiving SNAP had some previous experience with SNAP, but only 45% that were eligible participated during the survey period. The overwhelming majority of non-SNAP users stated that wage increases and assets were the reason for not participating in SNAP anymore. Others were not aware of SNAP, did not think they were eligible, or mentioned stigma associated with SNAP use. Over 24% of the SNAP users were food insecure with hunger, while nearly 49% of the non-SNAP users were food secure. SNAP users visited the doctor more often than non-SNAP users and had less concerns about their children's behavior than non-SNAP users (Gorman, et al., 2006).

WIC

The Special Supplemental Nutritional Program for Women, Infants, and Children (WIC) is a federal program that provides grants to states for food supplementation and nutrition education to eligible low-income pregnant and postpartum women and children less than six years old who are at risk for negative nutritional outcomes (USDA FNS, 2012a). Around nine million people participated in WIC in 2011, with an average monthly benefit of $46.67 (USDA, FNS, 2012b). Nutrition and administrative costs amounted to nearly two billion dollars, which covered a variety of activities related to nutrition education, health promotion, patient referral, food delivery, and monitoring (USDA FNS, 2012b). Many of the studies concerning WIC relate to their special Farmers' Market Nutrition Program, which is included in the farmer's market subsection.

Metallinos-Katsaras, Gorman, Wilde, and Kallio's (2011) longitudinal study of mothers and children participating in the Massachusetts WIC Program provided evidence that the earlier mothers participate in WIC and the longer they are able stay in the program, the odds of household food security increases. Those with very low food security have an even greater chance of achieving food security with more visits with WIC service providers.

Matthews, Neyman Morris, Schneider, and Gotto (2010) studied the health and food security status of 155 postpartum WIC participants in California. They found that 42% of their WIC participants were food insecure, of which 22% were very low food secure. Persons with low or very low food security were more likely to have poor mental health and less likely to consume the recommended daily vegetable intake (Matthew, et al., 2010).

Private Food Assistance Programs

Emergency food assistance programs include food that is distributed or consumed through shelters, food pantries, or soup kitchens (Mabli, Cohen, Potten, & Zhao, 2010).

These are meant to be short-term emergency programs. Food pantries distribute a variety of food that is donated directly to pantries by individuals, groups, and food stores. A regional food bank generally operates a distribution program to emergency food programs. Soup kitchens provide prepared meals for community members. Foods prepared at shelters are often donated and may be prepared by staff, residents, or volunteers. Feeding America (2011) is the largest national anti-hunger organization that has 205 certified members within their network. Certifications require adherence to distributions, food handling, and storage standards (Mabli, Cohen, Potten, & Zhao, 2010). Every distribution site determines their own regulations and policies, although when USDA commodities are distributed certain restrictions apply. Feeding America (2011) reported that over 3 billion pounds of food and groceries are distributed annually through their food bank network.

A food pantry study in Allegeny County, Pennsylvania showed that pantry use was not necessarily short-term. Daponte, Lewis, Sanders, and Taylor (1998) interviewed 400 pantry users and nonusers who were below 185% of the FPL between April 1993 and June 1993. The median length for pantry use was two years. Pantry users were also less likely to eat nutritiously and more likely to have problems feeding their families and running out of food each month (Daponte, et al., 1998). Their logistic regression model showed that those who did not own a car were significantly likely to be food insecure. The authors noted that this was likely due to extremely low incomes (Daponte, et al., 1998).

Bhattari, Duffy, and Raymond (2005) used CPS data from March 1999 and April 1999 that included the 18-question USDA Food Security Module and demographic variables. The study included 3,059 households below 125% of the FPL. They hypothesized that food pantry use and availability of donated food were positively related. Demographic variables included age, educational status, number of children, income, whether they received cash welfare assistance, household size, gender, household make-up, race, poverty level, whether they received WIC, and whether they owned a home. Limitations included that inability to determine causality, confounding effects of participation in food assistance programs on food security, and measurement error. Bhattari, et al. (2005) showed that food insecurity and receiving welfare benefits were positively related to food pantry use. They found that Food Stamp use and food pantries were likely used together to meet household food needs in food insecure situations. They also found higher participation in food programs in nonmetro areas (Bhattari, et al., 2005).

Bartfeld (2003) analyzed data from the 1999 Wisconsin Survey of Food Pantry Clients. This survey took place in 27 counties during October 1999. Bartfeld's (2003) sample included 839 single mothers younger than 65 whose income was below the Food Stamp cutoff levels. Univariate analyses provided demographic and economic information. Most participants earned less than $1000 each month. There was a fairly equal distribution of pantry users that were considered new users (22%), light users (29%), moderate users (20%), and heavy users (29%). Health, utility, and housing hardships contributed to economic difficulties associated with food insecurity. Around two-thirds of pantry users who had been out of work for 12 months (23%) visited the pantry almost each month for a six-month period. Unlike Bhattari, et al.'s (2005) study, Bartfeld (2003) found that only 26% of the sample had Food Stamps. Emergency food assistance was interpreted as "an alternative, rather than a supplement" (Bartfeld, 2003, p. 296). Food Stamp use was further analyzed using a probit model. Full-time working participants were less likely to use Food Stamps, while those who received welfare assistance were more likely to use Food Stamps (Bartfeld, 2003).

Biggerstaff, McGrath Morris, and Nichols-Casebolt (2002) analyzed data collected using a multistage sampling method in 1997 and 1998. A total of 1500 surveys were collected at between 50 and 55 Virginia sites that included soup kitchens, food pantries, and regional distribution areas that served at least 15 people during their distribution. Researchers were trying to ascertain as to why people needed emergency food assistance and what economic hardships they were experiencing. Their study showed that 14.9% were homeless, 15.1% had to move because of housing costs, 9.1% experienced domestic violence, 11.5% had to have additional people move in to pay for housing costs, 11% recently lost jobs, 13% recently lost Medicaid, and 16.1% recently lost Food Stamp benefits (Biggerstaff, et al., 2002).

Food Production

Community Supported Agriculture (CSA)

CSAs rely upon relationships that are intended to be beneficial for both consumers and farmers (Brehm & Eisenhauer, 2008). Consumers buy a share of the harvest prior to the start of each growing season and share in any risks (such as insect infestation or droughts) with farmers (Winne, 2008). They are often requested to work with other CSA members at the farm, performing tasks like pulling weeds, planting seeds, adding compost to the soil, mixing compost, harvesting crops, and washing crops (Winne, 2008). Each week, consumers receive seasonal products. The challenge for low-income people is that governmental assistance (SNAP, WIC) cannot be used to purchase produce since money directly purchases shares, not food.

CSAs are a viable option for creating a sustainable localized food system because it involves a network of collaborators working together (Lass, Stevenson, Hendrickson, & Ruhf, 2010). Brehm and Eisenhauer (2008) state that CSAs result in increased civic engagement and community cohesion. The localized food system supported by the CSA model helps increase access to fresh produce through sustainable production (Brehm & Eisenhauer, 2008; Feenstra, 1997). This has been shown to have positive health and ecological benefits (Feenstra, 1997). Brehm and Eisehnauer (2008) collected data from a small sample of CSAs in New Hampshire (N=4) and Illinois (N=3). They specifically were looking at motivations for participation in CSAs as a way to examine whether CSAs are viable options for rural communities and low-income communities. Their results indicated that participants were motivated by concerns for the local economy and the environment. Participants highlighted the importance of community attachment as a motivating factor in their decision to support a CSA farm (Brehm & Eisenhauer, 2008). While these results indicated support for CSA as a tool to promote a localized food system, their findings that community attachment and environmental concerns outweighed issues related to affordability.

Andreatta, Rhyne, and Dery (2008) addressed the concern for research about low-income households participating in alternative food networks. They developed a program called Project Green Leaf that provided funding to small-scale farmers in the Piedmont area of North Carolina. This money was used to purchase CSA shares for low-income households. They identified 44 households (N=174) to participate through local faith communities, state health agencies, and WIC offices. Andreatta, et al. (2008) stressed the importance of providing participants with an opportunity to document their experiences through food journals. The project also encouraged education by providing opportunities for farm-sponsored events and information about farmers' markets. Additionally, a guide was developed showing the available produce and recipes that could be used with those items. Their project emphasized the need to address transportation issues too. Their results showed that CSAs are a viable option for low-income households. Over 90% of shareholders spent less money at the grocery store because they did not have to purchase fresh produce. The majority of households also tried new recipes weekly and incorporated more vegetables into their meals. Andreatta, et al. (2008) found that more projects using this model must be explored to engage low-income households in the CSA network.

Community Gardens

Community gardens have been proposed as a method to produce fresh produce, strengthen social relationships, encourage sustainable development practices, and promote entrepreneurship (Pothukuchi & Kaufman, 1999). In fact, "40% of vegetables consumed in the U.S. were produced in an urban victory garden" (Nettle, 2010, p. 18). Ferris, Norman, & Sempik's (2001) survey of community gardens revealed various outcomes related to the implementation of gardens. This included the creation of green and open spaces to revitalize communities, as well as a way to provide affordable produce for schools, institutions, and neighborhoods.

Nettle (2010) described the use of community gardens to address food insecurity in Australia. Nettle (2010) noted that teaching people to grow their own food within the community context means that people are aware of one another and caring for one another. Equally important is the idea of consuming fresh food that has not travelled far from where it was grown, thus having a higher nutrient content (Nettle, 2010).

Community gardens have been identified as ways to increase vegetable and fruit consumption that may then impact health outcomes (Ferris, et al., 2001). Twiss, et al.'s (2003) study of California community gardens showed increased vegetable and fruit consumption, physical activity, and increased opportunities for public health education. Furthermore, studies have shown that community gardens provide opportunities for sustainable practices that limit exposure to pesticides and decrease dependence on fossil fuels that positively impacts public health outcomes (Taylor, 2009; Twiss, et al., 2003).

Farmers' Markets

Farmers' markets have been considered places to promote healthy eating and increase community-level economic benefits. McCormack, Nelson, Larson, and Story (2010) reviewed nutrition-related outcomes related to the WIC Farmers' Market Nutrition Program (FMNP), the Senior FMNP, and community gardens. Kamphuis, et al.'s (2006) literature review showed that local availability and improved opportunities to access fruit and vegetables improved dietary consumption patterns in low-income populations.

The WIC FMNP was established in 1992 to improve health and nutrition of women and children by providing access to fresh produce, to support small farmers, and to increase community economic development (Conrey, Frongillo, Dollahite, & Griffin, 2003). In 2008, 2.3 million WIC recipients participated in the FMNP, with benefits ranging from $10-$30 per year for each recipient, at an annual cost of $19.8 million appropriated by Congress (USDA Food and Nutrition Service, 2010b).

The SFMNP has proven successful in ensuring that low-income seniors who are at least 60 years of age can access locally grown fruits, vegetables, and herbs from farmers' markets, and roadside stands (USDA, 2009c). In FY2008, 963,685 people received SFMNP coupons, with around $20.60 allotted each year to recipients (USDA, 2009c). South Carolina researchers mailed surveys to 1500 randomly sampled participants of the program, who were allotted 50% in SFMNP coupons, and 62.8% reported that having coupons changed the way they ate, while 54.6% reported buying more fruits and vegetables with Food Stamps or cash (Kunkel, Luccia, & Moore, 2003).

The WIC and Seniors FMNP's have contributed valuable revenue at farmers' markets through direct sales and changes in consumer behaviors. Of the $1 billion in farmers' market sales in 2005, $34,000 was through WIC and Seniors FMNP's (Raglan & Tropp, 2009). In 2005, about 14% of farmers' markets accepted SNAP, 59% accepted WIC FMNP vouchers, and 44% accepted SFMNP vouchers (USDA Agriculture Marketing Service, n.d.). WIC and SFMNP vouchers were accepted at 3367 farmers' markets and 2398 roadside stands in 2008 (USDA FNS, 2010b). This resulted in $20 million in revenue USDA (USDA FNS, 2010b). Farmers gained around 8% more than the coupon redemption value (Conrey, et al., 2003). Every dollar spent in Iowa farmers' markets generated $1.58 in additional sales (Otto & Varner, 2005). For every 100 farmers' market jobs, 145 additional jobs were created within the complex food production and distribution system (Otto & Varner, 2005). Pirog, Van Pelt, Enshaven, and Cook (2001) added that a 10% increase in fruit and vegetable purchases from local sources yielded 4094 new jobs and $112.6 million in labor income. For every $5 in new SNAP benefits, households spent an additional $9.20 in community spending (USDA, 2010a). SNAP sales at farmers' markets may boost local economies, which is consistent with the community food security model.

Environmental Sustainability

Although the intent of this study is not to address substantial environmental measures, CFS models have an underlying value system of which sustainability is a part. Specifically, environmental sustainability is considered an important part of improving the food system and the public health outcomes associated with unsustainable and destructive methods of production, distribution, processing, and overconsumption (Hamm, 2004; Harvie, et al., 2009; Jensen, 2010; Lang, 2009; Wallinga, 2009).

Abi-Nader, et al. (2009) described the challenges of measuring the complex issues related to sustaining ecosystems as a part of the many aspects of CFS development. Sustainability includes an emphasis on long-term economic sustainability created through the development of local food systems that support environmental health in the community. Abi-Nader, et al. (2009) discussed the importance of recognizing the interdependent relationships that keep the ecosystem balanced. CFS planners, then, must enhance those relationships, rather than destroy them through common practices that exist within the current industrialized food system (Abi-Nader, et al., 2009). Their whole measures of a sustainable ecosystem include four main goals: "to sustain and grow a healthy environment" by eliminating pesticides and contaminants, while protecting the soil, water, and air; to promote an ecological ethic; "to enhance biodiversity;" and "to promote agricultural and food distribution practices that mitigate climate change" by reducing dependence on fossil fuels (Abi-Nader, et al., 2009, p. 26). Economic sustainability, as a part of CFS development, "promotes sustainability while strengthening local food systems" by promoting local or regionally harvested food and encouraging green building practices for all aspects of the food system (Abi-Nader, et al., 2009, p. 28).

Jensen (2010) provided an in-depth review of intersecting social, environmental, and economic challenges in the U.S. food system. One environmental challenge relates to pollution and waste from pesticides, fertilizers, contained animal feeding operations (CAFOs), and food waste. Jensen (2010) described energy and resource use as "unsustainable," noting the great number of energy inputs required for food production, the high amount of greenhouse gas emissions from livestock operations, and the reliance on copious amounts of water in the agricultural process (p. 10). Lastly, the issue of biodiversity and loss of farmland is discussed as a potential threat to the long-term sustainability of a safe food supply.

Wallinga (2009) analyzed the impact of industrialization on production in terms of thinking about sustainability and health as one in the same. Wallinga's (2009) review of the roots of the current industrialized food system model emphasizes the consolidation and specialization of a select few crops that require an abundance of resources but threaten to deplete the soil. Further analysis shows that, beyond pollution, threats to the water supply are a major concern. This relates to airborne pesticides and the increased demand for water in crop production, which is coupled with climate change and global population increases (Wallinga, 2009). Wallinga (2009) suggested developing a sustainable food system by changing food and agricultural policy decisions to address some of the public health threats associated with the current food system.

Harvie, et al. (2009) also focused on policy decisions that could potentially address the ecological health problem related to the food system. Harvie, et al. (2009) described threats to the food system in relation to climate change. A major concern is the concern that the social-ecological system is becoming less resilient. Harvie, et al. (2009) stated that this is in large part due to the fragile food system that uses a centralized decision-making model based on economics. A healthy food system would sustain the growing population and not introduce contaminants into diets and reduce energy inputs that impact soil, water, air, and climate change (Harvie, et al., 2009). Their notion of sustainable food systems also addressed social inclusion, cultural understanding about food and food practices, fair trade, accessibility, affordability, and localized systems.

Chapter 3

METHOD OF INQUIRY

Sampling Frame

This study is intended to fill in the gaps in food security research by focusing on community-level factors in non-metropolitan environments. The use of "community" as a level of analysis is challenging because of the vast array of conceptual and methodological definitions (Anderson & Cook, 1999). Problems associated with defining community boundaries have resulted in biased research in which community effects are likely under measured (Coulton, 2005). Chaskin (1997) defines place-based communities as localized both geographically and symbolically around social and psychological meaning resulting in any number of outcomes for people who spend much of their time living or working there. One aspect of knowledge building is research about the dynamic community processes, outcomes, and interventions (Coulton, 2005). A researcher may be interested in the impact of a community-level intervention on a community, the moderating effects of contextual community factors on direct practice, the mediating effects of mechanisms intended to produce community change, or the aggregated effects of individual changes on a community (Coulton, 2005).

The Community Food Security Coalition describes the importance of defining community in terms of "geographic and socio-economic considerations" (Winne, Joseph, & Fisher, 1997, p. 11). They specifically state that community food security strategies should have "significant portions of the population in relation to local norms living near or below the poverty level" (Winne, Joseph, & Fisher, 1997, p. 11) in easily identifiable communities. Cities, towns, districts, or neighborhoods are commonly considered communities. Determining the target community is central to CFS especially considering the crucial relationship of CFS strategies with locally integrated food systems (Hamm, 2009; Winne, Joseph, & Fisher, 1997). Hamm (2009) defines communities in terms of "the sense of place and the people, institutions, natural resources, and human networks that comprise that place" (p. 244). Tchumtchoua and Lopez (2005) highlight the importance of expanding CFS research to include both community food access variables and components of the community food system (see also Lopez, Drake, Martin, & Tchumtchoua, 2008).

Studies addressing community characteristics have used a variety of methods to define their study area. The Rural Poverty Research Institute [RUPRI] (2004) notes that community studies usually use county-level data, while contextual studies look at individual characteristics nested within communities. Research conducted concerning access and affordability have determined community areas in terms of Census tracts (see Cassady, Jetter, & Culp, 2007; Morland, Diez-Roux, Wing, 2006; Moore & Diez-Roux, 2006), Census blocks (see Galvez, et al., 2007; Sharkey and Horel, 2008), specific population sizes obtained from the Census (see Liese, et al., 2007), Geographic Information Systems mapping (see Apparicio, et al., 2007; Freedman, 2008; Paez, et al., 2010; Short, et al., 2007; Zenk, et al., 2009), and urban, rural, and suburban Census definitions (Garasky, et al., 2004).

Other research has addressed multiple factors at the community level. Bernell, Weber, and Edwards (2006) addressed community-level variables affecting household food insecurity in Oregon. They recognized that households are embedded within community contexts that may increase or decrease the likelihood of household food security. They determined that the use of county-level indicators would be most appropriate as surrogates for community-level influences based on the data available for the largely rural state (Bernell, et al., 2006). Tchumtchoua and Lopez (2005) "use towns as the proxy for communities" (p. 3) noting that those "geographic and political boundaries" do not necessarily align with "CFS boundaries" (p. 2).

Secondary Data

This analysis uses secondary data. This is due to the feasibility concerning the geographic scope of the study, the large number of variables, and the aforementioned challenges for obtaining community-level data. Much data already exists for analysis and is free, easily accessible, and mostly measured at the ratio level. The majority of the available data is from research organizations and was collected for analytic purposes. This data comes from the USDA, Census Bureau, Farmland Trust, and the National Agricultural Statistics Services. Additional public records and directory listings are used as a way to verify data or map data.

County Level Dependent Variable

Food Security

At this time, no agreed-upon measure exists for community food security. The USDA releases a Current Population Survey (CPS) Food Security Supplement each December based on the Food Security Module. The most recent Food Security Supplement is from 2009. Nord, Coleman-Jensen, Andrews, and Carlson (2010) indicate that 2153 households were sampled in Missouri. Coleman-Jensen (personal communication, 4/28/11) states that the sample is based on data from 2007-2009. This is due to small sample sizes in states. Confidentiality in rural communities is protected in the CPS FSS. Nearly 60% of counties are not labeled to protect the confidentiality of rural households in the CPS FSS (Coleman-Jensen, personal communication, 4/28/11).

All counties, however, are identified as metropolitan or non-metropolitan. These designations are based on the Office of Management and Budget [OMB] (2003) definitions. A Metropolitan Statistical Area has one or more urban areas of 50,000 or more. Metropolitan areas include communities that are near the urban center that have "a high degree of social and economic integration with the core" (OMB, 2003, p. 2) are where persons are likely to commute to work. Micropolitan Statistical Areas are defined similarly but represent areas in which the community of at least 10,000 residents exists, but is not larger than 50,000 (OMB, 2003). According to the USDA's (2007) analysis based on OMB definitions, 33 Missouri counties are metropolitan. Although the CPS FSS offers household-level food security, the sample is not seen as representative of the largely rural households in Missouri.

Since no county food security measures are available because of sample size and confidentiality, a modeling technique used to estimate the county's food security rate is calculated.

Rural Considerations

Cotter (2002), who uses nonmetropolitan and metropolitan designations, discusses the "urban and racial bias" (p. 534) that exists in poverty research, noting that rural poverty is an extremely important, prevalent, and persistent concern. RUPRI (2004) stresses the unique characteristics of rural communities in terms of "access to resources, different economic structures, different institutions, different social norms, and different demographics" (p. 3).

The USDA (2007) uses nine rural definitions that are based on the Census Bureau, Office of Management and Budget, and the Economic Research Service (ERS). RUPR] (2004) stresses the unique characteristics of rural communities in terms of "access to resources, different economic structures, different institutions, different social norms, and different demographics" (p. 3).

The USDA (2007) uses nine rural definitions which are based on the Census Bureau, Office of Management and Budget, and the Economic Research Service (ERS). The Census Bureau list of places is based on the 2000 population and includes incorporated places which have State-defined legal boundaries and unincorporated places, which are identifiable by name only (USDA, 2007). Rural may be defined using Census places as those with areas outside Census places with 2,500 or more people, 10,000 or more people, or 50,000 or more people (USDA, 2007). The Census also identified urban areas (UA) as an area with at least 50,000 people and urban clusters with between 2,500 and 50,000 people. Rural areas are any areas outside of urban areas. One definition denotes areas with no more than 2,500 people, areas outside UA's with less than 10,000 people, and areas outside UA's with less than 50,000 people (USDA, 2007). The Office of Management and Budget (OMB) identifies rural areas as counties that are outside metropolitan statistical areas, which include at least one county with a core UA of 50,000 people (USDA, 2007). The ERS is similar to the OMB designations, coding census tracts rather than counties, based on population density, daily travel distances, and urbanization (USDA, 2007). The USDA Business and Industry Loan Program defines rural areas as those places with populations less than 50,000 (USDA, 2007).

Based on the considerations of data availability, what constitutes a community, and what is meant by rural, a purposive sample of all counties and one city in a Midwest state are used to represent communities in this study. The OMB classification system is used as a way to distinguish metropolitan and nonmetropolitan areas. Current data is available for all 114 counties and St. Louis City, which is an independent city equal to a county in Missouri.

Table 2.

Nonmetropolitan and Metropolitan Designations

Nonmetropolitan		Metropolitan
Adair	Maries	Andrew
Atchison	Marion	Bates
Audrain	Mercer	Boone
Barry	Miller	Buchanan
Barton	Mississippi	Caldwell
Benton	Monroe	Callaway
Bollinger	Montgomery	Cass
Butler	Morgan	Christian
Camden	New Madrid	Clay
Cape	Nodaway	Clinton
Girardeau	Oregon	Cole
Carroll	Ozark	Dallas
Carter	Pemiscot	DeKalb
Cedar	Perry	Franklin
Chariton	Pettis	Greene
Clark	Phelps	Howard
Cooper	Pike	Jackson
Crawford	Pulaski	Jasper
Dade	Putnam	Jefferson
Daviess	Ralls	Lafayette
Dent	Randolph	Lincoln
Douglas	Reynolds	McDonald
Dunklin	Ripley	Moniteau
Gasconade	Saline	Newton
Gentry	Schuyler	Osage
Grundy	Scotland	Platte
Harrison	Scott	Polk
Henry	Shannon	Ray
Hickory	Shelby	St. Charles
Holt	St. Clair	St. Louis
Howell	St. Francois	St. Louis City
Iron	Ste. Genevieve	Warren
Johnson	Stoddard	Washington
Knox	Stone	Webster
Laclede	Sullivan	
Lawrence	Taney	
Lewis	Texas	
Linn	Vernon	
Livingston	Wayne	
Macon	Worth	
Madison	Wright	

County-Level Food Security Estimations

Several studies have modeled county-level food security based on different socio-demographic indicators (Dawdy, et al., 2010; Foulkes, Heflin, & Hermsen, 2010; Grussing, 2007; Gundersen, Brown, Engelhard, & Waxman, 2011).

Dawdy, et al. (2010) and Foulkes, et al.'s (2010) model for estimating "food uncertainty" is "based on modeling of variables related to citizenship, age (elderly or children), race (Black or Hispanic), female-headed households, poverty rate, median household income, and unemployment" (p. 9), which are all common predictors of food insecurity. State-level data was modeled to "estimate county-level patterns based on county-level socio-demographic information" (Dawdy, et al., 2010, p. 10). Data combined from 2005-2008 was obtained from the "American Community Survey, U.S. Census Bureau, Bureau of Labor Statistics, USDA, and Small Area Income and Poverty Estimates" (Dawdy, et al., 2010, p. 9; Foulkes, et al., 2010). The dependent variable will be modeled using the Dawdy, et al. (2010) and Foulkes, et al. (2010) multivariate OLS regression model with the following equation:

$$Y = \alpha_i + X_i\beta_i + e_i$$

In the model, Y is the food insecurity rate (state or county level). The socio-demographic variables are represented by the vector, X, and e_i is the error term (Foulkes, et al., 2010). Three years of state-level data were used to produce the coefficients for the estimation of county-level food uncertaninty for large counties in New Jersey and California. This model explained 58.19% of variance, although citizenship, higher proportions of Hispanic households, and higher percent of elderly were not statistically significant (Foulkes, et al., 2010). The results compared to CPS data showed that between 50% and 83.3% of the estimates were within the 95% Confidence Interval. A similar modeling technique was used for this study. However, in order to begin to understand the reliability and validity of the model, similar models that have been used will be outlined. Research results using those approaches are included.

Grussing (2007) uses Taponga, et al.'s (2004) state-level food security analysis to estimate county-level food security rates similar to Dawdy, et al. (2010. Grussing (2007) also used socio-demographic variables in the analysis. Specifically, this included household mobility (dh_i), unemployment rates (pu_i), poverty rates (po_i), housing affordability rates (re_i), percent of non-Hispanic whites (*nhw*), and the percentage of the population under the age of 18 (age_i) (Grussing, 2007). Data was obtained through the U.S. Bureau of Labor (unemployment), the 2000 Decennial Census, the U.S. Census Supplemental Survey Summary File 3 (household mobility), and the Small Area Estimates (poverty level) (Grussing, 2007). Grussing (2007) explained that county data and state-level data are comparable for analytic purposes. Taponga, et al.'s (2004) model used for both food insecurity and food insecurity with hunger is represented by the ordinary least squares regression equation:

$$Y_i = \beta_0 + \beta_1 dh_i + \beta_2 pu_i + \beta_3 po_i + \beta_3 re_i + \beta_4 nhw_i + \beta_5 age_i$$

Taponga, et al.'s (2004) model was limited to the population of 51 (U.S. States, District of Columbia), but resulted in 70% variance explained for food insecurity and 64% explained for food insecurity with hunger (very low food security) at the state level.

Grussing's (2007) model weighted state predictors at the county level and ranked counties and regions. Kendall's tau rank correlation was used to show the direction and strength of the relationship between ordinal pairs of observations (Weinbach & Grinnell, 2004). Comparisons were also made with the Oregon Population Survey results that were comparable, but lower than the Taponga, et al. (2004) model.

Taponga, et al.'s (2004) regression coefficients are used in the county level model. Taponga, et al.'s (2004) food insecurity and food insecurity with hunger equations are included below.

$$FI \text{ (Food Insecurity)}_i = -.164 + .280dh_i + .187pu_i + .360po_i + .276re_i + .014nhw_i + .434age_i$$

$$FI/Hunger \text{ (Food Insecurity)}_i = -.069 + .132dh_i + .314pu_i + .034po_i + .130re_i + .011nhw_i + .112age_i$$

Results indicated that the further away from major metropolitan areas in Oregon, the greater the increases in both food insecurity and food insecurity with hunger (Grussing, 2007). Grussing (2007) stated that these results may indicate high unemployment rates and high poverty rates in rural areas. Grussing (2007) discussed the idea that the presence of university communities may have impacted their results related to housing mobility and housing affordability. Counties with high rates of food insecurity were positively correlated with Food Stamp use, except in a university community. Food insecurity with hunger was not strongly correlated with Food Stamp participation. Grussing's (2007) county-level estimates are a manageable starting point for studying county-level food security rates and food insecurity with hunger rates.

State-level CPS data from 2001-2009 and county-level American Community Survey data from 2005-2009 were used to estimate county-level and Congressional District-level food insecurity rates across the U.S. (Gundersen, et al., 2011). Socio-demographic variables used in the model included poverty rates (POV), percent of the population that was Hispanic (HISP) or African American (BLACK), median income (MI), and unemployment (UN). The state level coefficients were used to model county-level food insecurity rates. Income and food security were summed together to create state-level estimates. The Bureau of Labor Statistics 2009 data provided annual average unemployment rates at the county-level (Gundersen, et al., 2011).

Gundersen, et al.'s (2011) first model estimates the individual food insecurity rate at the state level using the CPS data.

$$FI\ \text{(Food Insecurity)}_{st} = \alpha + \beta_{UN}UN_{st} + \beta_{POV}POV_{st} + \beta_{MI}MI_{st} + \beta_{HISP}HISP_{st} + \beta_{BLACK}BLACK_{st} + \mu_t + \nu_s + \varepsilon_{st}$$

State is represented by an *s,* while *t* represents year. The year fixed effect is symbolically written as μ_t. The state fixed effect is ν_s , and the error term is ε_{st} (Gundersen, et al., 2011). Like the aforementioned models, predictors were based on previous research that had been found to predict individual or household level food insecurity. The fixed effects are included as a way to consider the likelihood that other variables may impact food insecurity (Gundersen, et al., 2011).

The second equation estimates county-level food insecurity based on Beta coefficients derived from the first equation. In this model, county is labeled with a *c*, T indicates the year in which county-level data was used (Gundersen, et al., 2011). "Food insecure persons in a county" is "defined as $FI^*_{cs}*N_{cs}$ where N is the number of persons" (Gundersen, et al., 2011, p. 1). The equation for county-level estimates is:

$$FI^*_{cT} = \widehat{\alpha} + \widehat{\beta_{UN}}UN_{cs} + \widehat{\beta_{POV}}POV_{cs} + \widehat{\beta_{MI}}MI_{cT} + \widehat{\beta_{HISP}}HISP_{cT} + \widehat{\beta_{BLACK}}BLACK_{cs} + \hat{\mu}_T + \hat{\nu}_s$$

Unemployment and poverty rates were strong indicators of food insecurity rates, although the effect size for unemployment was higher (Gundersen, et al., 2011). Race and ethnicity did not impact food insecurity rates except for their model for households below 130% of the FPL. Gundersen, et al. (2011) noted that their estimates are based over time, and little change in the racial/ethnic composition of counties occurred during their study years. Gundersen, et al. (2011) also estimated food insecurity based on different income bands to reflect SNAP and National School Lunch Program eligibility levels. The overall econometric model is beneficial for understanding county-level food insecurity rates. However CFS factors may also influence county-level food insecurity.

County Level Independent Variables

Demographics

Lopez, et al.'s (2008) town-level assessment of CFS in Connecticut included a factor analysis based on 38 indicators. Their study did not model a dependent variable. However, several of their indicators are included in the modeled dependent variable, food uncertainty/food insecurity for this study. They will be included for the purposes of understanding the indicators at this point in the present research study. The current study did not to use an indicator twice as to avoid overestimation of the the model. For example, Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) have indicators related to older populations and female-headed households. These were mapped onto the factor called, demographics. However, the estimation modeling technique (Dawdy, et al., 2010) this study uses to initially obtain the food insecurity/uncertainty rate uses the percentage of the population that is elderly and the percentage of female-headed households. Those indicators will not be included in a Principal Components Analysis (PCA) to obtain the component scores that are used to predict food insecurity/uncertainty. They are used in an initial regression model to estimate county-level food security rates.

Demographic indicators included in Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) were: the proportion of the population older than 65, the proportion of the population younger than 18, the proportion of the population who are 25 and older and does not have a high school diploma, the proportion of single female-headed households with a child younger than 18, the proportion of female-headed households, and the number of people per square mile. They obtained data from the Connecticut Department of Economic and Community Development.

Much of this data is now free and open to the public. State-level and county-level data for the percentage of female-headed households with children, the percentage of people under the age of five, the percentage of people older than 65, the percentage of African Americans, the percentage of Hispanic individuals, and the percentage of non-citizens was obtained from the American Community Survey (2005-2009). The percent of households with high school education or less was also included, although it is not used in the estimation model or PCA. The literature review provides details about studies that have found relationships between demographic predictors and food insecurity (Olson, et al., 1997; Olson, et al., 2004 Rose, 1999).

The New American Fact Finder (http://factfinder2.census.gov) allows data to be downloaded for various geographies (e.g., state, county, town, Census tract, Congressional District). Many data tables are available that include the demographic data. The Center for Applied Research and Environmental Studies (CARES) staff assisted in the initial downloading of county-level data. Data was saved in Excel files.

Some data is available for households, while other data is available for families or individuals. It is important to be sure the proper population is chosen, which is largely dependent upon the table used. It is also important because some of the variables needed to be calculated as percentages. This means careful consideration must be made in order to have the appropriate denominator. Table 3 displays the ACS 2005-2009 tables that were used for the demographic data.

Table 3.

Demographic Data Sources

Variable	Source
% not a U.S. Citizen (2005-2009)	DPO 2 Selected Social Characteristics in the U.S. 2005-2009; American Community Survey 5-Year Estimates
Educational Attainment (2005-2009)	DPO 2 Selected Social Characteristics in the U.S. 2005-2009; American Community Survey 5-Year Estimates
% of people > 65 (2005-2009)	DPO 4 ACS Demographic and Housing Estimates: 2005-2009 American Community Survey 5-Year Estimates
% of people < 5 (2005-2009)	DPO 4 ACS Demographic and Housing Estimates: 2005-2009 American Community Survey 5-Year Estimates
% Female-Headed Households with Children < 18 (2005-2009)	DPO 2 Selected Social Characteristics in the U.S. 2005-2009; American Community Survey 5-Year Estimates
% Hispanic (2005-2009)	DPO 4 ACS Demographic and Housing Estimates: 2005-2009 American Community Survey 5-Year Estimates
% African American (2005-2009)	DPO 4 ACS Demographic and Housing Estimates: 2005-2009 American Community Survey 5-Year Estimates

Income and Wealth

Income and wealth indicators are representative of county-level measures related to poverty (Lopez, et al., 2008). Income indicators include the median household income and the county-level income distribution. Wealth represents assets considered as protective factors against food insecurity including the property values per capita, housing affordability measures for rental units and owner-occupied units (Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). Gross & Rosenberger (2005), Rose (1999), and Taponga, et al. (2004) have shown relationships between income, assets, and food insecurity. Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) obtained their data from the Connecticut Department of Economic and Community Development. The property tax mil rate and property values were not included because they are not available at the county level, but rather for independent towns and cities. Table 4 displays the data sources for income and wealth variables. The ratio of renter-occupied to owner-occupied units was derived from the data. Estimated foreclosure rates were obtained through the Community Information Management System provided by CARES. Estimates are based on data collected by The U.S. Department of Housing and Urban Development's (HUD) National Stabilization Program using data from the Mortgage Bankers Association National Delinquency Survey (June 2008).

Table 4.

Data and Data Sources Related to Income and Wealth

Variable	Source
Owner-Occupied Housing Units (2005-2009)	DPO4 Selected Housing Characteristics: 2005-2009 American Community Survey 5-Year Estimates
Renter-Occupied Housing Units (2005-2009)	DPO4 Selected Housing Characteristics: 2005-2009 American Community Survey 5-Year Estimates
% Households paying > 30% for rent (2005-2009)	DPO4 Selected Housing Characteristics: 2005-2009 American Community Survey 5-Year Estimates
% Households paying > 30% for mortgage	DPO4 Selected Housing Characteristics: 2005-2009 American Community Survey 5-Year Estimates

Variable	Source
(2005-2009)	
Median Household Income (2005-2009)	DPO3 Selected Economic Characteristics: 2005-2009 American Community Survey 5-Year Estimates
Foreclosure Rates (2007-2008)	CIM Network via HUD's Neighborhood Stabilization Program and Mortgage Bankers Association National Delinquency Survey; 2007-2008

Poverty

Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) included four indicators of poverty. This included the number of renter-occupied housing units divided by the total number of households, the proportion of children younger than 18 living in poverty, the poverty rate, and the unemployment rate. Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) obtained data from the Connecticut Department of Economic and Community Development. Several studies have indicated relationships between poverty indicators and food insecurity (Holben & ADA, 2006; Rose, 1999).

Unemployment rates are average annual unemployment rates for 2005-2009, which have been provided by the Bureau of Labor Statistics Small Area Income and Poverty Estimates Program. This data is also available on the USDA website. Poverty data is also available through the 2005-2009 American Community Survey. Table 5 displays the data and data sources pertaining to poverty that are included in the current study.

Table 5.

Data and Data Sources Related to Poverty and Unemployment

Variable	Source
Unemployment Rates (2005-2009)	Bureau of Labor Statistics, Local Area Unemployment data; Bureau of Census, Small Area Income & Poverty Estimates Program; http://www.ers.usda.gov/data/unemployment/RDList2.asp?ST=

Variable	Source
	MO
% Living < 100% Poverty Level (2005-2009)	DPO3 Selected Economic Characteristics: 2005-2009 American Community Survey 5-Year Estimates

Food Access

While a PCA will be conducted to reduce the number of variables, previous reviewed literature revealed potential components. For example, food access may include issues related to transportation and distance to food stores. The USDA Food Environment Atlas (n.d.) has collected data from several sources and has made it downloadable for every county in the United States. Food access data of interest includes the percentage of households without a car living more than one mile from a food store (2006), the percentage of low income households living more than one mile from a food store (2006), the percentage of households without a car living more than 10 miles from a food store (2006), and the percentage of low income households without a car living more than 10 miles from a food store (2006) (USDA, n.d.).

VerPloeg, et al.'s (2009) report to Congress originated the USDA (n.d.) data. The Food, Conservation, and Energy Act of 2008 (also called the Farm Bill, (Pub. L.110-234, 122 Stat. 923) administered the nationwide yearlong study concerning access to affordable healthy foods in the U.S. Food stores with $2 million or more in sales were identified and cross-referenced using the Trade Dimensions (2008) guidebook. Street addresses were geocoded using data from the 2006 Trade Dimensions Data Linx store directory and the 2006 STARS directory of stores accepting SNAP. Large food stores were chosen based on the likelihood that they would have all of the major food departments (i.e., produce, dairy, meat). The national data set includes 40,108 supermarkets and supercenters (Ver Ploeg, et al., 2009).

The Socioeconomic Data and Applications Center (SEDAC) provided the 2000 Census Data at the Block level (USDA, n.d.). This data was plotted on one-square kilometer grids throughout the U.S (USDA, n.d.). The distance from the center of each square grid to a supermarket was measured (Ver Ploeg, et al., 2009). Access distances were determined by both walking and driving modules. The walking measure was based on walking at two miles per hour (MPH), thus a 15-minute walk is equivalent to .50 miles and is considered highly accessible. Driving access was measured as being within 10 miles. VerPloeg, et al. (2009) noted that safety, physical capability, and other factors may impede walkability and drivability and is also limited by the use of straight-line distances which may not be accurate routes. Rural areas are highly accessible if there is a supermarket less than 10 miles away. Rural areas with supermarkets more than 20 miles away are considered low accessible. There is not currently an agreed upon definition of appropriate accessible driving distances in the literature (Ver Ploeg, et al., 2009).

The number of low-income households is based on 200% FPL (VerPloeg, et al., 2009). Low-income households living greater than one mile to a mapped food store were summed and divided by the county population (USDA, n.d.). Data pertaining to vehicle ownership was based on the Census long form that asked about whether households had access to a vehicle (USDA, n.d.).

Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) used three indicators as part of their food access factor. This included the percentages of households without a car, the number of public transportation routes divided by the number of households without a car, and the total revenues of public transportation divided by the number of passenger trips. Their data was obtained through their state Department of Economic and Community Development and the Department of Transportation.

Cohen, Andrews, and Kantor (2002) suggest the researchers use the Census to determine the number of occupied housing units, the number of households units owning at least one vehicle, and obtain detailed information about public transportation for communities. Lopez, et al.'s (2008) PCA indicated that housing information mapped to income and wealth rather than access. In this study, housing units were included in the PCA as was previously described. The literature review describes several studies that have identified food access as an important barrier to food security in terms of transportation and distance to food stores (Apparacio, et al., 2007; Caraher, et al., 1998; Donkin, et al., 1999; Drewnoski & Specter, 2004; Eisenhauer, 2001; Freedman, 2008; Garasky, et al., 2004; Gross & Rosenberger, 2005; Holben, et al., 2004; Morland, et al., 2002; Nayaga & Winberg, 1999; Paez, et al., 2010; Sharkey & Horel, 2008; Winne, 2008; Wright Morton & Blanchard, 2007). Table 6 shows the Food Access variables and data sources. Data was downloaded from the USDA Food Environment Atlas website.

Table 6.

Food Access Data and Data Sources

Variable	Source
# and % of Households w/o vehicle and > 1 mile to food store (2006)	USDA Food Environment Atlas (based on 2000 Census, geocoded street addresses from STARS and Trade Dimensions, Business Patterns); http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# and % of Low Income w/o vehicle and > 1 mile to food store (2006)	USDA Food Environment Atlas (based on 2000 Census, geocoded street addresses from STARS and Trade Dimensions, Business Patterns); http://www.ers.usda.gov/FoodAtlas/downloadData.htm

Variable	Source
# and % of Households w/o vehicle and > 10 miles to food store (2006)	USDA Food Environment Atlas (based on 2000 Census, geocoded street addresses from STARS and Trade Dimensions, Business Patterns); http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# and % of Low Income w/o vehicle and > 10 miles to food store (2006)	USDA Food Environment Atlas (based on 2000 Census, geocoded street addresses from STARS and Trade Dimensions, Business Patterns); http://www.ers.usda.gov/FoodAtlas/downloadData.htm

Availability of food stores

The USDA Food Environment Atlas data set uses U.S. Census Bureau data to identify the number of supermarket and grocery stores (USDA, n.d). Supermarkets are those with a full range of foods that gross more than $2 million in sales, while grocery stores have a full range of foods and gross less than $2 million in sales (Cohen, Andrews, Kantor, 2002). Convenience stores have a limited range of foods, specialty stores have one or two product lines and may or may not sell gasoline (Cohen, Andrews, Kantor, 2002). The 2008 data is available from the U.S. Census Bureau County Business Patterns (2010), including the number of grocery stores, supercenters, convenience stores and specialized food stores per 1000 people (USDA, n.d.). County Business Patterns obtains data from the Business Register and includes a 6-digit North American Industry Classification System (NAICS) code, size of business, number of employees, location, and payroll for many industries in accordance with U.S. Code, Title 13 and 26 (County Business Patterns, 2010).

Availability of food stores is also included in terms of the number of SNAP and WIC authorizations and redemptions. This data comes from the USDA Food and Nutrition Service SNAP Benefits Redemption Division, the Census Bureau Population

Estimates, and the Program Analysis and Monitoring Branch of the Supplemental Food Programs Division of the USDA Food and Nutrition Service (USDA, n.d.).

The USDA Food Environment Atlas also provides data concerning the number of fast food and full service restaurants where people access food. Fast food restaurants include establishments where people usually select food and pay before eating. Food is eaten on site, delivered to customers, or as part of takeout services (USDA, n.d.). Full-service restaurants generally include places where people eat on site and pay after eating their meal. Data for both are from the U.S. Census County Business Patterns data. Population is based on the U.S. Census Bureau population estimates.

Lopez, et al. (2008) suggests using the square footage compared to the population, the number of convenience stores divided by the population, and the number of farmers' market divided by the number of people. For this study, farmers' markets are included initially in the local production data. Many studies addressed the availability of food stores (see Apparaicio, et al., 2007; Chung & Myers, 1999; Cohen, et al., 2002; Dibsdall, et al., 2003; Donkin, et al., 1999; Freedman, 2008; Galvez, et al., 2007; Garasky, et al., 2004; Hendrickson, et al., 2006; Horowitz, et al., 2004; Liese, et al., 2007; Lopez, et al., 2008; Moore & Diez-Roux, 2006; Moore, et al., 2008; Short, et al., 2007; and Zenk, et al., 2009). Table 7 shows the data and data sources for the availability of food stores.

Table 7.

Availability Data and Data Sources

Variable	Source
# Grocery Stores and # Grocery Stores/1000 people (2008)	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns) http://www.ers.usda.gov/FoodAtlas/downloadData.htm

Variable	Source
# Supercenters and club stores and Supercenters and # club stores/1000 people (2008)	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Convenience stores w/ gas and # of Convenience stores w/gas/1000 people (2008)	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Specialized food stores and # of Specialized food stores/1000 people (2008)	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# SNAP-authorized stores and # SNAP-authorized stores/1000 people (2009)	USDA Food Environment Atlas (based on USDA Food and Nutrition Service SNAP Benefits Redemption Division, the Census Bureau Population Estimates, and the Program Analysis and Monitoring Branch of the Supplemental Food Programs Division of the USDA Food and Nutrition Service) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# WIC-authorized stores and # WIC-authorized stores/1000 people (2009)	USDA Food Environment Atlas (based on USDA Food and Nutrition Service SNAP Benefits Redemption Division, the Census Bureau Population Estimates, and the Program Analysis and Monitoring Branch of the Supplemental Food Programs Division of the USDA Food and Nutrition Service) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
SNAP redemptions/SNAP-authorized stores (2009)	USDA Food Environment Atlas (based on USDA Food and Nutrition Service SNAP Benefits Redemption Division, the Census Bureau Population Estimates, and the Program Analysis and Monitoring Branch of the Supplemental Food Programs Division of the USDA Food and Nutrition Service) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
WIC redemptions/WIC-authorized stores (2009)	USDA Food Environment Atlas (based on USDA Food and Nutrition Service SNAP Benefits Redemption Division, the Census Bureau Population Estimates, and the Program Analysis and Monitoring Branch of the Supplemental Food Programs Division of the USDA Food and Nutrition Service) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Fast-food restaurants and # of	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns)

Variable	Source
Fast-food restaurants/1000 people (2008)	http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Full-service restaurants and # of Full-service restaurants/1000 people (2008)	USDA Food Environment Atlas (based on U.S. Census Bureau and County Business Patterns) http://www.ers.usda.gov/FoodAtlas/downloadData.htm

Food Assistance

Food assistance is considered in terms of private and public assistance programs. Several studies have found relationships among participation and eligibility for WIC and SNAP with food insecurity (Bhattari, et al., 2005; Cassady, et al., 2007; Gross & Rosenberger, 2005; Kropf, et al., 2007; Needles Fletcher, 2008; Rose, 1999). Others have studied private food assistance programs (Bartfeld, 2003; Bhattari, et al., 2005; Biggerstaff, et al., 2002; Daponte, et al., 1998).

Participation rates for SNAP, free and reduced lunches, summer food programs, and WIC are available from the USDA Food Nutrition Service, the National Center for Education Statistics of the U.S. Department of Education, and the U.S. Department of Commerce Bureau of Economic Analysis (USDA, n.d.). Much of this information has already been collected as part of the MO Hunger Atlas (see Dawdy, et al., 2010; Foulkes, Hermse, Raedeke, & Rikoon, 2008). Lopez, et al. (2008) uses WIC participation costs per participant and food service expenditures per student.

Lopez, et al. (2008) and Bletzacker, Holben, and Holcomb (2009) calculated the proximity to WIC and SNAP offices. While it was not significant in Lopez, et al.'s (2008) study, it was in Bletzacker, et al.'s (2009). CARES staff assisted with the calculation of the average distance travelled within counties to both SNAP and WIC offices using ESRI ArcGIS network analysis. The U.S. Census 2010 population was used to determine the 4583 centroids for each block group. Population was weighted based on the origin-destination distance matrix (OMD). The distance was calculated for people within their own country. It is important to note that some data may be skewed and there is no way of knowing through this method, which offices people actually use.

Public food assistance indicators include the ratio of food pantries to the population living below the poverty level and the number of soup kitchens divided by the number of people living below the poverty level (Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). The Connecticut Study obtained this data from the 2-1-1 information system. This study will use several online sources and information from the six Missouri Food Banks. This includes the America's Second Harvest of Greater St. Joseph that serves 19 counties and 119 agencies, the Southeast Missouri Food Bank in Sikeston that serves 16 counties and 135 agencies, the Food Bank for Central and Northeast Missouri that serves 33 counties and 140 agencies, the Harvesters-Community Food Network in Kansas City that serves 26 counties (some in Kansas) and 835 agencies, the Ozarks Food Harvest Food Bank in Springfield that serves 33 counties and 289 agencies, and the St. Louis Food Bank that serves 26 counties and 516 agencies (Dawdy, et al., 2010). The Missouri Hunger Atlas houses data for the number of pounds of food per capita distributed by food pantries (Dawdy, et al., 2010; Foulkes, et al., 2008). Table 8 displays the data and data sources pertaining to private and public food assistance programs.

Table 8.

Data and Data Sources for Private and Public Food Assistance Programs

Variable	Source
% Income-	Missouri Hunger Atlas (2010) (based on Missouri Department of

Variable	Source
eligible, participating in SNAP (2009)	Social Services and Missouri Census Data Center, US Census Bureau, American Community Survey, MU Office of Social and Economic Data Analysis (OSEDA); http://www.missourifamilies.org/mohungeratlas/
% Income-eligible, participating in WIC (2008)	Missouri Hunger Atlas (2010) (based on Missouri Department of Health and Senior Services); http://www.missourifamilies.org/mohungeratlas/
% National School Lunch Program eligible (October, 2008)	Missouri Hunger Atlas (2010) (based on Missouri Department of Elementary and Secondary Education); http://www.missourifamilies.org/mohungeratlas/
% National School Lunch Program eligible, participating (October, 2008)	Missouri Hunger Atlas (2010) (based on Missouri Department of Elementary and Secondary Education); http://www.missourifamilies.org/mohungeratlas/
# Summer Feeding Program sites and # average # meals served (2001)	USDA Food Environment Atlas (USDA Economic Research Service) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Emergency Food Distribution sites (2011)	Hunger Atlas (2010); America's Second Harvest of Greater St. Joseph (http://www.ourcommunityfoodbank.org/index.cfm/m/46/Agency%20Listing/); Southeast Missouri Food Bank (http://www.semofoodbank.org/assistance.html); Food Bank for Central and Northeast Missouri (http://sharefoodbringhope.org/agency-listing/); Harvesters Community Food Network (http://www.harvesters.org/GetHelp/Agency.asp?x=070%7C030&~=); Ozarks Food Harvest Food Bank (http://ozarksfoodharvest.org/directory.html); St. Louis Area Food Bank (http://www.stlfoodbank.org/GetHelp/ListofAgencies.aspx)
Total SNAP Benefits ($1000) (2008)	USDA Food Environment Atlas (based on U.S. Department of Commerce Bureau of Economic Analysis) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
Average monthly SNAP benefits (2006)	USDA Food Environment Atlas (based on U.S. Department of Commerce Bureau of Economic Analysis)http://www.ers.usda.gov/FoodAtlas/downloadData.htm

Variable	Source
Pounds of food distributed (2009)	Missouri Hunger Atlas (2010) (based on data from the six regional food banks); http://www.missourifamilies.org/mohungeratlas/
Pounds of food distributed < 100% poverty level (2009)	Missouri Hunger Atlas (2010) (based on data from the six regional food banks, U.S. Census Bureau Small Area Income and Poverty Estimates); http://www.missourifamilies.org/mohungeratlas/
Average distance to county SNAP office (2012)	CARES (based on ESRI ArcInfo network analyst OCD matrix, Census 2010 block groups for centroids); Missouri Department of Social Services director of Income Maintenance and Self-Sufficiency Programs (http://dss.mo.gov/fsd/office/)
Average distance to county WIC office (2012)	CARES (based on ESRI ArcInfo network analyst OCD matrix, Census 2010 block groups for centroids); Missouri Department of Health and Senior Services director of WIC Clinics (http://health.mo.gov/living/families/wic/locations.php)

Local Foods

The 2007 Agriculture Census provides county-level data that show the percent of farms that sell directly to consumers, the ratio of vegetable acres harvested for the population, and the direct sales per capita (USDA, n.d). The Agriculture Census also provides information on whether farms participate in a CSA program. Other local food information may be obtained from the Missouri Agriculture Department, Missouri Farmers' Market Coalition, the Food Circles Project, the National Sustainable Agriculture Resource Center, and public websites. This study uses the number of farmers' markets in each county. The USDA (n.d.) defines a farmers' market as a place where there are at least two vendors selling agricultural products in which 51% of sales are from direct consumer sales.

Lopez, et al. (2008) and Tchumtchoua and Lopez (2005) have four indicators of food production resources. While the indicator that includes the number of public transportation trips divided by the number of households without cars mapped onto food production resources in their PCA, it does seem to fit. For this study, the indicator will not be used. Their farmers' market indicator will be theoretically considered part of food production resources. Other indicators include the total preserved farmland per capita, the proportion of land earmarked for agriculture and farms, and the number of community supported agriculture programs per capita (Lopez, et al., 2008; Tchnumtchoua & Lopez, 2005).

Farmland Trust provides information about the total acreage that is preserved by state programs (Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). Local USDA Extension Offices and the National Agricultural Library provide data about farm acreage and crop production, while the National Agricultural Statistics Services provides detailed information about the number of farms, acreage, crops, and products sold) (Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). Table 9 displays the data and data sources for agricultural production, direct farm sales, and local food production.

Table 9.

Agricultural Production and Local Food Production Data and Data Source

Variable	Source
# and % Farms w/ Direct Sales (2007)	USDA Food Environment Atlas (based on USDA U.S. Agriculture Census, 2007) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
Direct Farms Sales ($) and Direct Farms Sales per capita (2007)	USDA Food Environment Atlas (based on USDA U.S. Agriculture Census, 2007) http://www.ers.usda.gov/FoodAtlas/downloadData.htm
# Farms (2007)	USDA U.S. Agriculture Census, 2007 http://www.agcensus.usda.gov/Publications/2007/ Online_Highlights/County_Profiles/Missouri/index.asp
Land in farms (acres) and average size of farm (2007)	USDA U.S. Agriculture Census, 2007 http://www.agcensus.usda.gov/Publications/2007/ Online_Highlights/County_Profiles/Missouri/index.asp
Crop sales (2007)	USDA U.S. Agriculture Census, 2007 http://www.agcensus.usda.gov/Publications/2007/

	Online_Highlights/County_Profiles/Missouri/index.asp
Livestock sales (2007)	USDA U.S. Agriculture Census, 2007 http://www.agcensus.usda.gov/Publications/2007/ Online_Highlights/County_Profiles/Missouri/index.asp
Average sales/farm (2007)	USDA U.S. Agriculture Census, 2007 http://www.agcensus.usda.gov/Publications/2007/ Online_Highlights/County_Profiles/Missouri/index.asp
# of CSA sites (2011)	Organic Consumers Association (http://www.organicconsumers.org/state/ greenbiz.cfm?state=MO&type=csa); Local Harvest (http://www.localharvest.org/csa/); various producer websites found from multiple directories using Food Circles Networking Project (http://foodcircles.missouri.edu/sources.htm)
# Farmers' markets and Farmers' markets/1000 people (2011)	USDA Food Environment Atlas (2010) (based on USDA Agricultural Marketing Service, 2009); http://www.ers.usda.gov/FoodAtlas/downloadData.htm; cross-referenced with Missouri Farmers' Market Directory (http://agebb.missouri.edu/fmktdir/view.htm); USDA Farmers' Market Directory, Agricultural Marketing Service, http://search.ams.usda.gov/farmersmarkets/

Data Analysis

Initial Regression Model

The first step of the analysis is to use the Dawdy, et al. (2010) regression model to find the county-level food insecurity/uncertainty rates. While the rates have been calculated, new available data was used to update the estimates. The Interdisciplinary Center for Food Insecurity provided the regression formula used in their analyses (Dawdy, et al., 2010; Foulkes, et al., 2008). Lopez, et al. (2008) and Tchmutchoua and Lopez (2005) identified underlying components related to demographics and poverty that theoretically would be in the proposed analysis. However, this study will run a regression using PASW 18.0 (SPSS) with some of the original indicators that are identical to the variables used in the Dawdy, et al. (2010) model estimating county-level food insecurity. Thus, the analysis will not be identical to Lopez, et al. (2008) and Tchmutchoua and Lopez (2005) for socio-demographic and poverty indicators.

Principal Components Analysis

A data reduction strategy, PCA, is used to determine which county-level factors will be used in the model to predict county-level food security. Factor analysis techniques are used to find the underlying constructs for latent (unobserved) variables, reduce the number of variables, and to develop questionnaires (Field, 2009; Tabachnick & Fidell, 2007). PCA is used reduce the dimensionality of the matrix by finding new variables, which are linear combinations of the indicators (Tabachnick & Fidell, 2007). Factor analyses are used to achieve parsimony, i.e., simpler explanations based on a large number of observations are preferred to more complex explanations (Field, 2009). Data reduction is based on reducing the correlation matrix of correlation coefficients in a meaningful way (Field, 2009). PCA reduces the original data into a set of linear variates and can be used to determine which original variables contribute to the component (Field, 2009). Different statistical textbooks refer to components as factors. For ease of understanding, the word "factor" is analogous with component and both will be used in the methodological description. PCA analyzes the variance and the components account for as much variance as possible from the original indicators but are unrelated and orthogonal (Suhr, n.d.; Tabachnick & Fidell, 2007).

The factor analysis serves several purposes. The first is to reduce the large number of indicator variables into a manageable set of components that will produce coefficients. Coefficients are computed using a weighted variable score that is similar to regression coefficients used in multiple regression (Tabachnick & Fidell, 2007). The coefficients will be used to produce component scores that are used as variables in subsequent modeling (Field, 2009; Tabachnick & Fidell, 2007). Another purpose is to summarize the relationships between sets of variables (Tabachnick & Fidell, 2007). Lopez, et al. (2008) uses Spearman's rank correlation to examine relationships between overall ranking and each of their identified components. While this does not indicate causality, it allows for comparisons for each component and each original indicator among all counties. This may be useful as a comparison to studies concerning food deserts (Ver Ploeg, et al., 2009) and as a way to identify counties in which resources may be invested to improve community food security. The largely descriptive nature of the PCA will be an important part of this study and will expand upon the measures used by Dawdy, et al. (2010) and Foulkes, et al. (2008). Frequency distributions and descriptive statistics showing measures of central tendency are included in the analysis. Data has been screened for any missing data and outliers.

While some indicators may map onto components, the literature provides direction in determining components for the analysis. As noted earlier, a few of the indicators used in Lopez, et al. (2008) and Tchmutchoua and Lopez (2005) did not theoretically match the literature. Common methods for retention are Kaiser's rule and examination of scree plots. Kaiser's rule states that only principal components with eigenvalues greater than 1 will be retained. The eigenvalue is the sum of the squared loadings for a component (Tabachnick & Fidell, 2007). Scree plots are also used as a way to plot the eigenvalues against their indices. A sharp bend, or elbow, is the point at which the plot's decline flattens out. Scree plots can be used to support or reject the decision to retain a certain number of components in PCA (Tabachnick & Fidell, 2007).

Rotation is used to examine the relationships between the observed variables and their components. The idea is that by rotating the components, the larger relationships in the component matrix will become larger, and the smaller relationships will be reduced. Mathematically, they are identical, but it helps identify the relationships more easily. PCA does not use rotation methods as much as other factor analysis techniques, such as Exploratory Factor Analysis (EFA) (Tabachnick & Fidell, 2007). The main rotation methods are orthogonal and oblique. Orthogonal rotations (Direct Oblimin, Promax) assume factors are uncorrelated, while oblique rotations (Varimax, Equimax) assume the factors are correlated (Tabachnick & Fidell, 2007).

PASW 18.0 (SPSS) is used for the PCA. Reliability, a measure of internal consistency, has been checked for each of the factors extracted from the PCA (Field, 2009). PASW 18.0 also provides the squared multiple correlations of factor scores which can be used to estimate internal consistency (Tabachnick & Fidell, 2007). These range from 0 to 1; a higher score (generally .70 or better) indicates the variance accounted for in the factor scores by the observed variables (Tabachnick & Fidell, 2007). If the number is negative, it means that too many components have been retained. Squared multiple correlations above 1 are examined (Tabachnick & Fidell, 2007). A power analysis has also been conducted based on the sample size, the number of predictors, and the effect size.

Multiple Regression Analysis

The component scores are used in the regression analysis to identify county-level risk factors and protective factors associated with modeled county-level food security rates. Ordinary Least Squares (OLS) regression is used since assumptions were met.

An R^2 value has been obtained for the OLS regression. This is the proportion of variance in food insecurity rates that is explained by all of the independent variables (factors) (Pedhauzer, 1997). Beta weights, or the standardized regression coefficients, are calculated for each predictor (component) that can help determine which components affect the dependent value (Pedhauzer, 1997). An F-test is used to determine whether the set of independent variables (components) can predict the dependent variable (Tabachnick & Fidell, 2007).

Assumptions for OLS include independence of observations, normal distribution of residuals and the dependent variable, linearity between independent variables and the dependent variables, lack of measurement error among the independent variables, and homoscedasticity (Mertler & Vannatta, 2005; Pedhauzer, 1997; Tabachnick & Fidell, 2007). Univariate outliers are assessed using the standardized z-scores. The criterion of +/-3.29 SD is used as a criterion because it corresponds to the normal distribution (Tabachnick & Fidell, 2007). Multivariate outliers are assessed using the Mahalanobis distance, which measures the multidimensional distance a case is from the rest of the data when all variables are considered. The chi-square value is based on the number of variables in the model and the chosen p-value. Histograms, skewness, kurtosis, and scatterplots are also used to determine normality. Multicollinearity were identified by looking at the tolerance levels and the VIF levels. Generally, tolerance should be at least 0.1 and VIF values should be less than 10 (Tabachnick & Fidell, 2007). However, by conducting a PCA, multicollinearity is not likely to be an issue.

Estimation of Community Food Uncertainty

The unstandardized B coefficients from the regression analysis are used as multipliers to estimate community food uncertainty. This allows for comparison between original estimates of food uncertainty. This is a new method for estimating community food security that goes beyond the Spearman rank correlations used in other studies (see Bletzacker, et al., 2009; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005).

Chapter 4

DATA ANALYSIS

The purpose of this chapter is to provide the data analysis results intended to answer the three main research questions. Univariate descriptive statistics are used to describe the overall sample for socio-demographic variables used in the regression analysis to predict food uncertainty, contextual variables excluded from the study that describe the sample, and the 46 indicator variables used in the Principal Components Analysis (PCA). Independent samples t-tests and Mann Whitney U tests are used as a way to compare any significant potential differences between nonmetropolitan and metropolitan food environments.

An extensive discussion describes the regression analysis used to predict food uncertainty, which is used as the dependent variable in later analyses. Included in this section are descriptive statistics for 50 states and the District of Columbia for each of the nine predictor variables (median household income, percent African American, percent Hispanic/Latino, percent under the age of five, percent over the age of 65, percent living below the poverty level, unemployment rate, and percent female-headed households with children under age 18). This section results in a detailed list of estimated food uncertainty rates for the all 114 Missouri counties and St. Louis City. Comparisons are made between counties experiencing high and low levels of food insecurity.

The next major section models various studies that use the PCA to reduce the community food security variables (Bletzacker, Holben, & Holcomb, 2009; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). Next is a description about the process of extracting factors, creating weighted factor scores, and ranking counties based on community food security. Groupings based on rankings for weighted scores are described in brief.

The final section is the largest contributor of new knowledge concerning community food security. The weighted factor scores are used in a regression analysis using food uncertainty as a dependent variable. Coefficients are used to estimate the percentage of households that would be considered community food uncertainty based on the new model of food environment components. Various analyses are conducted to determine whether there are significant differences between nonmetro and metro counties.

Descriptive Statistics

The study sample included 114 counties and one city. This includes 81 OMB-designated nonmetropolitan areas and 34 metropolitan areas. The terms “rural” and “nonmetro” are used interchangeably with “nonmetropolitan.” The terms “urban” and “metro” are used interchangeably with “metropolitan.” Table 10 displays selected characteristics of the study sample.

Demographics

The mean population of the 115 areas was 49,850 (*SD*=120,133.54) people, ranging from 1,984 to 973,710 people. Counties averaged about 599 (*SD*=160.33) square miles, with a population density of 132 (*SD*=522.94) people per square mile. In the most rural county, there were eight people per square mile, while in the most urban county, there were 5157 people living per square mile. On average, this is 2.42 (*SD*=0.17) people per household.

On average, 5% (*SD*=1.65%) of households in the study state were female-headed households with children younger than 18 years old, ranging from 1.29% to 11.95%. Around 6.38% (*SD*=0.86%) of the population was under the age of five, while 16.44% (*SD*=3.54%) were over 65 years old. The percent of elderly persons ranged from 8.67% to 26.34%. Overall, the sample was mostly Caucasian, with only an average of 3.24% (*SD*=6.28%) African American/Black and 2.09% (*SD*=2.32%) Hispanic/Latino. However, there was a large range of the percent of minority populations in the state (0% to 48%). African Americans represented less than 1% of the population in nearly 48% of the study areas. On the other end of the spectrum, there were eight counties where African Americans made up more than 10% of the population. Hispanic/Latino persons represented less than 1% of the population in 23.5% of the sample. Nearly 70% of the sample had less than 1% of their population identified as non-U.S. citizens. Only two counties has more than 5% of their population identified as non-U.S. citizens. Around 40% of the population achieved more than a high school education, with 15.7% of counties with 50% of their population educated at a high school level or less.

The median household income was $39,055.83 (*SD*=$8210.80). Around 92% of the sample had a median household income between $24,502 and $51,556, meaning that the median income of the study sample was generally under the U.S. 2006-2009 median household income of $52,321(Weinberg, 2011). Over 16% of the population, on average, had incomes below the poverty level in the study sample, which ranged from less than 10% in 12.2% of the sample and greater than 20% in 23 counties (20%). The mean percent of children living below the poverty level ranged from 6.6% to 44.7%, with a mean of 24.15% (*SD*=8.08). Unemployment is calculated monthly and fluctuates greatly. The average unemployment between 2005-2009 for the sample was 6.23% (*SD*=1.05%), ranging from 4.24% to 9.84%. Nearly 64% of counties had an average of at least 6% of their population that was unemployed. Households spent an average of 17.50% (*SD*=3.75%) of their income on food, ranging from 9.99% to 30.26%, with an average cost per meal of $2.48 ($0.23).

Housing

Housing characteristics revealed a high percent of home ownership, ranging from 54.44% to 88.11%, with an average of 75.14% (*SD*=6.44%) of the sample owning their home. On average, 28.17% (*SD*=5.00%) of homeowners were cost burdened, which is paying more than 30% of their income for their housing (HUD, 2012). A higher percentage of renter-occupied units were considered cost burdened. Foreclosure rates ranged between 1.59% and 7.93%, with an average of 4.65% (*SD*=1.22%). Between 16.30% and 64.26% of households paid more than 30% of their income for rent, with an average of 42.44% (*SD*=8.32%).

Transportation

Transportation and distance to food sources are potential barriers to food security, especially for low-income populations. On average, less than 4% (*SD*=1.55%) of the households in the study sample did not have a vehicle and lived more than one mile to the store. This ranged from 35 households to 6193 households. However, on average, 26.12% (*SD*=10.44%) of low-income people that did not have a vehicle lived more than one mile from a food store. Less than 1% (*M*=0.88%, *SD*=1.26%) of households without a vehicle lived more than 10 miles away from a store, although between 0% and 49.47%

of low income persons did not have a vehicle and lived more than 10 miles away from a food store.

Food Sources

The USDA collects data concerning a wide variety of food sources. On average, there were 9.37 (*SD*=20.87) grocery stores in each county or 0.26 (*SD*=0.16) stores per 1000 people. Just over 50% of the counties had four grocery stores, with the total range of one store in five of the areas to over 100 grocery stores in two counties. On average there was 0.94 (*SD*=1.59) supercenters/club stores in each county and 21.65 (*SD*=33.81) convenience stores with gas in each county. Over 75% of the sample had more than 23 convenience stores with gas in their county, with two counties having over 100 convenience stores with gas, representing 1.13 convenience stores with gas per 1000 people. There was a mean of 3.01 (*SD*=9.06) specialized food stores, ranging from zero in 47 counties, to 76 in one county.

Fast food restaurants existed in every county, ranging from less than five in 15.7% of the sample, to over 80 in 10% of the sample. This is an average of 0.76 (*SD*=0.33) fast-food restaurants per 1000 people and 38 (*SD*=88.16) restaurants in each county. Over 11% of the sample had one or no full-service restaurants, with an average of 34.49 (*SD*=96.93) full service restaurants in each county, or 0.48 (*SD*=0.22) full-service restaurants per 1000 people.

Table 10.

Characteristics of Study Sample

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Population ***	49,850.30 (120,133.54)	18,442.31 (13,412.60)	124,680 (203,053)	1,984- 973,710
Land Area (square miles)	599.01 (160.33)	615.43 (156.88)	559.88 (164.03)	61.92- 1178.54
Population Density (persons/sq. mile)***	131.69 (522.94)	32.94 (26.44)	366.96 (928.46)	8.10-5156.60
Food Uncertainty Rate***	15.43% (2.94%)	16.26% (2.56%)	13.47% (2.88%)	9.18%- 24.28%
Female-Headed Households with Children < 18 yrs. old	5.03% (1.65%)	4.96% (1.68%)	5.20% (1.60%)	1.29%- 11.95%
Age				
< 5 yrs old**	6.38% (0.86%)	6.21% (0.88%)	6.77% (0.68%)	3.89%-8.74%
> 65 yrs old***	16.44% (3.54%)	17.79% (3.15%)	13.21% (1.99%)	8.67%- 26.34%

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Race & Ethnicity				
African American/Black**	3.24% (6.28%)	2.47% (4.39%)	4.38% (9.21%)	0-48.24%
Hispanic or Latino***	2.09% (2.32%)	1.80% (2.78%)	2.78% (2.42%)	0.05%-15.55%
Citizenship				
Non-U.S. Citizen Status**	0.99% (1.14%)	0.80% (1.00%)	2.78% (2.42%)	0-6.06%
Education				
≤ High School Education***	59.21% (8.79%)	62.02% (5.97%)	52.52% (10.72%)	31.51%-75.93%
Income				
Median Household Income***	$39,055.83 ($8210.80)	$35,766.19 ($5004.73)	$46,892.92 ($9073.68)	$24,502-$70,077
% Population < Poverty Level***	16.32% (5.15%)	17.76% (4.595)	12.87% (4.82%)	4.58%-31.60%
Child Poverty Rate ***	24.15% (8.08%)	26.75% (6.97%)	17.96% (3.15%)	6.6%-44.7%
Housing				
Estimated Foreclosure Rate**	4.65%	4.87%	4.12%	1.59%-

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
	(1.22%)	(1.18%)	(1.18%)	7.93%
% Owner-Occupied Housing Units	75.14% (6.44%	74.77% (6.19%)	76.01% (7.02)	54.44%- 88.11%
% Renter-Occupied Units	24.86% (6.44%)	25.23% (6.19%)	23.99% (7.02%)	11.89%- 45.56%
% Households paying > 30% of income for rent	42.44% (8.32%)	42.56% (8.97%)	42.14% (6.61%)	16.30%- 64.26%
% Households paying > 30% of income for mortgage	28.17% (5.00%)	28.54% (5.35%)	27.28% (3.96%)	14.08%- 41.21%
Unemployment Rate**	6.23% (1.05%)	6.31% (1.02%)	6.04% (1.11%)	4.24%-9.84%
Transportation # of Households w/o vehicle and > 1 mile to food store***	476.75 (928.42)	291.67 (177.84)	917.68 (1213.21)	35-6193

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
% Households w/o vehicle and > 1 mile to food store***	3.96% (1.55%)	4.27% (1.45%)	3.21% (1.53%)	1.15%-8.66%
# of Low-Income People w/o vehicle > 1 mile to store**	6630.39 (6408.87)	4844.32 (2916.86)	10,885.44 (9735.53)	905-43,760
% of Low-Income People w/o vehicle and > 1 mile to food store***	26.12% (10.44%)	29.26% (8.98%)	18.65% (9.96%)	4.40%58.58 %
# of Households w/o vehicle and > 10 miles to food store*	41.95 (42.51)	47.26 (45.10)	29.29 (32.81)	0-191
% of Households w/o vehicle and > 10 miles to food store***	0.88% (1.26%)	1.08% (1.38%)	0.41% (0.71%)	0-6.68%
# of Low-Income People w/o vehicle and > 10 miles to food store**	733.26 (699.86)	848.81 (714.54)	457.97 (448.88)	0-2889

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
% of Low-Income People w/o vehicle and > 10 miles to food store***	6.20% (8.45)	7.81% (9.29%)	2.36% (4.03%)	0-49.47%
Food Sources				
# Grocery Stores***	9.37 (20.87)	4.62 (2.857)	20.71 (36.00)	1-176
Grocery Stores/1000 Population***	0.26 (0.16)	0.30 (0.17)	0.18 (0.10)	0.05-1.21
# Supercenters/club stores***	.94 (1.59)	0.52 (0.64)	1.94 (2.51)	0-11
Supercenters and club stores/1000 population	0.21 (.003)	0.02 (0.03)	0.02 (0.02)	0.00-0.11
# Convenience stores w/gas***	21.65 (33.81)	12.63 (9.24)	43.15 (55.38)	2-270
Convenience stores w/gas/1000	0.62	0.68	0.57	0.22-1.13

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
population***	(.020)	(0.18)	(0.16)	
# Specialized food stores***	3.01 (9.06)	0.81 (1.18)	8.24 (15.49)	0-76
Specialized food stores/1000 population	0.04 (0.06)	0.04 (0.07)	0.05 (0.03)	0.00-0.11
# Fast-food restaurants***	38.00 (88.16)	16.67 (17.22)	88.82 (149.49)	1-701
Fast-food restaurants/1000 population***	0.76 (0.33)	0.93 (.35)	0.60 (0.19)	0.07-2.48
#Full-service restaurants***	34.49 (96.93)	10.41 (11.28)	91.85 (165.14)	0-803
Full-service restaurants/1000 population*	0.48 (0.22)	0.45 (0.22)	0.55 (0.19)	0-1.08
# Community Supported Agriculture (CSA) Sites***	1.67 (4.08)	0.52 (0.92)	4.41 (6.67)	0-27
	0.04			

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
	(0.06)			
CSA's/1000 Population**	1.73 (2.25)	0.03 (0.06)	0.05 (0.06)	0-0.32
# Farmers' Markets ** *	.06 (.07)	1.15 (0.963)	3.12 (3.51)	0-17
Farmers' Markets/1000 Population*		0.07 (0.07)	0.04 (0.04)	0-0.43
Average Household Size***	2.43 (0.17)	2.38 (0.14)	2.56 (0.19)	2.05-3.21
Food Assistance Programs				
# Emergency Food Distribution Sites***	13.16 (60.34)	3.98 (3.24)	35.03 (108.87)	1-635
Emergency Food Distribution Sites/1000 Population***	1.76 (1.60)	1.66 (1.58)	1.99 (1.65)	0.30-8.63
# Summer Food Program Sites	5.29 (18.91)	2.69 (4.69)	11.47 (33.55)	0-173

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Average # meals served at Summer Food Program Site	2674.15 (3067.81)	2872.20 (3153.28)	2202.32 (2894.87)	0-12,317
# SNAP-authorized stores***	36.41 (76.53)	17.46 (11.97)	81.56 (130.01)	2-557
SNAP-authorized stores/1000 population***	0.91 (0.36)	1.01 (0.35)	0.68 (0.27)	0.29-2.08
SNAP redemptions/SNAP authorized stores***	$219,029.69 ($121,456.15)	$207,218.93 ($127,622.12)	$247,167.07 ($101,574.27)	$14,185.22-$502,546.05
Total SNAP Benefits ($1000)***	$7320.70 ($18,451.51)	$3112,14 ($2537.31)	$17,347.00 ($31,835.09)	$171-$123,741
Average monthly SNAP Benefits***	$69.95 ($4.96)	$68.31 ($3.95)	$73.85 (4.98)	$56-$86
% Low-Income receiving SNAP benefits	46.23% (12.12%)	45.12% (12.46%)	48.87% (10.98%)	28.30%-76.89%
% Income-eligible participating in SNAP	64.11% (14.88%)	62.47% (15.39%)	67.99% (12.97%)	22.19%-100%

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
# WIC-authorized stores**	5.93 (9.31)	3.46 (3.14)	11.82 (15.41)	1-1973
WIC authorized stores/1000 population***	0.19 (0.10)	0.22 (0.10)	0.13 (0.06)	0.06-0.58
WIC redemptions/WIC authorized stores	$107,898.95 ($59,053.64)	$102,497.72 ($577,506.10	$120,766.56 ($609,99.98)	$14,229.13- $302,218.74
WIC redemptions***	$802,523.87 ($1,775,686.36)	$387,031.73 ($347,105.75)	$1,792,372.70 ($3,027,720.00)	$14,229.13- $14,000,000
% WIC income eligible, participating***	70.65% (18.64%)	75.07% 17.01%	60.11% (18.33%)	19.42%- 100%
% Free and reduced eligible***	46.31% (10.19%)	49.62% (7.94%)	38.43% (10.73%)	15.58%- 66.77%
% Free and reduced eligible, participating**	80.39% (6.26%)	81.55% (5.77%)	77.64% (6.60%)	

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Pounds of Food Distributed**	526,003.86 (1,295,669.82)	26,5910 (336,313)	1,145,600 (2,227,900)	63.45%-100%
Pounds Per Capita < 100% poverty level	101.14 (109.22)	119.50 (13.28)	86.91 (79.35)	28,541-11,600,000
				11-609
% of Weekly Income Spent on Food***	17.50% (3.75%)	18.49% (3.53%)	15.13% (3.17%)	9.99%-30.26%
Average Cost/Meal	$2.48 ($0.23)	$2.49 $0.25)	$2.45 ($0.18)	$2.02-$2.97
Direct and Direct to Consumer[+]				
# Farms w/direct sales***	38.08 (25.84)	29.75 (19.76)	58.52 (27.85)	0-149
% Farms w/direct sales***	3.85%	3.31%	5.14%	1-9.5%

[+] No data for St. Louis City or New Madrid and Mississippi counties

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
	(1.67%)	(1.39%)	(1.60%)	
% Farm sales dollars that designated as direct to consumer**	0.37% (0.39%)	0.32% (0.34%)	0.51% (0.48%)	0-2.9%
Direct Farm Sales ($)***	$158,696 ($132,498)	$125,778 ($115,012)	$237,119 ($139,941)	$0-$7360
Direct Farms Sales Per Capita	$8170 ($8372)	$8708 ($8942)	$6891 ($6777)	$0-$47,220
Agriculture/Production[++]				
# Farms***	945.74 (406.93)	861.07 (372.96)	1153.52 (417.55)	203-2004
Land in Farms (acres)	254,619.06 (96,946.30)	262,630 (100,840)	234,960 (84,891.50)	32,292-543,224

[++] St. Louis City and St. Louis County data from the Agriculture Census is combined.

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Average Size of Farm (acres)***	300.37 (166.49)	337.98 (181.74)	208.06 (54.31)	117-1203
Crop Sales	$30,604,964.91 ($32,965,667.00)	$32,902,000 ($37,009,000)	$24,968,000 ($19,1163,900)	$116,000- $167,000,000
Livestock Sales	$35,227,964.90 ($43,619,429.08 0)	$34,200,00 ($44,238,300)	$37,750,00 ($42,625,700)	$39,999- $328,000,000
Average sales/farm	$76,509.95 ($75,518.70)	$85,061.40 ($86,777.70)	$55,226.30 ($28,9155.00)	$9739- $475,525.00
Farmland as % of total land	67.29% (22.01%)	68.11% (22.34%)	65.27% (31.39%)	8.86%- 98.38%
Distance to Food Assistance Programs				
Average Distance to County SNAP Office (miles)	11.06 (6.10)	11.18 (6.59)	10.78 (4.82)	3.47-43.61

	All Counties & St. Louis City (N=115) Mean (SD)	Nonmetropolitan Counties (n=81) Mean (SD)	Metropolitan Counties (n=34) Mean (SD)	Range
Average Distance to County WIC Office (miles)	11.11 (4.40)	11.27 (4.67)	10.71 (3.73)	3.68-23.36

*p<.05, **p<.01, ***p<.001

The number of CSA distribution sites was positively skewed with 55.7% of the sample having zero CSA sites, and 21.7% having only one site. On average, there were 1.67 (*SD*=4.08) sites per county, with five counties having more than 10 CSA sites. There was a mean of 1.73 (*SD*=2.25) farmers' markets per county, with 27 counties (23.5%) having no farmers' markets, and 68 counties (59%) having one ore two markets. This represents about 0.06 (*SD*=0.07) farmers' markets per 1000 people.

Food Assistance Programs

Every county had at least one emergency food distribution site that was part of one of the major food bank distribution areas. There were an average of 13.16 (*SD*=60.34) sites per county, or 1.76 (*SD*=1.60) sites per 1000 people living below the poverty level. Over 70% of the counties had between one and five sites, with one county as an outlier with 635 sites. An average of 526,003.86 (*SD*=1,295,669.82) pounds of food was distributed annually, which is a mean of 101.14 (*SD*=109.22) pounds of food per capita of persons living below the poverty line. The lowest 10 counties distributed between 11 and 19 pounds of food per capita, while the highest 10 counties distributed between 255 and 609 pounds per capita of persons living at or below 100% of the poverty level.

An average of 5.29 (*SD*=18.91) summer feeding program sites served an average of 2674.15 (*SD*=3067.81) meals. However, it should be noted that 45 (39.1%) of the sample counties did not have a summer feeding program site. The mean percent of children who were eligible for the National School Lunch Program (NSLP) was 46.31% (*SD*=10.19%), ranging from 15.58% to 66.77%. On average, 80.39% (*SD*=6.26%) who were eligible participated in the NSLP.

The mean percent of low-income persons receiving SNAP benefits was 46.23% (*SD*=12.12%), ranging from 28.30% to 76.89%. This means that, on average, 66.1% of the sample had 50% or less of their low-income population receiving SNAP benefits. According to the 2010 Hunger Atlas (Dawdy, et al., 2010), an average of 64.11% (*SD*=14.88%) of those income-eligible were participating in SNAP, with only 20% of counties having 50% or less participating. An average of 36.41 (*SD*=76.53) stores were authorized SNAP vendors, with every county having at least two SNAP-authorized stores. The average monthly benefits were $69.95 ($4.96), ranging from $56-$86. In total, counties averaged $7.3 million in SNAP benefits, with an average of $219,029.69 (*SD*=$121,456.15) worth of SNAP redemptions per SNAP authorized stores. The average distance travelled to county SNAP offices was 11.06 miles (*SD*=6.10) with a range of 3.47 miles to 43.61 miles.

There was an average of 5.93 (*SD*=9.31) WIC-authorized stores in the study sample. Almost 10% of the sample had one WIC-authorized stores, while 9% had more than 10. The average amount of WIC redemptions was $802,523.87 (*SD*=$1.78 million), with $107.898.95 (*SD*=$59,053.64) worth of WIC redemptions per WIC authorized stores. On average, 70.65% (*SD*=18.64%) of those who were income eligible for WIC, were participating in the program. About 15.7% of the counties had less than 50% of income eligible persons participating in the program. The average distance travelled to WIC offices was 11.11 (*SD*=4.40) miles, ranging from 3.68 miles to 23.36 miles.

Agricultural Production and Farm Sales

The mean number of farms in each county was 945.74 (*SD*=406.93), which covered an average of 67.29% (*SD*=22.01%) of the total acreage in each county.

Between 8.86% and 98.38% of total land was designated as farmland, with an average of 254,619.06 (*SD*=96,946.30) acres per county. Farms averaged about 300 (*SD*=166.49) acres and $76,509.95 (*SD*=$75,518.70) in annual sales. Annual crop sales averaged $30,604,964.91(*SD*=$32,965.667.00), and annual livestock sales averaged $35,227,964.90 (*SD*=$43,619,429.08). The average percent of farms with direct sales was 3.85% (*SD*=1.67%), or 38.08 (*SD*=25.94) farms per county. A very small percentage of farm sales were designated as direct to consumer sales, with an average of 0.37% (*SD*=0.39%) of sales dollars. In 93.6% of the counties, direct to consumer sales were less than 1% of total farm sales. The mean amount of direct farm sales was $158,696 (*SD*=$132,498), or $8170 (*SD*=$8372) per capita.

Some data was missing in this category. The percent of direct sales was replaced with the median for Clinton, St. Louis County, and St. Louis City because of data that was missing and skewed. Direct sales were then calculated based on total farm sales for these three areas. Two counties did not list any direct farms or sales (New Madrid, Mississippi).

Comparative Analyses Between Metro and Nonmetro Counties

Bivariate analyses were used to explore the differences between nonmetropolitan (*N*=81) and metropolitan (*N*=34) subsamples. Independent samples t-tests were used to compare means for variables that met the following assumptions: normal sampling distributions, interval level data, independence of observations, and homogeneity of variance (Field, 2009). Levene's test was used to test for equality of variances (Levene, 1960). Table 11 shows the means, standard errors, p-value, and effect size (*r*), for each variable. The Mann-Whitney test is the nonparametric test comparable to the independent samples t-test and was used to compare the medians of variables that did not meet the independent samples t-test assumptions (Field, 2009; Garson, 2011). Table 12 displays the medians, U-score, p-value, and effect size (*r*), for each variable. Small effect sizes are below the 0.30 criterion, while medium effect sizes are between 0.30 and 0.49, and large effect sizes are above 0.50 (Field, 2009).

Demographics

Population and population density are related to metropolitan and nonmetropolitan designations, so it is not surprising that significant differences exist between the subsamples. Nonmetropolitan populations (*Mdn*=13,660) significantly differed from metropolitan counties (*Mdn*=44,790), U=519.00, z=-5.259, p=.000. Metro counties had higher population densities of persons per square mile (*Mdn*=79.4) compared to nonmetro counties (*Mdn*=24.6), U=444.00, z=-5.718, p=.000. Effect sizes were also calculated by dividing the Z-score by the square root of the total sample size (N=115). The effect size for population was -0.49, representing a fairly large effect size. Similarly, the effect size for population density was large, r=-0.53. Land area in nonmetro areas (M=615.43, SE=17.43) was not statistically different than that of metro areas (M=559.88, SE=28.13), $t(113)$=1.710, p=0.09.

Socio-demographic variables were compared between metro and nonmetro counties. Metro counties had a statistically significant greater number of African Americans (*Mdn*=1.98%) than nonmetro counties (*Mdn*=0.54%), U=870.00, z=-3.108, p=.002, with a small effect size of -0.29. Metro counties also had significantly larger populations of Hispanic and Latino households (*Mdn*=2.02%) when compared to nonmetro counties (*Mdn=1.25%)*, U=667.00, z=-4.351, p=.000, with a medium effect size of -0.41. Overall, there were statistically significant differences between the average percentage of the population who were identified as non-citizens, with a higher percentage in urban areas (*Mdn*=1.03%) than rural areas (*Mdn*=0.48%), *U*=820.00, z=3.414, *p*=.001, *r*=-0.08.

Metropolitan counties generally had a higher percentage of their population under the age of 5 (*M*=6.77%, *SE*=0.12) compared to nonmetro counties (*M*=6.21%, *SE*=0.10). This was statistically significant, *t(*113)=-3.285, *p*=.001, *r*=.30. Nonmetro counties, however, had a statistically higher average percentage of people older than 65 (*M*=17.79%, *SE*=0.35) than metro counties (*M=13.21%, SE=0.34),* t(95.465)=9.383, p=.000. This represented a large effect size, *r*=0.69. On average, urban counties had higher average household sizes (*M*=2.56, *SE*=.03) than rural counties (*M*=2.38, *SE*=.02), *t*(113)=-5.682, *p*=.000, *r*=.47.

On average, rural counties had a higher percentage of people with a high school education or less (*M*=62.02%, *SE*=0.66) than urban communities (*M*=52.52%, *SE*=1.8). This was statistically significant, *t*(41.86)=4.859, *p*=.000. This represented a large effect size of *r*=0.60. Nonmetro counties had higher single female-headed households with children under the age of 18 (*Mdn*=4.83%) compared to metro counties (*Mdn=4.70%)*, *U*=1299.00, *z*=-.478, *p*=.633, but the difference was not statistically significant.

Table 11.

Independent Samples T-tests

	Nonmetropolitan Counties (n=81) Mean (Standard Error)	Metropolitan Counties (n=34) Mean (Standard Error)	t-value Effect size p-value
Land Area (square miles)	615.43 (17.43)	559.88 (28.13)	t=1.710 r=.16 p=.090
Food Uncertainty Rate	16.26% (0.28%)	13.47% (0.40%)	t=5.123 r=.43 p=.000
< 5 yrs old	6.21% (0.10%)	6.77% (0.12%)	t=-3.285 r=.30 p=.001
> 65 yrs old	17.79% (0.35%)	13.21% (0.34%)	t=9.383 r=.69 p=.000
≤ High School Education	62.02% (0.66%)	52.52% (1.84%)	t=4.859 r=.60 p=.000
Median Household Income	$35,766.19 ($556.08)	$46,892.92 ($1556.12)	t=-6.733 r=.72 p=.000
Child Poverty Rate	26.75% (0.77%)	17.96% (1.23%)	t=6.118 r=.50 p=.000
Estimated Foreclosure Rate	4.87% (0.13%)	4.12% (0.20%)	t=3.127 r=.28 p=.000

	Nonmetropolitan Counties (n=81) Mean (Standard Error)	Metropolitan Counties (n=34) Mean (Standard Error)	t-value Effect size p-value
% Owner-Occupied Housing Units	74.77% (0.69%)	76.01% (1.20%)	t=-.939 r=.09 p=.350
% Renter-Occupied Units	25.23% (0.69%)	23.99% (1.20%)	t=.939 r=.09 p=.350
% Households paying > 30% of income for rent	42.56% (1.00%)	42.14% (1.13%)	t=.249 r=.02 p=.804
% Households paying > 30% of income for mortgage	28.54% (0.59%)	27.28% (0.68%)	t=1.238 r=.12 p=.218
Unemployment Rate	6.31% (0.11%)	6.04% (0.19%)	t=-3.218 r=.48 p=.003
% Households w/o vehicle and > 1 mile to food store	4.27% (0.16%)	3.21% (0.26%)	t=3.492 r=.31 p=.000
# of Low-Income People w/o vehicle > 1 mile to store	4844.32 (324.10)	10,885.44 (1669.63)	t=-3.552 r.51 p=.001
% of Low-Income People w/o vehicle and > 1 mile to food store	29.26% (1.00%)	18.65% (1.71%)	t=5.594 r=,47 p=.000

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	t-value
	Mean (Standard Error)	Mean (Standard Error)	Effect size p-value
# of Households w/o vehicle and > 10 miles to food store	47.26% (5.01%)	29.29% (5.63%)	t=2.099 r=-.19 p=.038
# of Low-Income People w/o vehicle and > 10 miles to food store	848.81 (79.39)	457.97 (79.98)	t=3.534 r=.34 p=.001
Supercenters and club stores/1000 population	0.02 (0.00)	0.02 (0.00)	t=.541 r=.06 p=.590
Convenience stores w/gas/1000 population	0.68 (0.02)	0.57 (0.03)	t=5.890 r=.48 p=.000
Full-service restaurants/1000 population	0.45 (0.02)	0.55 (0.03)	t=-2.166 r=.20 p=.032
Average Household Size	2.38 (0.02)	2.56 (0.03)	t=-5.682 r=.47 p=.000
Average # meals served at Summer Food Program Site	2872.50 (350.37)	2202.32 (487.55)	t=1.069 r=.10 p=.287
SNAP-authorized stores/1000 population	1.01 (0.04)	0.68 (0.05)	t=4.717 r=.41 p=.000
SNAP redemptions/SNAP	$207,218.93	$247,167.07	t=4.717

	Nonmetropolitan Counties (n=81) Mean (Standard Error)	Metropolitan Counties (n=34) Mean (Standard Error)	t-value Effect size p-value
authorized stores	($14,180.24)	($17,419.84)	r=.41 p=.000
Average monthly SNAP Benefits	$68.31 ($0.44)	$73.85 ($0.85)	t=-6.343 r=.51 p=.000
% Low-Income receiving SNAP benefits	45.12% (1.38%)	48.87% (1.88%)	t=-1.522 r=.14 p=.131
% Income-eligible participating in SNAP	62.47% (1.71%)	67.99% (2.22%)	t=-1.834 r=.17 p=.131
# WIC-authorized stores	3.46% (0.24%)	11.82% (2.64%)	t=-3.154 r=.48 p=.003
WIC authorized stores/1000 population	0.22 (0.01)	0.13 (0.01)	t=5.465 r=.47 p=.000
WIC redemptions/WIC authorized stores	$102,497.72 ($64,167.30)	$120,766.56 ($10,459.70)	t=-1.523 r=.14 p=.131
% WIC income eligible, participating	75.07% (1.89%)	60.11% (3.14%)	t=4.206 r=.37 p=.000
% Free and reduced eligible	49.62% (0.88%)	38.43% (1.84%)	t=5.481 r=.62 p=.000

	Nonmetropolitan Counties (n=81) Mean (Standard Error)	Metropolitan Counties (n=34) Mean (Standard Error)	t-value Effect size p-value
% Free and reduced eligible, participating	81.55% (0.64%)	77.64% (1.13%)	t=3.167 r=.29 p=.002
% of Weekly Income Spent on Food	18.49% (0.39%)	15.13% (0.54%)	t=4.794 r=.41 p=.000
# Farms w/direct sales	29.75 (2.20)	58.52 (4.85)	t=-5.405 r=.51 p=.000
% Farms w/direct sales	3.32% (0.15%)	5.14% 0.27%)	t=-6.123 r=0.50 p=.000
Direct Farm Sales	$125,778 ($12,779)	$237,119 ($24,000)	t=-4.436 r=.39 p=.000
Direct Farms Sales Per Capita	$8708 ($994)	$6891 ($1162)	t=1.063 r=.10 p=.290
# Farms	861.07 (41.44)	1153.52 (72.69)	t=-3.666 r=.33 p=.000
Land in Farms (acres)	262,630 (11,204.40)	234,960 (14,777.78)	t=1.387 r=.13 p=.002
Crop Sales	$32,902,000 ($4,112,110)	$24,968,000 ($3,336,000)	t=1.498 r=.14 p=.137

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	t-value
	Mean (Standard Error)	Mean (Standard Error)	Effect size p-value
Farmland as % of total land	68.11% (2.48%)	65.27% (3.72%)	t=.622 r=.06 p=.535
Average Distance to County WIC Office (miles)	11.27 (0.52)	10.71 (.64)	t=.678 r=.08 p=.500

Table 12.

Non-Parametric Mann Whitney U Tests

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	Mann-Whitney U
	Median	Median	Effect size p-value
Population	13,660	44,790	U=519.00 r=-.49 p=.000
Female-Headed Households with Children < 18 yrs. old	4.83%	4.70%	U=1299.00 r=-.04 p=.633
African American/Black	0.54%	1 .98%	U=870.00 r=-.29 p=.002

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	Mann-Whitney U Effect size
	Median	Median	p-value
Hispanic or Latino	1.25%	2.02%	U=667.00 r=-.41 p=.000
Non-U.S. Citizen Status	0.48%	1.03%	U=820.00 r=-.08 p=.001
% Population < Poverty Level	16.65%	10.98%	U=655.00 r=-.41 p=.000
# of Households w/o vehicle and > 1 mile to food store	239	540	U=682.50 r=-.40 p=.000
% of Households w/o vehicle and > 10 miles to food store	0.56%	0.14%	U=762.00 r=-.35 p=.000
% of Low-Income people w/o vehicle and > 10 miles to food store	5.07%	0.95%	U=633.50 r=-.43 p=.000
# Grocery Stores	4	6.5	U=519.00 r=-.49 p=.000
Grocery Stores/1000 Population	0.24	0.16	U=707.00 r=-.38 p=.000
# Supercenters/club stores	0	1	U=844.5 r=-.33 p=.000

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	Mann-Whitney U Effect size
	Median	Median	p-value
# Convenience stores w/gas	9	21.5	U=519.00 r=-.49 p=.000
# Specialized food stores	1	2	U=688.50 r=-.41 p=.000
Specialized food stores/1000 population	0.02	0.05	U=1079.00 r=-.18 p=.058
# Fast-food restaurants	11	23.5	U=786.00 r=-.34 p=.000
Fast-food restaurants/1000 population	0.76	0.63	U=761.00 r=-.35 p=.000
#Full-service restaurants	7	21	U=608.00 r=-.44 p=.000
# Community Supported Agriculture (CSA) Sites	0	1.5	U=519.00 r=-.49 p=.000
CSA's/1000 population	0	0.03	U=939.00 r=-.28 p=.003
# Farmers' Markets	1	2	U=791.50 r=-.26 p=.000
Farmers' Markets/1000 Population	0.06	0.04	U=1055.00 r=-.19

	Nonmetropolitan Counties (n=81) Median	Metropolitan Counties (n=34) Median	Mann-Whitney U Effect size p-value
			p=.047
# Emergency Food Distribution Sites	3	7	U=733.50 r=-.37 p=.000
Emergency Food Distribution Sites/1000 population	1.13	1.37	U=1285.00 r=-.05 p=.573
# Summer Food Program Sites	1	1	U=1217.00 r=-.04 p=.703
# SNAP-authorized stores	14	31.5	U=733.50 r=-.37 p=.000
Total SNAP Benefits ($1000)	$2,169	$6,076	U=727.00 r=-.37 p=.000
WIC redemptions	$261,090	$579,970	U=721.00 r=-.37 p=.000
Pounds of Food Distributed	140,940	318,740	U=811.00 r=-.32 p=.001
Pounds Per Capita < 100% poverty level	52	56.5	U=1361.50 r=-.01 p=.924
% Farm sales dollars designated as direct to consumer	0.20%	0.51%	U=829.00 r=-.32 p=.001

	Nonmetropolitan Counties (n=81)	Metropolitan Counties (n=34)	Mann-Whitney U
	Median	Median	Effect size p-value
Average Size of Farm (acres)	306	205	U=365.50 r=-.57 p=.000
Livestock Sales	$23,118,000	$28,730,000	U=1215.00 r=-.07 p=.423
Average sales/farm	$60,007	$48,837	U=1618.00 r=-.10 p=.295
Average Distance to County SNAP Office (miles)	11.03	10.03	U=1350.00 r=-.02 p=.869

Statistically significant differences existed between the percentage of people living below the poverty level in nonmetro and metro counties. Nonmetro counties have a significantly higher percentage of their populations living below the poverty level (*Mdn*=16.65%) compared to their metro counterparts (*Mdn*=10.98%), *U*=655.00, *z*=-4.425, *p*=.000, *r*=-0.41. Child poverty rates were also higher, on average, in rural areas (*M*=26.75%, *SE*=0.77) than in urban areas (*M*=17.96%, *SE*=1.23), *t*(113)=6.118, *p*=.000, with a medium effect size of *r*=0.50.

Income and unemployment rates were also compared. Median household income, on average, was higher in metro counties (*M*=$46,892.92, *SE*=$1556.12) than in nonmetro counties (*M*=$35,766.19, *SE*=$556.08), *t*(41.686)=-6.733, *p*=.000. The effect size was large, *r*=0.72. Rural areas generally had higher percentages of unemployment

(*M*=6.31%, *SE*=0.11) than urban counties (*M*=6.04%, *SE*=0.19). This was statistically significant, *t*(35.10)=-3.218, *p*=.003. This represented a medium effect size, *r*=0.48.

Housing

Issues related to housing stock, housing costs, and foreclosures were compared between the urban and rural counties. Rural areas had a statistically higher mean percentage of foreclosures (*M*=4.87%, *SE*=0.13) than urban areas (*M*=4.12%, *SE*=0.20), *t*(113)=3.127, *p*=.002. The effect size was small, *r*=0.28.

There were no statistically significant differences between the average percentage of owner-occupied housing (*M*=74.77%, *SE*=0.69) and renter-occupied housing (*M*=25.23%, *SE*=0.69) in rural areas when compared to owner-occupied housing in urban areas (*M*=76.01%, *SE*=1.20) and renter-occupied housing in urban areas (*M*=23.99%, *SE*=1.20). There were also no statistically significant differences in the average percentage of households paying more than 30% of their income for rent in rural areas (*M*=42.56%, *SE*=1.00) compared to urban areas (*M*=23.99%, *SE*=1.13), *t*(113)=.249, *p*=.804, *r*=.02. Similarly, the average percentage of households paying more than 30% of their income towards mortgage payments was not statistically significant between urban areas (*M*=27.28%, *SE*=0.68) and rural counties (*M*=28.54%, *SE*=0.59), *t*(113)=1.238, *p*=.218, *r*=.12.

Transportation

Statistically more metro households did not own vehicles and lived more than one mile to the grocery store (*Mdn=540)* than nonmetro counties *(Mdn=*239)*, U*=682.50, *z*=-4.257*, p*=.000, *r*=-0.40. However, on average a higher percentage of rural counties had households without vehicles living more than one mile away from a food store

(M=4.27%, SE=0.16) compared to metro counties (M=3.21%, SE=0.26), $t(113)=3.492$, p=.000, r=.31. The number of low income persons without a vehicle living more than one mile from a food store was higher in urban counties (M=10,885.44, SE=1669.63) than in rural counties (M=4844.32, SE=324.10), $t(35.513)=-3.552$, p=.001. This represented a medium effect size, r=0.51. The mean percentage of low income people without a vehicle living more than one mile from a food store was also statistically higher in nonmetro counties (M=29.26%, SE=1.00) than in metro areas (M=18.65%, SE=1.71), $t(113)=5.594$, p=.000, r=0.47.

Nonmetro counties also had a higher number of households without vehicles living more than 10 miles from a food store (M=47.26, SE=5.01) than metro counties (M=29.29, SE=5.63). This was statistically significant, $t(113)=2.099$, p=.038, with a small effect size, r=-0.19. When population was considered, nonmetro counties also had a higher percentage of households without vehicles living greater than 10 miles to the grocery store (Mdn=0.56%) than metro counties (Mdn=0.14%), U=762.00, z=-3.771, p=.000, r=-0.35. However, it should be noted that the overall percent of households meeting his criteria was less than 1%. The number of low income people without vehicles living more than 10 miles away from a food store was statistically higher in nonmetro areas (M=848.81, SE=79.39) than in metro areas (M=457.97, SE=79.98), $t(95.817)=3.534$, p=.001, r=0.34. The average percentage of low-income households without a vehicle living more than 10 miles to the food store was also significantly higher in nonmetro counties (Mdn=5.07%) than metro counties (Mdn=0.95%), U=633.50, z=-4.558, p=.000, with a medium effect size of r= -0.43.

Food Sources

Metro counties had a statistically significant higher number of grocery stores (*Mdn*=6.5) than nonmetropolitan counties (*Mdn*=4), *U*=702.50, *z*=-4.1666, *p*=.000, *r*=-0.39. However, the number of grocery stores per 1000 people was statistically higher in nonmetro counties (*Mdn*=0.24) than metro counties (*Mdn*=0.16), *U*=707.00, *z*=-4.106, *p*=.000, *r*=-0.38. More supercenters/club stores (*Mdn*=1) were found in metro counties (*Mdn*=1) than nonmetro counties (*Mdn*=0), *U*=844.50, z=-3.568, *p*=.000, with a medium effect size of -0.33. When population sizes were considered for each county, there were no statistically significant differences in the number of supercenters/club stores per 1000 people between nonmetro (*M*=0.02, *SE*=.00) and metro areas (*M*=0.02, *SE*=.00), t(91.087)=.541, p=.050. Metro areas also had a significantly higher number of convenience stores that sold gas (*Mdn*=21.5) than nonmetro areas (*Mdn*=9), *U*=654.00, *z*=-4.438, *p*=.000, *r*=-0.41, although the reverse was true when population was considered. Rural areas had a statistically significant higher average number of convenience stores with gas per 1000 persons (*M*=0.68, *SE*=.02) than urban areas (*M*=0.57, *SE*=.03), *t*(113)=5.890, *p*=.000, with a medium effect size of 0.48. More specialized food stores existed in metro counties (*Mdn*=2) than nonmetro counties (*Mdn*=1), *U*=688.50, *z*=-4.448, *p*=.000, *r*=-0.41. This held true when population was considered, although the effect size was small (*r*=-0.18). The number of specialized stores per 1000 people in metro areas (*Mdn*=0.05) was greater than rural areas (*Mdn*=0.02), *U*=1079.00, *z*=-1.892, *p*=.000.

Overall, a greater number of fast food restaurants (*Mdn*=23.5)and full service restaurants (*Mdn*=21) were found in metro areas compared to rural areas (*Mdn*=11, *Mdn*=7*)*. The Mann Whitney U comparing fast food restaurants was equal to 786.00,

z=-3.625, p=.000, r=-0.34. For fast food restaurants, U=608.00, z=-4.718, p=.000, r=-0.44. When population was considered, a statistically significantly higher number of fast food restaurants were found in nonmetro areas (*Mdn*=0.76) when compared to metro counties (*Mdn*=0.63), U=761.00, z=-3.775, p=.000, r=-0.35. In urban areas, a statistically higher average number of full-service restaurants per 1000 people was observed (M=0.55, SE=.03), when compared to rural counties (M=0.45, SE=.02), $t(113)$=-2.1666, p=.032, r=.20.

Opportunities to purchase food from alternative food sources were compared between the metropolitan and nonmetropolitan subsamples. A statistically higher number of CSA sites existed in metro counties (*Mdn*=1.5) compared to nonmetro counties (*Mdn*=0), U=696.00, z=-4.618, p=.000, r=-0.43. Farmers' markets were more prevalent in metro counties (*Mdn*=2) than nonmetro counties (*Mdn*=1), U=791.50, z=-3.721, p=.000, r=-0.26. When population was considered, a statistically significantly higher number of CSA sites per 1000 people existed in metro counties (*Mdn*=0.03) compared to nonmetro counties (*Mdn*=0), U=939.00, z=-2.951, p=.003, r=-0.28, but nonmetro areas had higher numbers of farmers' markets per 1000 people (*Mdn*=0.06) compared to metro counties (*Mdn*=0.04), U=1055.00, z=-1.986, p=.047. This was significant at the $p<.05$ level with a small effect size of r=-0.19.

Food Assistance Programs

Various federal, state, and privately funded food assistance programs were compared using the Mann Whitney U parametric test and t-tests. Statistically significant differences existed between metropolitan and nonmetropolitan counties in terms of the absolute number of emergency food distribution sites. Metro areas had a greater number of sites (*Mdn*=7) compared to nonmetro areas (*Mdn*=3), U=733.50, z=-3.983, p=.000, with a medium effect size of r=-0.37. While metro areas had a median of 1.37 sites per 1000 people and nonmetro areas had a median of 1.13 sites per 1000 people, the difference was not statistically significant, U=1285.00, z=-.564, p=.573, r=-.05. Metro areas had more annual pounds of food distributed by food banks, pantries, social services agencies (*Mdn*=11,600,000) than nonmetro areas (*Mdn*=2,464,403), U=811.00, z=-3.469, p=.001, r=-0.32. No statistically significant differences were found when the pounds of food distributed were divided by the number of people living below 100% of the poverty level. Metro areas distributed a median of 56.5 pounds of food per capita, and nonmetro areas delivered a median of around 52.0 pounds, U=1361.00, z=-.095, p=.921, r=-.01.

No statistically significant differences existed in the number of summer food program feeding sites between metro counties (*Mdn*=1) and nonmetro counties (*Mdn*=1), U=1317.00, z=-.381, p=.703, r=-0.04. The average number of meals served at summer program sites was not statistically different between rural (M=2842.20, SE=350.37) and urban counties (M=2202.32, SE=487.55), $t(113)$=1.069, p=.287, r=.10.

Metro counties had a higher number of SNAP-authorized stores (*Mdn*=31.5) compared to nonmetro counties (*Mdn*=14), U=733.50, z=-3.947, p=.000, r=-0.37. However, when population was considered, nonmetro counties had a statistically higher average number of SNAP-authorized stores per 1000 people (M=1.01, SE=0.04) compared to metro counties (M=0.68, SE=0.05), $t(113)$=4.717, p=.000, with a medium effect size of r=0.41. Not surprisingly, total SNAP benefits ($1000s), were also greater in metro areas (*Mdn*=$6076) than in nonmetro areas (*Mdn*=$2169), U=727.00, z=-3.984, p=.000, r=-0.37. The average monthly SNAP benefits were significantly higher in metro areas too (M=\$73.85, SE=\$0.85) when compared to nonmetro areas (M=\$68.31, SE=\$0.44), $t(113)=-6.343$, $p=.000$, with a medium effect size of r=0.51. Additionally, the average amount of SNAP redemptions per SNAP-authorized stores was significantly higher in urban counties (M=\$247,167.07, SE=\$17,419.84) than rural counties (M=\$207,218.93, SE=\$14,180.24), $t(113)=4.717$, $p=.000$, with a medium effect size of 0.41.

There were no statistically significant differences between metro and nonmetro areas in terms of the percentage of the low-income population that was receiving SNAP and the percentage of income-eligible people participating in SNAP. For urban areas, an average of 48.7% (SE=1.88%) low-income people were receiving SNAP, which was similar to that of rural areas (M=45.12%, SE=1.38%), $t(113)=-1.522$, $p=0.131$, $r=.14$. The percent of persons who were income-eligible participating in SNAP in rural areas, on average was 62.47% (SE=1.71%). In urban areas, around 67.99% (SE=2.2%)of income-eligible persons participated in SNAP.

The number of WIC-authorized stores was statistically higher in urban areas (M=11.82, SE=2.64) than in rural areas (M=3.46, SE=0.24), $t(33.54)=-3.154$, $p=0.003$, $r=.48$. However, the number of WIC authorized stores per 1000 people was actually statistically larger in rural areas (M=0.22, SE=0.01) than in urban areas (M=0.13, SE=0.01), $t(103.695)=5.465$, $p=.000$, $r=0.47$. WIC redemptions were also statistically much larger in metro counties (Mdn=\$14,000,000) compared to nonmetro counties (Mdn=\$1,350,450), $U=721.00$, $z=-4.021$, p=.000, $r=-0.37$. The amount of WIC redemptions per WIC authorized stores, however, was not statistically significantly different between metro counties (M=\$120,766.56, SE=\$10,459.70) and nonmetro counties (M=\$102,497.72, SE=\$64,167.30), $t(113)=-1.523$, $p=.131$, $r=.14$. A statistically higher average percent of persons who were income-eligible, participated in the WIC program in rural areas (M=75.07%, SE=1.89%), compared to urban areas (M=60.11%, SE=3.14%), $t(113)=4.206$, $p=.000$, $r=0.37$.

The distance to the county SNAP office was not statistically significantly different between nonmetro counties (Mdn=11.03) and metro counties (Mdn=10.03), U=1350.00, $z=-.165$, $p=.869$, $r=-.02$. The average distance to county WIC offices was also not statistically significant between metro counties (M=10.71 miles, SE=0.64) and nonmetro counties (M=11.27 miles, SE=0.52), $t(76.91)=0.678$, $p=0.500$, $r=0.08$.

On average, a higher percentage of children in rural areas were eligible for the National Free and Reduced School Lunch Program (M=49.62%, SE=0.88%), compared to metro areas (M=38.43%, SE=1.84%), $t(48.846)=5.481$, $p=.000$, with a medium effect size of 0.62. A higher percentage of those children that were income eligible, were also participating in the NSLP (M=81.55%, SE=0.64%) compared to metro areas (M=77.64%, SE=1.13%), $t(113)=3.167$, $p=.002$, $r=0.29$.

Agricultural Production and Farm Sales

Differences between agricultural production and farm sales were compared between the two subsamples. Urban areas had a higher average number of farms (M=1153.52, SE=72.69) than rural areas (M=861.07, SE=41.44), $t(112)=-3.666$, p=.000, $r=0.33$. However, the size of rural farms (Mdn=306 acres)was statistically greater than urban farms (Mdn=205 acres), U=365.50, $z=-6.067$, $p=.000$, $r=-0.57$. The land in farms, on average, while greater in rural areas (M=262,630, SE=11,204.40) than in urban areas (M=234,960, SE=14,777.78), was not statistically significant, $t(112)=1.387$, $p=.168$, *r*=.13. The percentage of farmland was also not statistically significant, with an average of 68.11% (*SE*=2.48%) of rural areas being used as farmland, and 65.27% (*SE*=3.72%) of urban areas being used for farming, *t*(112)=.622, *p*=.535, *r*=.06.

No statistically significant differences exist between the average sales per farm in urban areas (*Mdn*=\$48,837) and rural areas (*Mdn*=\$60,007), *U*=1618.00, *z*=-1.053, *p*=.295, *r*=-0.10. Crop sales were not statistically significant either, with average urban county sales of \$24,968,000 (*SE*=\$336,000) and average rural sales of \$32,902,000 (*SE*=\$4,112,110), *t*(105.601)=1.498, *p*=.137, *r*=0.14. There were also no statistical difference in livestock sales, with nonmetro areas having a median of \$23,118,000 and metro areas having a median of \$28,730,000, *U*=1215.00, *z*=-.759, *p*=.423, *r*=-.07.

Metro areas had a greater percentage of farms with direct sales (*M*=5.14%, *SE*=0.27%) compared to nonmetro areas (*M=3.3*2%, *SE*=0.15%), *t*(113)=-6.123, *p*=.000, with a medium effect size of *r*=0.50. This amounts to an average of 58.52 urban farms with direct sales *(SE*=4.85) and 29.75 rural farms with direct sales (*SE*=2.20). The statistically significant difference was captured in a independent samples t-test, where *t*(45.699)=-5.407, *p*=.000, *r*=0.51. Although an average of less that 0.40% of farm sales in the entire sample, were designated as direct to consumer sales, metro areas had a statistically higher percent of their sales coming from direct sales to consumers (*Mdn*=0.51%) than nonmetro areas (*Mdn*=0.20%), *U*=829.00, *z*=-3.3939, *p*=.001, *r*=-0.32. Urban direct farms sales (*M*=\$237,119, *SE*=\$24,000) were significantly higher than rural areas (*M*=\$125,778, *SE*=\$12, 779), *t*(110)=-4.436, *p*=.000, with a small effect size of *r*=0.39. Urban and rural direct sales per capita was not statistically significant, with urban areas selling an average of \$6891 (*SE*=\$1162) per capita, and rural areas selling an average of \$8708 (*SE*=\$994) per capita, $t(113)=1.063$, $p=0.290$, $r=0.10$.

Modeling the Dependent Variable: County-Level Food Uncertainty

The original dependent variable, county-level food uncertainty, was modeled using state-level data for all U.S. states and the District of Columbia ($N=51$) because no county-level food insecurity data is available. The term, "food insecurity," is used by the USDA and is based on the USDA Food Security Module, part of the Current Population Survey (CPS) Food Security Supplement (see Chapter 1, Table 1 for a review of the distinctions made in levels of food security). The term, "food uncertainty," is used in this study to distinguish itself from the USDA Food Security Module since the calculation estimates are based on a modeling of socio-demographic characteristics.

The USDA annually provides average food insecurity rates for states and a sample of urban counties that have high population densities (Coleman-Jensen, et al., 2011). The 2010 CPS Food Security Supplement included 44,757 households that were weighted based on population (Coleman-Jensen, et al., 2011). The USDA food security rates are calculated annually and represent aggregated surveys for three-year time periods. The 2010 food insecurity rates represent 133,845 households interviewed annually between 2008 and 2010 (Coleman-Jensen, et al., 2011).

The county-level food uncertainty model used was based on a review of studies that modeled county-level food insecurity using socio-demographic indicators as independent variables(see Dawdy, et al., 2010; Foulkes, Heflin, & Hermsen, 2010; Grussing, 2007; Gundersen, Brown, Engelhard, & Waxman, 2011). Most data for these variables was obtained from the 2005-2009 American Community Survey.

Unemployment data is from annual average unemployment rates calculated by the Bureau of Labor Statistics (BLS).

Nine independent variables are used in the model for this study (Dawdy, et al., 2010; Foulkes, Heflin, & Hermsen, 2010). This includes the percent of people younger than five years old *(pchild),* the percent of people older than 65 *(pelderly)*, the median household income *(pmedhhinc)*, the percent of African American households *(pAA)*, the percent of Hispanic households *(pHisp)*, the percent of female-headed households with children younger than 18 years old *(pfemhh)*, the percent of households living below 100% of the poverty level *(pbelpov)*, the 2005-2009 average unemployment *(punempl)*, and the percent of people who are not U.S. citizens *(pnoncit)*. Table 13 displays the descriptive statistics for the state sample.

Table 13.

Characteristics of State Sample

	All U.S. States & District of Columbia (N=51) Mean (SD)	All U.S. States & District of Columbia (N=51) Range
Average Food Insecurity rate (2008-2010) (USDA, 2011)	13.81% (2.45%)	7.10%-19.40%
Unemployment (2005-2009)	5.49% (1.14%)	3.42%-8.48%
Median household income (ACS 2005-2009)	$51,323.63 ($8239.79)	$36,796-$69,475)
Percent of female-headed households with children < 18 years old (ACS 2005-2009)	7.15% (1.08%)	5.40%-10.50%
Percent of households < 100% Poverty Level (ACS 2005-2009)	13.18% (3.08%)	7.74%-21.41%
Percent of individuals < 5 years old	6.79%	5.24%-9.79%

	All U.S. States & District of Columbia (N=51) Mean (SD)	All U.S. States & District of Columbia (N=51) Range
(ACS 2005-2009)	(0.77%)	
Percent of individuals > 65 years old (ACS 2005-2009)	12.83% (1.68%)	6.97%-16.85%
Percent of African American individuals (ACS 2005-2009)	11.00% (11.33%)	0.55%-55.17%
Percent of Hispanic individuals (ACS 2005-2009)	9.63% (9.63%)	1.08%-44.76%
Percent of non-U.S. citizens (ACS 2005-2009)	4.87% (3.30%)	0.64%-15.00%

The previously tested model used three years of the ACS one-year data and included annual fixed effects. The model used for this study uses ACS 2005-2009 data for several reasons. First, modifications to the available Census data have been made since the original model (Dawdy, et al., 2010; Foulkes, Heflin, & Hermsen, 2010). Second, it is recommended that five-year estimates be considered for low-population geographic areas (U.S. Census, 2008). The ACS 2005-2009 data set is the best option since this study is most interested in non-metropolitan areas and the majority of counties are rural. While annual state data may be used, the aggregated five-year data was used to be consistent with the five-year estimates at the county-level. This study is also less interested in economic variation from unemployment or the recession, so using aggregated data helps control for such variation between annual data. Lastly, the ACS five-year estimates were used to align with the available USDA Food Environment Atlas data.

The regression equation below represents the initial step in the county-level food uncertainty estimation where Y is for the state-level food insecurity rate. The socio-demographic variables are represented by each B coefficient (slope) for each independent variable. The *a* in the equation is the constant or y-intercept.

$$Y' = a + B_1 punempl_s + B_2 pchild_s + B_3 pelderly_s + B_4 medhhinc_s + B_5 pHisp_s + B_6 pAA_s + B_7 noncit_s + B_8 pbelpov_s + B_9 pfemhh_s$$

The state-level regression model explains 48.4% of the variation in food insecurity between 2005and 2009 using the nine socio-demographic variables. Table 14 shows the bivariate Pearsons correlations between the variables. State-level food insecurity is significantly positively correlated with unemployment (r=.486, p<.01), the percent of African Americans (r=.297, p<.05), the percent of female-headed households with children (r=.474, p<.01), percent of people younger than five (r=.306, p<.05), and poverty level (r=.641, p<.01). It is negatively correlated with median household income (r=-.417, p<.01), meaning that states with lower median household incomes have higher food insecurity rates.

A strong positive correlation exists between unemployment and the percent of female-headed households with kids (r=.502, p<.01), the percentage of households below poverty level and the percent of female-headed households with kids (r=.640, p<.01), and the percent of non-citizens and median household income (r=.515, p<.01).

A strong negative correlation exists between the percent of people older than 65 and the percent of people younger than five (r=-.676, p<.01) and between the percent of households living below poverty level and median household income (r=-.780, p<.01).

Table 14.

Correlations Between State-Level Socio-demographic Variables

	Food Insecurity (%)	Unemployment (%)	> 65 (%)	AA or Black (%)	Hispanic (%)	Med. HH Income ($)	Female Headed-HH with Kids < 18 yrs old (%)	< 5 (%)	Non-Citizen (%)	< Pov. Level (%)
Food Insecurity (%)	1.00									
Unemployment (%)	.486**	1								
> 65years old (%)	-.120	-.183	1							
AA or Black (%)	.297*	.389**	-.118	1						
Hispanic (%)	.263	.072	-.278*	-.127	1					
Median HH Income ($)	-.417**	-.104	-.313*	-.031	.169	1				
Female Headed-HH with Kids < 18 yrs old (%)	.474**	.502**	-.156	-.246	.083	-.246	1			
< 5 years old (%)	.306*	-.065	-.676**	-.014	.438**	-.064	.096	1		
Non-Citizen (%)	.147	.187	-.273	.085	.797**	.515**	.071	.276*	1	
< Poverty Level (%)	.641**	.377**	.082	.457**	0.067	-.780**	.640**	.128	-0.171	1

*p<.05, **p<.01

Table 15 provides the coefficients, standard error, and significance level for each variable. Poverty level, unemployment, and the percent of people younger than five were the most important predictors of food insecurity in this model. The previous validated model explained 58.19% of variance. The percent of female-headed households, percent of African American households, and the percent of persons younger than five were all statistically significant (Foulkes, et al., 2010).

Table 15.

State-level Food Insecurity Regression Model

	B Coefficient	*Standard Error*	*P-value*
Constant	-10.936	12.676	.393
Unemployment	.747	.307	.020
Median household income	.00003979	.000	.670
Percent of female-headed households with children < 18 years old	.064	.499	.898
Percent of households < 100% Poverty Level	.476	.234	.048
Percent of individuals < 5 years old	1.194	.613	.058
Percent of individuals > 65 years old	.292	.286	.313
Percent of African American individuals	-.024	.050	.628
Percent of Hispanic individuals	-.006	.066	.923
Percent of non-U.S. citizens	.069	.209	.743

The coefficients from the state model were then used as a way to estimate county-level food uncertainty. While all variables were not significant in this model, all were used in the regression equation to be consistent with previous models that used three year's worth of state-level ACS annual data, as well as previous studies with the socio-demographic variables used in this study.

The regression equation for the county-level estimation is below. The coefficients are multiplied by the value of each independent variable for each Missouri county and added together with the constant obtained from the state-level regression model.

$$Y_c' = a_s + B_{1s}punempl_c + B_{2s}pchild_s + B_{3s}pelderly_c + B_{4s}medhhinc_c + B_{5s}pHisp_c + B_{6s}pAA_c + B_{7s}noncit_c + B_{8s}pbelpov_c + B_{9s}pfemhh_c$$

Estimated County Food Uncertainty

Table 16 displays the county name, food insecurity rate, and OMB designation. On average, 15.43% (*SD*=2.94%) of the population was food uncertain, ranging from 9.18% to 24.28%. On average, counties designated as nonmetropolitan had a higher percentage of the population that was considered food uncertain (*M*=16.26%, *SE*=0.28) than those counties designated as metropolitan (*M*=13.47%, *SE*=0.49). This difference was statistically significant $t(113)=5.123$, $p=.000$. The effect size was medium, $r=0.43$.

Table 16.

County-Level Food Uncertainty Rates

County	*Food Uncertainty (%)*	*OMB Designation*
Adair	18.10	Nonmetro
Andrew	10.48	Metro
Atchison	13.39	Nonmetro
Audrain	15.39	Nonmetro
Barry	16.47	Nonmetro
Barton	15.94	Nonmetro
Bates	16.99	Metro
Benton	16.47	Nonmetro
Bollinger	16.58	Nonmetro
Boone	13.19	Metro
Buchanan	13.82	Metro
Butler	18.98	Nonmetro
Caldwell	15.56	Metro
Callaway	10.81	Metro
Camden	13.73	Nonmetro
Cape Girardeau	13.14	Nonmetro
Carroll	14.75	Nonmetro
Carter	20.47	Nonmetro
Cass	11.22	Metro
Cedar	17.84	Nonmetro
Chariton	15.53	Nonmetro

County	*Food Uncertainty (%)*	*OMB Designation*
Christian	10.95	Metro
Clark	13.86	Nonmetro
Clay	10.94	Metro
Clinton	11.37	Metro
Cole	10.42	Metro
Cooper	11.85	Nonmetro
Crawford	16.20	Nonmetro
Dade	15.81	Nonmetro
Dallas	16.48	Metro
Daviess	15.66	Nonmetro
DeKalb	9.49	Metro
Dent	17.14	Nonmetro
Douglas	15.20	Nonmetro
Dunklin	21.22	Nonmetro
Franklin	12.92	Metro
Gasconade	13.75	Nonmetro
Gentry	16.49	Nonmetro
Greene	13.36	Metro
Grundy	15.50	Nonmetro
Harrison	17.93	Nonmetro
Henry	15.74	Nonmetro
Hickory	17.08	Nonmetro
Holt	14.32	Nonmetro
Howard	13.82	Metro
Howell	17.79	Nonmetro
Iron	19.16	Nonmetro
Jackson	15.47	Metro
Jasper	16.72	Metro
Jefferson	11.85	Metro
Johnson	13.71	Nonmetro
Knox	15.10	Nonmetro
Laclede	16.23	Nonmetro
Lafayette	12.84	Metro
Lawrence	14.90	Nonmetro
Lewis	14.44	Nonmetro
Lincoln	12.89	Metro
Linn	16.99	Nonmetro
Livingston	18.18	Nonmetro
Macon	15.41	Nonmetro
Madison	16.50	Nonmetro
Maries	12.79	Nonmetro
Marion	16.14	Nonmetro
McDonald	16.78	Metro
Mercer	15.22	Nonmetro

County	*Food Uncertainty (%)*	*OMB Designation*
Miller	14.92	Nonmetro
Mississippi	21.34	Nonmetro
Moniteau	12.61	Metro
Monroe	13.53	Nonmetro
Montgomery	15.68	Nonmetro
Morgan	17.02	Nonmetro
New Madrid	19.26	Nonmetro
Newton	14.39	Metro
Nodaway	14.97	Nonmetro
Oregon	19.74	Nonmetro
Osage	12.61	Metro
Ozark	15.11	Nonmetro
Pemiscot	24.28	Nonmetro
Perry	11.83	Nonmetro
Pettis	16.12	Nonmetro
Phelps	15.96	Nonmetro
Pike	13.23	Nonmetro
Platte	9.18	Metro
Polk	17.98	Metro
Pulaski	12.56	Nonmetro
Putnam	15.47	Nonmetro
Ralls	11.34	Nonmetro
Randolph	16.46	Nonmetro
Ray	11.59	Metro
Reynolds	16.63	Nonmetro
Ripley	19.81	Nonmetro
Saline	14.75	Nonmetro
Schuyler	16.43	Nonmetro
Scotland	21.83	Nonmetro
Scott	16.84	Nonmetro
Shannon	20.51	Nonmetro
Shelby	15.13	Nonmetro
St. Charles	9.22	Metro
St. Clair	16.10	Nonmetro
St. Francois	14.95	Nonmetro
St. Louis	11.39	Metro
St. Louis City	19.23	Metro
Ste. Genevieve	11.32	Nonmetro
Stoddard	16.94	Nonmetro
Stone	16.26	Nonmetro
Sullivan	19.21	Nonmetro
Taney	16.58	Nonmetro
Texas	16.81	Nonmetro
Vernon	18.72	Nonmetro

County	*Food Uncertainty (%)*	*OMB Designation*
Warren	14.46	Metro
Washington	19.88	Metro
Wayne	18.50	Nonmetro
Webster	17.06	Metro
Worth	11.54	Nonmetro
Wright	21.88%	Nonmetro

The counties were grouped into quintiles, with Quintile 1 representing the counties with the highest estimated number of food insecure households. These quintiles are in Table 17. Differences between the food uncertainty and community food uncertainty models will be addressed in Chapter 5.

Table 17.

County-Level Food Uncertainty Quintiles.

Quintile 1 17.79%-24.28%	*Quintile 2 16.23-17.14%*	*Quintile 3 14.97%-16.20%*	*Quintile 4 12.89%-14.95%*	*Quintile 5 9.18%-12.84%*
Pemiscot	Dent	Crawford	St. Francois	Lafayette
Wright	Hickory	Marion	Miller	Maries
Scotland	Webster	Pettis	Lawrence	Osage
Mississippi	Morgan	St. Clair	Saline	Moniteau
Dunklin	Bates	Phelps	Carroll	Pulaski
Shannon	Linn	Barton	Warren	Jefferson
Carter	Stoddard	Dade	Lewis	Cooper
Washington	Scott	Henry	Newton	Perry
Ripley	Texas	Montgomery	Holt	Ray
Oregon	McDonald	Daviess	Clark	Worth
New Madrid	Jasper	Caldwell	Howard	St. Louis
St. Louis City	Reynolds	Chariton	Buchanan	Clinton
Sullivan	Bollinger	Grundy	Gasconade	Ralls
Iron	Taney	Jackson	Camden	Ste. Genevieve
Butler	Madison	Putnam	Johnson	Cass
Vernon	Gentry	Macon	Monroe	Christian
Wayne	Dallas	Audrain	Atchison	Clay
Livingston	Benton	Mercer	Greene	Callaway
Adair	Barry	Douglas	Pike	Andrew
Polk	Randolph	Shelby	Boone	Cole
Harrison	Schuyler	Ozark	Cape Girardeau	DeKalb

Quintile 1 17.79%- 24.28%	*Quintile 2 16.23- 17.14%*	*Quintile 3 14.97%- 16.20%*	*Quintile 4 12.89%- 14.95%*	*Quintile 5 9.18%- 12.84%*
Cedar Howell	Stone Laclede	Knox Nodaway	Franklin Lincoln	St. Charles Platte

Table 18 outlines the predictors of food uncertainty for the 10 counties with the highest percentage of food uncertainty and Table 19 shows the 10 counties with the lowest percentage of food uncertainty.

Table 18.

Ten Highest Percent Of Food Uncertain Counties & Predictors

County	Food Uncertainty (%)	Unemploy-ment (%)	> 65 (%)	AA or Black (%)	Hispanic (%)	Med. HH Income ($)	Female Headed-HH with Kids < 18 yrs old (%)	< 5 (%)	Non-Citizen (%)	< Pov Level (%)
Pemiscot	24.28	7.94	14.46	2.61	2.21	28,290	11.75	7.96	0.54	31.60
Wright	21.88	6.92	17.52	0.23	1.40	27,598	6.22	7.48	1.03	26.15
Scotland	21.83	5.46	19.15	0.00	0.33	35,548	1.29	8.52	0.25	24.15
Mississippi	21.34	7.20	15.68	1.92	1.84	28,966	6.56	6.92	1.37	27.91
Dunklin	21.22	8.14	17.17	9.22	4.37	29,124	8.55	7.35	2.06	23.60
Shannon	20.51	8.13	15.05	0.00	0.87	28,474	4.46	5.98	0.45	26.65
Carter	20.47	7.02	15.88	0.02	1.12	24,502	5.79	7.01	0.00	25.62
Washington	19.88	9.84	13.42	2.26	1.08	35,510	5.84	6.96	0.42	20.70
Ripley	19.81	6.84	18.26	0.21	1.06	29,289	6.85	6.06	0.55	24.97
Oregon	19.74	6.04	19.38	0.34	0.73	24,803	3.72	6.02	0.30	25.89

Table 19.

Ten Lowest Percent Food Uncertain Counties and Predictors

County	Food Uncertainty (%)	Unemploy-ment (%)	> 65 (%)	AA or Black (%)	Hispanic (%)	Med. HH Income ($)	Female Headed-HH with Kids < 18 yrs old (%)	< 5 (%)	Non-Citizen (%)	< Pov Level (%)
Platte	9.18	4.94	10.54	4.36	4.20	65,383	4.69	6.28	2.28	6.77
St. Charles	9.22	5.22	10.49	3.94	2.29	70,077	3.67	6.89	1.56	4.58
DeKalb	9.49	6.36	13.76	8.40	1.42	43,302	3.24	4.79	1.63	9.06
Cole	10.42	4.60	12.25	9.76	1.86	52,385	5.68	6.61	1.57	9.46
Andrew	10.48	5.08	14.24	0.65	1.38	52,330	3.72	6.24	0.94	8.16
Callaway	10.81	5.36	11.64	4.42	1.43	49,425	4.85	6.26	0.75	10.42
Clay	10.94	5.34	11.06	3.04	4.92	57,797	4.66	7.29	2.27	7.55
Christian	10.95	4.98	11.64	0.81	2.24	50,830	4.45	7.26	0.69	8.55
Cass	11.22	6.02	11.77	2.99	3.49	60,628	5.36	6.68	1.12	8.09
Ste. Genevieve	11.32	5.94	15.19	1.41	1.03	49,712	3.75	5.27	0.37	10.78

Comparison of Highest and Lowest Food Uncertain Counties

An independent samples t-test was used to compare the mean differences of the nine socio-demographic predictor variables between the 10 counties with the highest percentage of food uncertain people and the 10 counties with lowest percentage of food uncertain people. Table 20 displays the means, standard errors, t-value, and significance levels.

In counties with the highest percentage of their population estimated to be considered food uncertain, the average unemployment was significantly greater (*M=7.35, SE=0.39)* when compared to the counties with the lowest percentage of food uncertain people (*M=5.38, SE=0.18), t*(18)=-4.4611, *p*=.000. The same was true for the percent of people living below the poverty level, where then mean for the highest food uncertain counties was 25.72% (*SE*=0.90%) and the mean for the lowest food uncertain counties was 8.34% (*SE*=0.57%), *t*(18)=-16.284, *p*=.000. The highest food uncertain counties had a significantly higher percent of people older than age 65 (*M*=16.60%, *SE*=0.64%) compared to the lowest food uncertain counties (*M=12.26%, SE=0.51%), t*(18)=-5.318, *p*=.000. Counties with lowest percentage of food uncertainty had a statistically significantly higher average median household income (*M*=$55,186.90, *SE*=$2585.24) than the highest food uncertain counties (*M*=$29, 210.40, *SE*=$1180.90), *t*(12.599)=9.140, *p*=.000. The percentage of non-citizens was significantly higher in the lowest food uncertain counties (*M*=1.32%, *SE*=0.21%) than the highest food uncertain counties (*M*=0.70%, *SE*=0.20%), *t*(18)=2.181, *p*=.043. Other mean differences were not statistically significant.

Table 20.

Mean Differences Between Highest and Lowest Food Uncertain Counties for Socio-demographic Predictors

	Highest % Food Uncertainty (n=10) Mean (SE)	Lowest % Food Uncertainty (n=10) Mean (SE)	t-value
Unemployment	7.35 (0.39)	5.38 (0.18)	t=-4.611***
% < Poverty Level	25.72% (0.90%)	8.34% (0.57%)	t=-16.284***
< 5 yrs old	7.03% (0.27%)	6.36% (0.25%)	t=-1.811
> 65 yrs old	16.60% (0.64%)	12.26% (0.51%)	t=-5.318***
% Non-Citizen	0.70% (0.20%)	1.32% (0.21%)	t=2.181*
Median Household Income	$29,210.40 ($1180.90)	$55,186.90 ($2585.24)	t=9.140***
% African American	5.75% (3.00%)	3.98% (0.96%)	t=-.564
% Hispanic or Latino	1.50% (0.36%)	2.43% (0.42%)	t=1.667
% Female Headed Households with Children < 18 yrs old	6.10% (0.88%)	4.41% (0.25%)	t=-1.845

*p<.05, **p<.01, ***p<.001

Table 21 are the correlations between the socio-demographic variables used in the original modeling of county-level food uncertainty. In the county-level model, food uncertainty is significantly positively correlated with unemployment (*r*=.455, p<.01), the percent of people older than 65 (*r*=.350, p<.01), the percent of female-headed households with kids younger than 18 (*r*=.409, p<.01), the percent of individuals younger than five (*r*=.254, p<.01), and with the percentage of households living below the poverty level (*r*=.919, p<.01). Food insecurity is significantly negatively correlated with median household income (*r*=-.822, p<.01).

A negatively significant relationship exists between median household income and the percentage of individuals older than 65 (*r*=-.551, p<.01), the percent of individuals younger than five and those older than 65 (*r*=-.524, p<.01), and median household income and the percent of households living below the poverty level (*r*=-.832, p<.01).

Significantly positive correlations exist between the percent of single females with children and the percent of individuals who identify as African American (*r*=.595, p<.01), the percent of individuals identifying as Hispanic/Latino and the percent of individuals identified as non-citizens (*r*=.860, p<.01), and the percent of single mothers and people living below the poverty level (*r*=.640, p<.01).

Table 21.

Correlations Between County-Level Socio-demographic Variables

	Food Uncert-ainty (%)	Unem-ploy-ment (%)	> 65 (%)	AA or Black (%)	Hispanic (%)	Med. HH Income ($)	Female Headed-HH with Kids < 18 yrs old (%)	< 5 (%)	Non-Citizen (%)	< Pov Level (%)
Food Uncert-ainty (%)	1.00									
Unem-ploy-ment (%)	.455**	1								
> 65 years old (%)	.350**	.172	1							
AA or	.121	.173	-	1						

	Food Uncertainty (%)	Unemployment (%)	> 65 (%)	AA or Black (%)	Hispanic (%)	Med. HH Income ($)	Female Headed-HH with Kids < 18 yrs old (%)	< 5 (%)	Non-Citizen (%)	< Pov Level (%)
Black (%)			.343**							
Hispanic (%)	.007	-.164	-.375**	.142	1					
Median HH Income ($)	-.822**	-.304**	-.551**	.063	.108	1				
Female Headed-HH with Kids < 18 yrs old (%)	.409**	.225*	-.156	.595**	.228*	-.200*	1			
< 5 years old (%)	.254**	-.076	-.524**	.238**	.477**	.100	.361**	1		
Non-Citizen (%)	-.050	-.173	-.402**	.364**	.860**	.165	.256**	.364**	1	
< Poverty Level (%)	.919**	.241**	.226*	.177	-.009	-.832**	.640**	.123	-0.015	1

*p<.05, **p<.01

Principal Components Analysis

Bivariate correlations were conducted for the original 46 variables intended for the PCA. Due to the large number of variables, Table 22 includes only correlations that were both significant and strong (absolute value between 0.50 and 1.00).

Table 22.

Table of Highly Correlated Variables

Variable 1	*Variable 2*	*Correlation Coefficient*
% Low income and > 10 miles to store	% HH w/o vehicle > 10 miles to store	.968**
WIC redemptions	Total SNAP Benefits	.952**
# Summer Feeding Program sites	Total SNAP Benefits	.878**
Lbs. of Food Distributed	WIC redemptions	.853**
Average Sales/Farm	Average size of farm	.852**
# Farms	# Farms w/Direct Sales	.821**
Lbs of Food Distributed	Total SNAP benefits	.818**
% Low income and > 1	% HH w/o vehicle > 1 mile	.815**

Variable 1	*Variable 2*	*Correlation Coefficient*
mile to store	to store	
Farmland as Total % of Land	Land in Farms	.751**
Direct Farm Sales ($)	# Farms w/direct sales	.747**
WIC redemptions	Number of CSA's	.740**
WIC redemptions	# Summer Feeding Program sites	.738**
Average Sales/Farm	Crop sales	.733**
WIC redemptions/WIC authorized stores	SNAP redemptions/SNAP authorized stores	.704**
% Farms w/ Direct Sales	# Farms w/Direct Sales	.692**
Lbs of Food Distributed	# Summer Food Program sites	.684**
% Free and Reduced eligible	% Low income and > 1 mile to store	.682**
WIC authorized stores/10000	Grocery stores/1000 population	.680**
SNAP Benefits	Number of CSA's	.678**
% Low income and > 10 miles to store	% Low income and > 1 mile to store	.665**
Crop Sales	Average size of farm	.663**
WIC redemptions/WIC authorized stores	WIC authorized stores/1000	-.630**
# Farms	$ Direct Farm Sales	.629**
% HH w/o vehicle > 10 miles to store	% Low Income > 1mile to store	.620**
% HH w/o vehicle > 10 miles to store	% HH w/o vehicle > 1 mile to store	.616**
Land in Farms	# Farms	.607**
Grocery stores/1000	% HH w/o vehicle > 10 miles to store	.596**
SNAP-authorized stores/1000	Grocery stores/1000 population	.589**
SNAP-authorized stores/1000	% Low income and > 1 mile to store	.585**
% Free and Reduced eligible	SNAP authorized-stores/1000	.578**
Full-service restaurants/1000 population	% Low income and > 1 mile to store	-.578**
Crop Sales	Land in Farms	.569**
% Low income and > 10 miles to store	% HH w/o vehicle > 1 mile to store	.568**
Grocery stores/1000	% Low income and > 10 miles to store	.565**

Variable 1	*Variable 2*	*Correlation Coefficient*
Full-service restaurants/1000 population	% HH w/o vehicle and > 1 mile to store	-.561**
Average monthly SNAP benefits	Total SNAP Benefits	.553**
Avg. Size of Farms	% Farms w/Direct Sales	-.552**
Farmland as Total % of Land	% Farm Sales Direct to Consumer	-.549**
% Farm Sales Direct to Consumer	% Farms w/Direct Sales	.548**
SNAP redemptions/SNAP authorized stores	Supercenters and club stores/1000 population	.542**
% Free and Reduced eligible	% HH w/o vehicle and > 1 mile to store	.542**
WIC authorized stores/10000	SNAP-authorized stores/1000	.541**
WIC redemptions	Average monthly SNAP benefits	.523**
SNAP-authorized stores/1000	% Low income and > 10 miles to store	.518**
Average monthly SNAP benefits	Number of CSA's	.510**
Livestock Sales	# Farms	.510**

**p<.01

PCA was used to reduce the data from the 46 initial indicator variables to a manageable amount. PCA is enhanced by normally distributed variables, but only multivariate normality must be assumed to determine the number of components ((Tabachnick & Fiddell, 2007). An orthogonal rotation method, Varimax, was used to create unique factor components that are not allowed to correlate highly with one another (Tabachnick & Fiddell, 2007). Again, since different statistical textbooks refer to components as factors, the word "factor" is analogous with component and both will be used interchangeably. Varimax is the most common extraction method and is used to "simplify factors by maximizing the variance of the loadings, across variables" (Tabachnick & Fiddell, 2007, p.638). A benefit to using the orthogonal method is the resulting uncorrelated component scores that may be useful in data analysis techniques, such as regression, where assumptions regarding multicollinearity must be met (Field, 2009; Tabachnick & Fiddell, 2007).

Several methods were used to determine the number of components. Scree plots, which plot eigenvalues on the y-axis with the component on the x-axis are a cursory method to examine the potential factors (Cattell, 1966). Eigenvalues show the amount of variance that is explained by each factor (Field, 2009, Mertler & Vannatta, 2005). The inflexion of the curve indicates a cut-off point and is fairly reliable for sample sizes greater than 200 (Stevens, 2002). Since the sample size for this study was 115, other methods were used.

Kaiser's criterion (1960) recommends retaining factors with eigenvalues that are greater than one, which represents a large amount of variation (Field, 2009). Tabachnick & Fiddell (2007) recommend this as a starting point since the number of components retained is often overestimated, especially if there are more than 40 variables or the sample size is small.

After examining the scree plot and retaining components with eigenvalues greater than one, several other criteria were used to evaluate the factors based on statistical and theoretical considerations (Cattell, 1966). Tabachnick and Fiddell (2007) recommend retaining items that have loadings of an absolute value of 0.32 or more. However, Stevens (2002) provides a critique of traditional loading recommendations, suggesting that sample size should be a consideration when determining whether loadings should be considered significant. Items of loadings greater than or equal to 0.4538 were retained, based on the sample size of 115.

Any items that cross-loaded with at least one other component were examined more closely. Generally, items that had factor loadings with a difference of an absolute value of 0.15 were removed from the analysis (Wang, 2011). Furthermore, a reliability analysis was used to explore the items that loaded onto the components and consider deletion of items for improved reliability (Field, 2009). The variable, direct farm sales per capita, loaded on two components with less than 0.15 difference between the two. However, theoretically it made sense to retain this variable and retain the higher loading. Additionally, components were only retained if at least three items loaded significantly. An entire component would have been removed had direct farm sales per capita been removed. Since one of the main reasons for the study is to explore variables related to the food environment, it was retained. The variable, SNAP authorized stores/1000 was also retained despite cross-loading on two factors less than 0.15. The higher loading was retained for Component 6. In only one case was a lower loading chosen for theoretical reasons and to improve the reliability score (Cronbach's alpha). Grocery stores/1000 was moved from Component 4 to Component 2 in order to improve the reliability of Component 4 and because it theoretically made sense to use the Component 2 loading.

PCA Loadings

Table 23 displays the components, loadings after rotation, percent of variance explained, eigenvalue, and the Cronbach's alpha. They account for 76.43% of the variance. The original 46 variables was reduced to 23 variables and six components. Component 1 relates to ways people access food. It accounts for 28.14% of the variance and has a reliability of 0.933. The total amount of SNAP benefits loaded the highest (0.952). Component 1 also includes the amount of WIC redemptions (0.931), pounds of food distributed by emergency food assistance programs (0.876), and the number of Summer Food Program sites (0.823). The number of CSA's (0.729) also loaded onto Component 1 and represents a way people access food, but generally not through a private or government-funded food program.

Component 2 relates to accessibility and availability. The five indicator variables that load onto Component 2 account for 15.16% of the variance and have a reliability of 0.890. Variables include the percent of households without a vehicle living more than 10 miles from a food store (0.870), the percent of low income households without a vehicle living more than 10 miles from a food store (0.865), the percent of low income households without a vehicle living more than one mile from a food store (0.795), the percent of households living without a vehicle and more than one mile to a food store (0.784), and the number of grocery stores available per 1000 people (0.526).

Component 3 relates to agricultural production, accounting for 13.46% of the variance with a Cronbach's α of 0.864. The average sales per farm loaded at 0.929. The average size of the farms loaded at 0.877, while the crop sales loaded at 0.861. The percent of total land used for farming had the lowest loading (0.631).

The three items that loaded onto Component 4 account for 8.73% of the variance explained and have a reliability of 0.738. Two items relate to the use of food programs and the availability of food stores that accept WIC and SNAP. The percent of households paying more than 30% on rent relates to the contextual issues related to high housing costs that may influence eligibility or participation in food assistance programs. The amount of WIC redemptions per the number of WIC-authorized stores loaded at 0.768.

The amount of SNAP redemptions per authorized stores loaded at 0.682, while the percent of households paying more than 30% for rent loaded at 0.701.

Component 5 relates to direct farm sales to consumers. It includes three items that explain 5.07% of the variance and have a reliability of 0.638. The amount of direct farm sales loaded highly at 0.847. Direct sales per capita loaded the lowest at 0.549. The number of farms was related and loaded at 0.782.

Component 6, while having a less reliable Cronbach's α of 0.493, included 3 variables and accounted for 4.87% of the variance. This component also relates to availability of food sources and potential affordability. The number of farmers' markets per 1000 people loaded at 0.672. The percent of households paying more than 30% for their mortgage loaded at 0.658. The lowest loading was the number of SNAP-authorized stores/1000 people (0.638).

Table 23.

Component Loadings

		Loadings	*Variance Explained*	*Eigenvalue*	*Cronbach's α Std.*
Component 1 Food Programs	Total SNAP benefits ($1000s)	0.952	28.14%	6.472	.933
	WIC redemptions ($)	0.931			
	# Summer Food Program Sites	0.876			
	Pounds of Food Distributed	0.823			
	No. of CSA's	0.729			

		Loadings	*Variance Explained*	*Eigenvalue*	*Cronbach's α Std.*
Component 2 Access	% HH w/o vehicle and > 10 miles to store % Low Income and > 10 mile to store %Low Income and > 1 mile to store % HH w/o vehicle and > 1 mile to store Grocery Stores per 1000 people	0.870 0.865 0.795 0.784 0.526	15.16%	3.487	.890
Component 3 Agricultural Production	Average sales/Farm Average size of farm Crop Sales Farmland as % of total land	0.929 0.877 0.861 0.631	13.46%	3.095	.864

		Loadings	*Variance Explained*	*Eigenvalue*	*Cronbach's α Std.*
Component 4 Program Usage	WIC redemptions per WIC authorized stores % HH paying > 30% on rent SNAP redemptions per authorized stores	0.769 0.701 0.682	8.73%	2.008	.738
Component 5 Direct Farm Sales	$ Direct Farm Sales # Farms $ Direct Farm Sales per capita	0.847 0.782 0.549	6.07%	1.397	.638
Component 6 Availability and Afford-ability	Farmers' Markets/1000 % HH > 30% $$ for mortgage SNAP authorized stores/1000	0.672 0.658 0.573	4.87%	1.121	.493

Weighted Component Scores

Once the components were finalized, following methods first used by Lopez, et al. (2008), the component scores for each county were weighted based on the amount of variance explained by the component. For example, scores for Component 1 were multiplied by 0.2814 to obtain weighted component scores for each county. Table 24 displays the range for each component score and each weighted component score.

Table 24.

Minimum and Maximum Values for Component and Weighted Component Scores

Component Label	*Component Number*	*Minimum*	*Maximum*
Food Programs	Component 1 Score	-.76080	6.95917
	Component 1 Weighted Score	-.21409	1.95831
Access	Component 2 Score	-1.51373	4.14231
	Component 2 Weighted Score	-.229948	.62797420
Agricultural Production	Component 3 Score	-1.27713	4.26658
	Component 3 Weighted Score	-.171902	.574282
Program Usage	Component 4 Score	-2.86827	2.17195
	Component 4 Weighted Score	-.250400	.189611
Direct Farm Sales	Component 5 Score	-1.83325	2.76240
	Component 5 Weighted Score	-.111278	.167678
Availability and Affordability	Component 6 Score	-2.03426	3.91284
	Component 6 Weighted Score	-.099069	.190555

Spearman's Rank Correlations of Weighted Component Scores

Weighted component scores have been used as a way to rank study areas for each component (Bletzacker, Holben, & Holcomb, 2009; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). These studies have taken the average weighted factor scores and used them to create a ranking. This ranking has been considered a proxy for community food security.

The overall weighted component score rankings were divided into quintiles (Lopez, et al., 2005). The results are listed in Table 25. Quintile 1 reflects the counties that are considered the highest community food insecure, while Quintile 5 reflects the most community food secure communities according to the rankings.

Table 25.

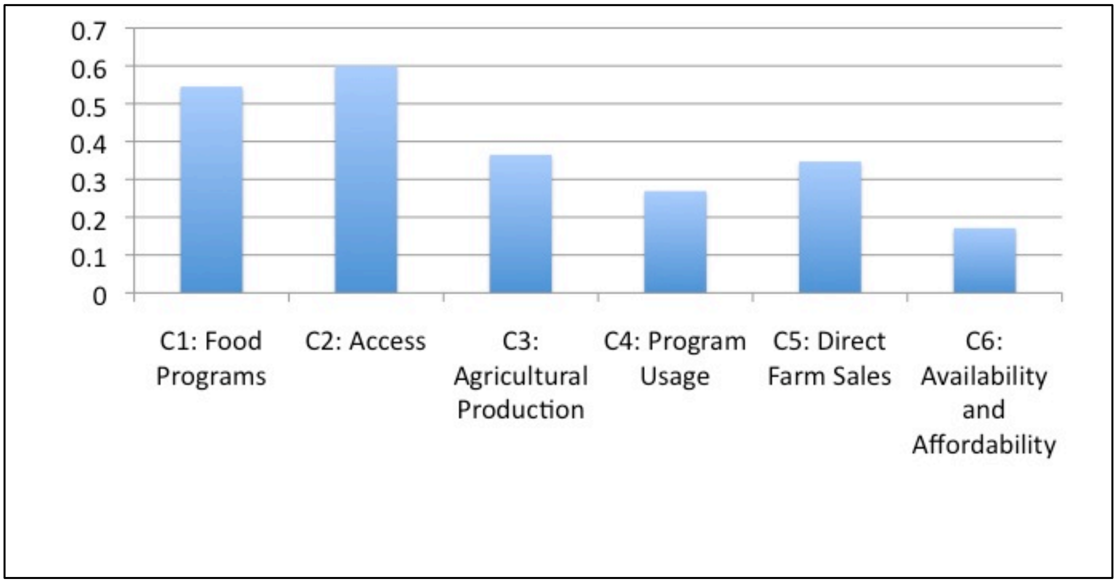
County-Level Community Food Security Quintiles Based on Spearman's Rank Correlations

Quintile 1	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Jackson	Barry	Chariton	Howard	Clay
St. Louis City	Dallas	Shelby	Macon	St. Francois
St. Louis	Greene	Carroll	Iron	Scotland
Pemiscot	Sullivan	Laclede	Atchison	Moniteau
New Madrid	Polk	Newton	Buchanan	Andrew
St. Clair	Wayne	Washington	Henry	Camden
Dunklin	Vernon	Webster	Franklin	Stone
Carter	Johnson	Harrison	Montgomery	Marion
Holt	Oregon	Grundy	Adair	Warren
Mississippi	Lawrence	Daviess	Randolph	Pulaski
Howell	Lewis	Cass	Worth	Cooper
Knox	McDonald	Benton	Linn	Ste. Genevieve
Butler	Gentry	Wright	Perry	Livingston
Pettis	Douglas	DeKalb	Miller	Ray
Ozark	Scott	Dent	Lincoln	Ralls
Jasper	Audrain	Hickory	Mercer	Crawford
Shannon	Texas	Cape Girardeau	Clark	Monroe
Stoddard	Bates	Dade	Cedar	Cole
Schuyler	Ripley	Callaway	St. Charles	Platte
Boone	Caldwell	Bollinger	Phelps	Taney
Morgan	Pike	Barton	Jefferson	Madison
Putnam	Saline	Osage	Christian	Gasconade
Lafayette	Nodaway	Reynolds	Maries	Clinton

Previous studies used Spearman's Rank correlations between each weighted component score and the overall ranking, which is still considered a proxy for community food security (Bletzacker, Holben, & Holcomb, 2009; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). Figure 1 displays the Spearman's Rank correlation coefficients between the CFS rankings and the weighted component scores. The positive correlations indicate a higher ranking from 1 to 115. The closer a county gets to 115, the more community food insecure they are considered to be according to the Spearman's Rank correlations.

Figure 1.

Spearman's Rank Correlation Coefficients Between Overall CFS Rankings and Components



A community that had a high number of food voucher and distribution programs (C1) was generally more food community food insecure. Counties where a high number of people lacked transportation and lived far from a food store (C2) were more community food insecure. Counties with a large number of farms, crop sales (C3), and direct farm sales (C5) were more community food insecure. High WIC and SNAP participation (C4) and a large number of unaffordable housing, farmers' markets, and SNAP-authorized stores (C6) correlated with a more community food insecure county.

Table 26 displays the Spearman's rank correlations for each component and indicator. For Component 1, there is a strong significant positive relationship with the overall CFS ranking (ρ=.545). The number of Summer Feeding Program sites is significantly positively correlated with the CFS ranking (ρ=.314). While the amount of pounds of emergency foods distributed was weakly correlated with CFS ranking and not significant, it is worth noting that there is a negative relationship with community food security.

A strong and significant positive relationship exists between Component 2 and the overall ranking (ρ=.600). Three of the indicators were statistically significant, with higher scores indicating higher community food insecurity. In terms of transportation, the percent of low income households without a vehicle and living more than one mile from a food store (ρ=.295) and the percent of households without a vehicle living more than one mile from a food store (ρ=.272) were significant. The number of grocery stores per 1000 people was significant (ρ=3.19) indicating that, in Missouri Counties, areas with more grocery stores per 1000 people actually related to community food insecure counties.

Weaker strong and positive relationships exist between overall CFS rank and Component 3 (ρ=.365) and Component 5 (ρ=.347). The average sales per farm was the only indicator that was significant (ρ=.324). There were no significant indicators within Component 5.

There was a significant positive relationship between Component 4 and the overall CFS ranking (ρ=.269). The percent of households paying more than 30% for rent was positively significantly correlated with the CFS ranking (ρ=.274). Although not significant, the amount of SNAP redemptions per authorized stores was negatively correlated with a higher ranking of community food insecurity.

The relationship between Component 6 and the overall ranking was not significant and weak (ρ=.171). The number of SNAP-authorized stores per 1000 people was positively correlated with a higher CFS ranking (ρ=.471). While the number of Farmers' Markets per 1000 people was not statistically significant, it approached significance at the $p<.05$ level and was negatively correlated with community food insecurity.

Table 26.

Spearman's Rho Between Overall CFS Ranking, Components, and Indicators

Component	*Spearman's Rho*
Component 1: Food Programs	.545***
Total SNAP benefits ($1000s)	.136
WIC redemptions ($)	.103
# Summer Food Program Sites	.314**
Pounds of Food Distributed	-.022
No. of CSA's	.125
Component 2: Access	.600**
% HH w/o vehicle and > 10 miles to store	.143
% Low Income and > 10 mile to store	.134
% Low Income w/o vehicle and > 1 mile to store	.295**

Component	*Spearman's Rho*
% HH w/o vehicle and > 1 mile to store	.272**
Grocery Stores per 1000 people	.319**
Component 3: Agricultural Production	.365**
Average sales/Farm	.324***
Average size of farm	.183
Crop Sales	.160
Farmland as % of total land	.085
Component 4: Program Usage	.269**
WIC redemptions per WIC authorized stores	.134
% HH paying > 30% on rent	.274**
SNAP redemptions per authorized stores	-.013
Component 5: Direct Farm Sales	.347**
$ Direct Farm Sales	.094
# Farms	.028
$ Direct Farm Sales per capita	.094
Component 6: Availability and Affordability	.171
Farmers' Markets/1000	-.176
% HH > 30% $$ for mortgage	.183
SNAP authorized stores/1000	.471***

*p<.05, **p<.01, ***p<.001

Component Rankings

Overall, three metro counties in the two most populated Missouri metropolitan areas ranked as the counties with the worst community food security ranking. One issue of note is the inclusion of St. Louis County. As noted in Chapter 3, the data concerning agricultural food production and direct farm sales was collected for St. Louis County and St. Louis City and combined together. The rankings for these two areas should be considered in light of this issue. Nonmetro counties made up 70% of the most community food insecure communities, which is approximately equivalent to the percent of nonmetro counties in the state. Four of the counties at the greatest risk are in the Southeast corner of Missouri's Ozark Mountain region. Half of the most community food secure counties are geographically located near the largest metropolitan areas and are likely to be considered suburban.

Table 27.

Lowest and Highest Average WCS

Ranking	***County***	***OMB (M/NM))***	***Score***	***Ranking***	***County***	***OMB (M/ NM)***	***Score***
1	Jackson	M	.3270	115	Clinton	M	-.0858
2	St. Louis City	M	.2936	114	Gasconade	NM	-.0767
3	St. Louis County	M	.1435	113	Madison	NM	-.0764
4	Pemiscot	NM	.1195	112	Taney	NM	-.0704
5	New Madrid	NM	.1105	111	Platte	M	-.0684
6	St. Clair	NM	.0975	110	Cole	M	-.0656
7	Dunklin	NM	.0915	109	Monroe	NM	-.0653
8	Carter	NM	.0835	108	Crawford	NM	-.0643

Ranking	*County*	*OMB (M/NM))*	*Score*	*Ranking*	*County*	*OMB (M/ NM)*	*Score*
9	Holt	NM	.0829	107	Ralls	NM	-.0628
10	Mississippi	NM	.0819	106	Ray	M	-.0601

Tables 27-33 shows the highest and lowest 10 counties for each weighted component score, their OMB designation, and their ranking for each score. A low ranking or high weighted component score means the county is more likely to be at risk for community food insecurity for that component, whereas a lower weighted component score and higher ranking indicates some positive relationship between the component exists as a protective factor in terms of community food security.

Table 28.

Lowest and Highest WCS1-Food Programs

Ranking	*County*	*OMB (M/NM))*	*Score*	*Ranking*	*County*	*OMB (M/ NM)*	*Score*
1	Jackson	M	1.9583	115	Madison	NM	-.2141
2	St. Louis City	M	1.500	114	Hickory	NM	-.1740
3	St. Louis County	M	1.282	113	Crawford	NM	-.1671
4	Boone	M	.4367	112	Douglas	NM	-.1649
5	Greene	M	.3106	111	Livingston	NM	-.1572
6	St. Charles	M	.2929	110	Adair	NM	-.1567
7	Clay	M	.1921	109	Cedar	NM	-.1474
8	St. Clair	NM	.1531	108	Ste. Genevieve	NM	-.1457
9	Lafayette	M	.1465	107	Bollinger	NM	-.1439
10	Schuyler	NM	.1380	106	Nodaway	NM	-.1429

The counties that had the highest amount of overall food distribution through private, government, and CSA programs, were more likely to be experiencing the highest level of community food security relative to the other counties in Missouri. There is an overrepresentation of metropolitan counties in this category.

Table 29.

Lowest and Highest WCS2-Access

Ranking	***County***	***OMB (M/NM))***	***Score***	***Ranking***	***County***	***OMB (M/ NM)***	***Score***
1	Carter	NM	.6280	115	Adair	NM	-.1133
2	Holt	NM	.4893	114	Cooper	NM	-.1067
3	Shannon	NM	.4450	113	Franklin	M	-.1061
4	St. Clair	NM	.4320	112	Mercer	NM	-.1043
5	Schuyler	NM	.3794	111	Randolph	NM	-.1039
6	Wayne	NM	.3066	110	Saline	NM	-.1026
7	Ozark	NM	.2845	109	Moniteau	M	-.1025
8	Reynolds	NM	.2841	108	Andrew	M	-.1024
9	Douglas	NM	.1851	107	St. Francois	NM	-.0972
10	Lewis	NM	.1717	106	Linn	NM	-.0953

Nonmetro areas were overrepresented in this category, showing that transportation, number of grocery stores available, and the distance to stores is a potential barrier for overall community food security.

Table 30.

Lowest and Highest WCS3-Agricultural Production

Ranking	***County***	***OMB (M/NM))***	***Score***	***Ranking***	***County***	***OMB (M/NM)***	***Score***
1	Mississippi	NM	.5743	115	Jefferson	M	-.1719
2	New Madrid	NM	.5708	114	Reynolds	NM	-.1664
3	Pemiscot	NM	.5629	113	Taney	NM	-.1527
4	Dunklin	NM	.4006	112	Madison	NM	-.1490
5	Stoddard	NM	.3054	111	Stone	NM	-.1444
6	Atchison	NM	.2396	110	Shannon	NM	-.1408
7	Saline	NM	.2284	109	Pulaski	NM	-.1310
8	Scott	NM	.1932	108	St. Francois	NM	-.1282

Ranking	*County*	*OMB (M/NM))*	*Score*	*Ranking*	*County*	*OMB (M/NM)*	*Score*
9	Audrain	NM	.1629	107	Christian	M	-.1265
10	Butler	NM	.1558	106	Iron	NM	-.1261

While nonmetro counties had the most agricultural production, this was not a protective factor in achieving overall community food security. Counties with the largest farms and sales were more likely to be in counties where community food security was problematic. The five counties of greatest concern were located adjacent to one another in the Southeast Ozark Mountain region of Missouri.

Table 31.

Lowest and Highest WCS4-Program Usage

Ranking	*County*	*OMB (M/NM))*	*Score*	*Ranking*	*County*	*OMB (M/NM)*	*Score*
1	Adair	NM	.1896	115	Schuyler	NM	-.2504
2	Butler	NM	.1635	114	Worth	NM	-.1861
3	St. Louis City	M	.1570	113	Scotland	NM	-.1731
4	New Madrid	NM	.1383	112	Gentry	NM	-.1709
5	Douglas	NM	.1369	111	Mercer	NM	-.1684
6	Pemiscot	NM	.1324	110	Chariton	NM	-.1676
7	Ripley	NM	.1294	109	Atchison	NM	-.1504
8	Jasper	M	.1289	108	Dade	NM	-.1360
9	Randolph	NM	.1215	107	Lafayette	M	-.1333
10	Newton	M	.1152	106	Holt	NM	-.1182

Component 4 takes into account the amount of WIC and SNAP redemptions per store and the percent of people paying more than 30% of their income towards rent. The rations of redemptions to stores may point to either a large number of stores that accept WIC or SNAP or a small amount of participants using the program, which means the amount of redemptions would be smaller, no matter the number of stores. Housing affordability is also considered, and may allude to more of the economic context.

Table 32.

Lowest and Highest WCS5-Direct Farm Sales

Ranking	***County***	***OMB (M/NM))***	***Score***	***Ranking***	***County***	***OMB (M/ NM)***	***Score***
1	Lafayette	M	.1677	115	Madison	NM	-.1113
2	Howell	NM	.1576	114	Taney	NM	-.0985
3	Johnson	NM	.1561	113	St. Louis	M	-.0965
4	Lawrence	NM	.1196	112	Mercer	NM	-.0892
5	Knox	NM	.1151	111	Mississippi	NM	-.0882
6	Webster	M	.1025	110	Atchison	NM	-.0836
7	Polk	M	.1018	109	Camden	NM	-.0836
8	Morgan	M	.1000	108	Iron	NM	-.0807
9	Franklin	NM	.0952	107	Pulaski	NM	-.0777
10	Pettis	NM	.0948	106	Pemiscot	NM	-.0738

Direct farm sales was not a protective factor against community food insecurity. Communities that sold a large percentage of their sales direct to consumers did not rate higher in terms of community food security. In fact, three of the 10 counties that represent the lowest amount of direct farm sales, were among the 10 most community food insecure.

Table 33.

Highest and Lowest WCS6-Availability and Affordability

Ranking	***County***	***OMB (M/NM))***	***Score***	***Ranking***	***County***	***OMB (M/NM)***	***Score***
1	Scotland	NM	.1906	115	Chariton	NM	-.0991
2	Putnam	NM	.1627	114	Holt	NM	-.0924
3	Mercer	NM	.1439	113	DeKalb	M	-.0871
4	St. Louis City	M	.0837	112	Reynolds	NM	-.0734
5	Gentry	NM	.0829	111	Andrew	M	-.0699
6	Cedar	NM	.0817	110	Cole	M	-.0689

Ranking	County	OMB (M/NM))	Score	Ranking	County	OMB (M/NM)	Score
7	Iron	NM	.0705	109	Nodaway	NM	-.0669
8	Ozark	NM	.0693	108	Ralls	NM	-.0668
9	Oregon	NM	.0645	107	Callaway	M	-.0598
10	Knox	NM	.0634	106	Audrain	NM	-.0595

Component 6 addresses the availability of particular types of food sources and considers potential issues related to food affordability. Part of this may be trade-offs made due to high housing costs (Bartfeld, 2003; Biggerstaff, et al., 2002; Gross & Rosenberger, 2005; Rose, 1999). Also at issue are places where SNAP is accepted and places to purchase fresh, local foods. Counties where these food sources existed were almost all located in nonmetro areas.

Regression Analysis to Estimate Community Food Uncertainty

This unique study extends the understanding of the relationship of food environment variables to community food security. A regression analysis was conducted in order to test the theory that the components extracted in the PCA predict or explain the percentage of households that are food insecure in a county. Recall that the dependent variable includes socio-demographic indicators. Other studies included those indicators as part of their PCA (Bletzacker, Holben, & Holcomb, 2009; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005). The regression analysis moves beyond looking at relationships between rankings that are relative to one another.

Normality was assessed by looking at the skewness value, histograms, and scatterpolots of the variables (Pedhauzer, 1997; Tabachnick & Fidell, 2007). The Weighted Component 1 scores and Weighted Component 3 scores did not meet the assumption and were slightly positively skewed. Univariate outliers were assessed using the standardized z-scores. The criterion of +/-3.29 SD is often used as a criterion because it corresponds to the normal distribution (Tabachnick & Fidell, 2007). Based on this criterion, three cases were deleted for the WCS1. This included Jackson, St. Louis City, and St. Louis County. One case was deleted for WCS2 (Carter). Three cases were removed for WCS3, which included Mississippi, New Madrid, and Pemiscot. Two cases were removed for WCS6, which included Scotland and Putnam. The sample size for the regression analysis was reduced to 106, 31 of which were urban counties, and 75 of which were rural. These are displayed in Table 34.

Table 34.

Counties removed from regression analysis

County	*OMB Designation*	County	*OMB Designation*	County	*OMB Designation*
Carter	*Nonmetro*	Pemiscot	*Nonmetro*	St. Louis City	*Metro*
Jackson	*Metro*	Putnam	*Nonmetro*		
Mississippi	*Nonmetro*	Scotland	*Nonmetro*	St. Louis County	*Metro*
New Madrid	*Nonmetro*				

The weighted component scores met the assumptions of independent observations, homoscedasticity, homogeneity of variance, and linearity. There were no multivariate outliers using the Mahalanobis distance critical vaulue of 16.81 for six degreees of freedom (p<.01) (Tabachnick & Fidell, 2007). Although the use of weighted component scores from an orthogonally rotated PCA should not be correlated, the VIF and Tolerance were reviewed to be sure this was not an issue. As expected, the Weighted Component Scores met the requirements of having a tolerance level of at least 0.1 and a VIF value less than to (Tabachnick & Fidell, 2007).

A power analysis was conducted using G*Power. A sample size of 89 is needed for a power of 0.95 for six variable. Thus, the adjusted sample size of 106 is sufficient for regression analysis.

Bivariate Correlations

Pearson's bivariate correlations were conducted between all six Weighted Component Scores and Food Uncertainty. Table 35 displays the correlation coefficients. Food uncertainty is significantly positively correlated with WCS2-Access (*r*=.398), p<.01, WCS4-Program Usage (*r*=.400, p<.01), and WCS6-Availability and Affordability. Negative significant correlations exist between WCS4-Program Usage and WCS1-Food Programs (*r*=-.262, p<.01) and WCS3-Agricultural Production (*r*=-.210, p<.05). A small significant correlation exists between WCS1-Food Programs and WCS5-Direct Farm Sales (*r*=.255, p<.01).

Table 35.

Pearson's Correlation Coefficients

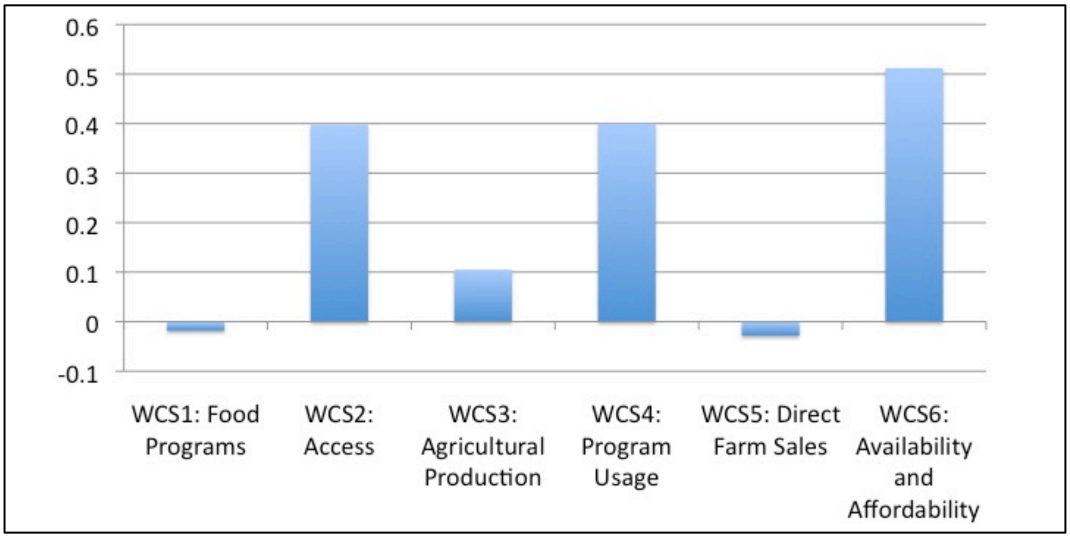
	WCS1 Food Programs	WCS2 Access	WCS3 Agricult-ural Production	WCS4 Program Usage	WCS5 Direct Farm Sales	WCS6 Availability and Afford-ability	Food Uncert-ainty
WCS1 Food Programs	1						
WCS2 Access	0.02	1					
WCS3 Agricultural Production	0.129	0.006	1				
WCS4 Program Usage	-.262**	-0.051	-.210*	1			
WCS5 Direct Farm Sales	.255**	0.032	0.185	0.041	1		

	WCS1 Food Programs	WCS2 Access	WCS3 Agricult-ural Production	WCS4 Program Usage	WCS5 Direct Farm Sales	WCS6 Availability and Afford-ability	Food Uncert-ainty
WCS6 Availability and Afford-ability	-0.168	0.072	-0.1	0.07	0.014	1	
Food Uncertainty	-0.179	.398**	0.105	.400**	-0.028	.512**	1

Figure 2 depicts to Pearson's r correlations between the Weighed Component Scores and the percentage of households estimated to be food uncertain in each county. This shows that counties that had a lower number of food programs had a higher percentage of food uncertain households. Counties with a large number of people who have problems accessing food stores, have a significantly higher percentage of food uncertain households. While not significant, counties with more farms and agricultural production had more food uncertain households, while counties with lower direct farm sales had higher percentage of food uncertain households. Higher food program redemptions, housing costs, and alternative food source availability equated to a higher percentage of households that were food uncertain.

Figure 2.

Pearson's r Correlations Between WCS and Food Uncertainty



The first regression model uses all six weighted component scores as independent variables. The second regression model uses the six weighted component scores and controls for the OMB designation. Table 36 displays the B coefficients, the standardized β coefficients, and the Standard Error for Model 1 and Model 2.

Table 36.

Regression Table Predicting Food Uncertainty for Model 1 and Model 2

	Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Constant	15.458***	.192		15.714	.234	
WCS1-Food Programs	.208	1.815	.008	1.157	1.862	.044
WCS2-Access	7.243	1.718	.388***	6.433	1.241	.344***
WCS3-Agricultural Production	7.154	1.771	.266***	5.894	1.873	.219**

Variable	Model 1			Model 2		
	B	*SE B*	*β*	*B*	*SE B*	*β*
WC4-Program Usage	14.027	2.098	.448***	13.706	2.079	.438***
WC5-Direct Farm Sales	-5.229	2.979	-.117	-3.351	3.108	-.075
WCS6-Availability and Affordability	30.046	4.000	.482***	27.726	4.139	.445***
OMB Designation (Rural=0)				-.865	.461	-.148
Adjusted R^2		.587***			.597	

R^2 for Model 1=.587, ΔR^2 =.013 for Model 2
*p<.05, **p<.01, ***p<.001

Model 1 exhibits that four out of six of the components significantly predict the percentage of households that are food insecure. Model 1 accounts for 58.7% of the variance. Component 6, the availability of local farmers' markets and stores that accept SNAP and a high percent of homeowners living in unaffordable housing, contributed the most to the model (β=.448, *SE*=4.00, p<.001). WIC redemptions/store SNAP redemptions/store, and unaffordable rent significantly predicted food uncertainty (β=.482, *SE*=2.098, p<.001). Limited accessibility and availability of grocery stores also was predictive of a high percentage of households in a county estimated to be food uncertain (β=.388, *SE*=1.718, p<.001). Areas with large amounts of agricultural production also contributed significantly to the percent of food uncertain households (β=.266, *SE*=1.771, p<.001).

A New Model for Measuring Community Food Uncertainty

Since the OMB designation did not significantly improve the model, the coefficients for Model 1 were used to calculate an estimate of our new dependent variable, community food uncertainty, which predicts the percentage of households in counties that would be considered community food secure when the food environment components are used as predictors, rather than socio-demographic variables.

The county-level regression model used for this prediction is below. This is used to estimate the Y value, or the percentage of households in a county that would be considered food insecure based on the community food security components. The coefficients can be referenced in the regression table. Estimates are listed in Table 37.

$$Y_{cfuncert}' = a + B_1 WCS_1 + B_2 WCS_2 + B_3 WCS_3 + B_4 WCS_4 + B_5 WCS_5 + B_6 WCS_6$$

Table 37.

Percentage of Households Considered Community Food Insecure in Each County

County	*Community Food Insecure (%)*	*OMB Designation*
Adair	16.00	Nonmetro
Andrew	11.95	Metro
Atchison	14.97	Nonmetro
Audrain	14.84	Nonmetro
Barry	17.24	Nonmetro
Barton	15.74	Nonmetro
Bates	16.14	Metro
Benton	16.41	Nonmetro
Bollinger	16.68	Nonmetro
Boone	12.54	Metro
Buchanan	13.59	Metro
Butler	19.10	Nonmetro
Caldwell	15.23	Metro
Callaway	13.05	Metro
Camden	15.29	Nonmetro
Cape Girardeau	14.73	Nonmetro
Carroll	13.81	Nonmetro

County	*Community Food Insecure (%)*	*OMB Designation*
Carter	18.30	Nonmetro
Cass	13.39	Metro
Cedar	17.21	Nonmetro
Chariton	11.84	Nonmetro
Christian	13.14	Metro
Clark	15.34	Nonmetro
Clay	11.13	Metro
Clinton	11.71	Metro
Cole	11.20	Metro
Cooper	12.77	Nonmetro
Crawford	15.30	Nonmetro
Dade	13.89	Nonmetro
Dallas	17.50	Metro
Daviess	15.44	Nonmetro
DeKalb	13.66	Metro
Dent	17.00	Nonmetro
Douglas	18.23	Nonmetro
Dunklin	20.39	Nonmetro
Franklin	12.88	Metro
Gasconade	13.51	Nonmetro
Gentry	15.55	Nonmetro
Greene	13.53	Metro
Grundy	15.91	Nonmetro
Harrison	15.45	Nonmetro
Henry	16.34	Nonmetro
Hickory	18.57	Nonmetro
Holt	15.68	Nonmetro
Howard	15.41	Metro
Howell	18.45	Nonmetro
Iron	17.33	Nonmetro
Jackson	15.69	Metro
Jasper	16.80	Metro
Jefferson	12.83	Metro
Johnson	15.24	Nonmetro
Knox	18.27	Nonmetro
Laclede	16.14	Nonmetro
Lafayette	14.30	Metro
Lawrence	16.85	Nonmetro
Lewis	15.05	Nonmetro
Lincoln	13.13	Metro
Linn	14.77	Nonmetro
Livingston	14.34	Nonmetro
Macon	15.20	Nonmetro
Madison	15.77	Nonmetro

County	*Community Food Insecure (%)*	*OMB Designation*
Maries	13.27	Nonmetro
Marion	13.04	Nonmetro
McDonald	16.31	Metro
Mercer	17.00	Nonmetro
Miller	15.00	Nonmetro
Mississippi	20.54	Nonmetro
Moniteau	11.63	Metro
Monroe	13.26	Nonmetro
Montgomery	13.96	Nonmetro
Morgan	17.77	Nonmetro
New Madrid	21.19	Nonmetro
Newton	15.57	Metro
Nodaway	14.91	Nonmetro
Oregon	18.42	Nonmetro
Osage	12.54	Metro
Ozark	20.43	Nonmetro
Pemiscot	22.88	Nonmetro
Perry	13.23	Nonmetro
Pettis	17.17	Nonmetro
Phelps	15.10	Nonmetro
Pike	15.00	Nonmetro
Platte	11.63	Metro
Polk	16.79	Metro
Pulaski	14.60	Nonmetro
Putnam	19.98	Nonmetro
Ralls	11.70	Nonmetro
Randolph	16.02	Nonmetro
Ray	12.83	Metro
Reynolds	13.58	Nonmetro
Ripley	18.93	Nonmetro
Saline	15.55	Nonmetro
Schuyler	15.92	Nonmetro
Scotland	17.57	Nonmetro
Scott	14.99	Nonmetro
Shannon	18.14	Nonmetro
Shelby	14.09	Nonmetro
St. Charles	10.11	Metro
St. Clair	18.19	Nonmetro
St. Francois	13.72	Nonmetro
St. Louis	12.52	Metro
St. Louis City	20.94	Metro
Ste. Genevieve	13.78	Nonmetro
Stoddard	17.72	Nonmetro
Stone	14.74	Nonmetro

County	*Community Food Insecure (%)*	*OMB Designation*
Sullivan	15.65	Nonmetro
Taney	14.07	Nonmetro
Texas	16.23	Nonmetro
Vernon	17.33	Nonmetro
Warren	14.81	Metro
Washington	17.53	Metro
Wayne	16.95	Nonmetro
Webster	15.48	Metro
Worth	12.65	Nonmetro
Wright	16.97	

The percentage of households in counties considered community food insecure, using the new community food security variable (CFS2) based on the coefficients and weighted component scores from the PCA and regression model ranged from 10.11% to 22.88%. The mean was 15.45% (*SD*=2.40).

All counties and St. Louis city were divided into quintiles, with Quintile 1 including the counties with highest percentage of household considered food insecure by the new definition for community food security (CFS2). These are depicted in Table 38.

Table 38.

County-Level Community Food Security Quintiles Based on CFS2

Quintile 1	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Pemiscot	Iron	Barton	Nodaway	Monroe
New Madrid	Barry	Jackson	Audrain	Perry
St. Louis City	Cedar	Holt	Warren	Christian
Mississippi	Pettis	Sullivan	Linn	Lincoln
Ozark	Mercer	Newton	Stone	Callaway
Dunklin	Dent	Saline	Cape Girardeau	Marion
Putnam	Wright	Gentry	Pulaski	Franklin
Butler	Wayne	Webster	Livingston	Ray
Ripley	Lawrence	Harrison	Lafayette	Jefferson
Hickory	Jasper	Daviess	Shelby	Cooper
Howell	Polk	Howard	Taney	Worth

Quintile 1	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Oregon	Bollinger	Clark	Montgomery	Osage
Carter	Benton	Crawford	Dade	Boone
Knox	Henry	Camden	Carroll	St. Louis
Douglas	McDonald	Johnson	Ste. Genevieve	Andrew
St. Clair	Texas	Caldwell	St. Francois	Chariton
Shannon	Laclede	Macon	DeKalb	Clinton
Morgan	Bates	Phelps	Buchanan	Ralls
Stoddard	Randolph	Lewis	Reynolds	Platte
Scotland	Adair	Miller	Greene	Moniteau
Washington	Schuyler	Pike	Gasconade	Cole
Dallas	Grundy	Scott	Cass	Clay
Vernon	Madison	Atchison	Maries	St. Charles

Community Food Uncertainty Rankings

Table 39 displays the Spearman's rank correlations for each component and indicator and community food uncertainty ranking. For Component 1, there is a non-significant weak, negative relationship with the overall CFU ranking (ρ=-.038), which is in the opposite direction from the CFS model. The number of Summer Feeding Program sites is significantly negatively correlated with the CFS ranking (ρ=-.277), which is also different than the CFS model and indicates that fewer Summer Feeding Program sites indicate higher percentages of community food uncertainty. The amount of pounds of emergency foods distributed significantly correlated with the CFU ranking (ρ=.235), which is in the opposite direction of the CFS ranking. Also significant was the number of CSA's. Fewer CSA's were indicative of higher CFU rankings (ρ=-.202),

A strong and significant positive relationship exists between Component 2 and the overall ranking (ρ=.559). Tall five of the indicators were statistically significant, with higher scores indicating higher community food uncertainty. In terms of transportation, the percent of low income households without a vehicle and living more than one mile from a food store (ρ=.522), the percent of low income households living more than 10 miles from a food store (ρ=.267), the percent of households without a vehicle living more than one mile from a food store (ρ=.402), and the percent of households without a vehicle living more than 10 miles from a food store (ρ=.221) were significant. The number of grocery stores per 1000 people was significant (ρ=.339) indicating that, in Missouri Counties, areas with more grocery stores per 1000 people actually related to community food insecure counties.

No statistically significant relationship exists between overall CFU rank and Component 3 (ρ=.162) and Component 5 (ρ=.013). The average sales per farm was the only indicator that was significant (ρ=.279). Even though they were not significant, a smaller percent of land used for farming and a lower number of crop sales was correlated with a higher CGU ranking. Direct sales was significantly negatively correlated with CFU ranking (ρ=-.200), as was the number of farms (ρ=-.209),

There was a significant positive relationship between Component 4 and the overall CFU ranking (ρ=.541). The percent of households paying more than 30% for rent was positively significantly correlated with the CFU ranking (ρ=.465).

The relationship between Component 6 and the overall ranking was not significant and weak (ρ=.655). The number of SNAP-authorized stores per 1000 people was positively correlated with a higher CFU ranking (ρ=.677). The number of Farmers' Markets per 1000 people was statistically significant, and positive (ρ=.250), which differed from the correlation with the CFS ranking. The percent of households paying more than 30% on mortgages was also positively statistically significant (ρ=.504).

Table 39.

Spearman's Rho Between Overall CFU Ranking, Components, and Indicators

Component	*Spearman's Rho*
Component 1: Food Programs	-.038
Total SNAP benefits ($1000s)	.008
WIC redemptions ($)	-.070
# Summer Food Program Sites	-.277**
Pounds of Food Distributed	.235*
No. of CSA's	-.202*
Component 2: Access	.559***
% HH w/o vehicle and > 10 miles to store	.221*
% Low Income and > 10 mile to store	.267*
%Low Income w/o vehicle and > 1 mile to store	.522***
% HH w/o vehicle and > 1 mile to store	.402***
Grocery Stores per 1000 people	.339***
Component 3: Agricultural Production	.162
Average sales/Farm	.097
Average size of farm	.279**
Crop Sales	-.162
Farmland as % of total land	-.089
Component 4: Program Usage	.541***
WIC redemptions per WIC authorized stores	.173

Component	*Spearman's Rho*
% HH paying > 30% on rent	.465**
SNAP redemptions per authorized stores	.010
Component 5: Direct Farm Sales	.013
$ Direct Farm Sales	-.200*
# Farms	-.209*
$ Direct Farm Sales per capita	.055
Component 6: Availability and Affordability	.655***
Farmers' Markets/1000	.250**
% HH > 30% $$ for mortgage	.504**
SNAP authorized stores/1000	.677***

*p<.05, **p<.01, ***p<.001

Comparison of Highest and Lowest Community Food Uncertain Counties

Independent samples t-tests were used to compare the mean differences of weighted component scores for the 10 counties with the highest percentage of households considered community food insecure and the 10 counties with the lowest percentage of households considered community food insecure. Since Component 1, Weighted Component Score 1, Component 3, and Weighted Component 3 were slightly positively skewed, the non-parametric Mann Whitney U test was used. The t-value or U-value and significance is reported in Table 40. There were significant differences between the two groups on all components, except for direct farm sales and food programs.

Table 40.

Mean Differences Between Highest and Lowest Community Food Uncertain Counties for Weighted Component Scores

Component Label	*Component Number*	Highest % Community Food Uncertain (n=10) Mean (SE)	Lowest % Community Uncertain (n=10) Mean (SE)	Critical Value
Food Programs	Component 1 Weighted Score	Mdn=-.04	Mdn=-.02	U=49.00
Access	Component 2 Weighted Score	.07 (.03)	-.12 (.04)	t=-4.097**
Agricultural Production	Component 3 Weighted Score	Mdn=-.03	Mdn=.10	U=24.00*
Program Usage	Component 4 Weighted Score	.10 (.02)	-.08 (.01)	t=7.150***
Direct Farm Sales	Component 5 Weighted Score	-.04 (.01)	-.03 (.01)	t=-.550
Availability and Affordability	Component 6 Weighted Score	.05 (.02)	-.05 (.01)	t=5.610***

*p<.05, **p<.01, ***p<.001

Comparing Mean Differences of WCS Between Nonmetro and Metro Counties

Independent samples t-tests were used to test whether significant differences existed between nonmetro and metro counties for each of the weighted component scores. Non-parametric Mann Whitney U tests were used for WCS 1 and WCS 3 because of their slightly positive skew. Table 41 displays the means or medians, critical value, and significance.

Table 41.

Mean Differences of WCS Between Metro and Nonmetro Counties

Component Label	*Component Number*	Nonmetropolitan Counties (n=81) Mean (SE)	Metropolitan Counties (n=34) Mean (SE)	Critical Value
Food Programs	Component 1 Weighted Score	Mdn=-.0695	Mdn=-.0375	U=897.00**
Access	Component 2 Weighted Score	.0279 (.02)	-.0665 (.02)	t=3.167**
Agricult-ural Production	Component 3 Weighted Score	Mdn=-.0030	Mdn=-.0365	U=1033.00*
Program Usage	Component 4 Weighted Score	.0021 (.01)	-.0051 (.01)	t=.404**
Direct Farm Sales	Component 5 Weighted Score	-.0097 (.01)	.0231 (.01)	t=2.809**

Component Label	*Component Number*	Nonmetropolitan Counties (n=81) Mean (SE)	Metropolitan Counties (n=34) Mean (SE)	Critical Value
Availability and Affordability	Component 6 Weighted Score	.0080 (.02)	-.0191 (.01)	t=2.809**

Significant differences existed between metropolitan and nonmetropolitan counties for every component, with all but agricultural production significant at the p<.01 level.

Chapter 4 was intended to provide in-depth data analysis of the initial regression equation used to predict county-level food uncertainty, the PCA used to extract components, and the new regression model using the weighted component scores extracted from the PCA. Chapter 5 will provide more discussion about the results, paying particular interest to which were the most significant differences between nonmetro and metro food systems in terms of community food security, how the new model of community food security may be used in the development of community-based strategies and polices, limitations of the study, and future research, education, and practice opportunities related to this issue.

Chapter 5

DISCUSSION

This exploratory study is based on the emerging concept of community food security. It attempts to extend and strengthen the concept by testing a variety of additional measures beyond the usual economic data used to explain why households do not have enough food. Extending the predictors of inadequate food, called food insecurity, to variables that could be manipulated at the community level is useful for three reasons. First, it extends our understanding of non-economic factors that influence food insecurity. Second, it identifies variables which could be manipulated at the community level. Third, with key variables known, interventions in the community food system become easier to design and implement.

Community Food Security

Community food security (CFS) is a complex idea. Hamm and Bellows (2003, p 37) provide this idealized definition:

"*Community food security is a condition in which all community residents obtain safe, culturally appropriate, nutritionally sound diet through an economically and environmentally sustainable food system that promotes community self-reliance and social justice.*"

Their definition illustrates the complexity of understanding how communities can meet the nutritional needs of all people in ways that promote long-term community viability. Community viability includes health, economic and social justice, and environmental sustainability. Academic research, university-community partnerships, and community-based agencies have conducted CFS projects. The projects have involved multiple disciplines (e.g., planning, sustainable agriculture, public health, nutrition, agricultural economics, and geography). While a few have critiqued the theoretical base of CFS (Anderson &Cook, 1999), a growing number of community-based agencies working with the Community Food Security Coalition and professional organizations, such as the American Dietetics Association, have adopted CFS as their model for change (Hamm & Bellows, 2003; Malhi, et al., 2009; Winne, et al., 1997).

As the current global economic recession erodes the safety net protecting the U.S. from hunger and malnutrition (Conceicao & Mendoza, 2009; Needles Fletcher, 2008), it becomes more important to explore ways in which communities can ensure the long-term livelihood and viability of its community members (Paez, et al., 2009). Although the focus of this study is on the U.S., it is extremely important to mention that the global food crisis has caused widespread suffering and death. Oxfam (2011) reported that over eight million Kenyans, Somalians, and Ethiopians have been impacted by droughts, volatile food prices, and poverty.

The U.S. is also facing an equally disastrous environmental crisis in which the globalized food system has played a major role (Hoff & Polack, 1993; McBeath & McBeath, 2009; Wallinga, 2009). The highly industrialized food system relies upon rapidly diminishing fossil fuels, fresh water-hungry irrigation systems, and carcinogenic pesticides in every phase of production, distribution, processing, and waste cycles (Story, et al., 2009; Wallinga, 2009). The U.S. projected 2025 population of 335 million people (Campbell, 1997) is facing multiple, interconnected and potentially damaging risks (Hamm, 2004; Lang, 2009). These include the safety and quality of the food supply (Campbell, 1991, Chilton & Rose, 2009), the public's health as it relates to diet and chronic diseases (Dibsdall, et al., 2003; Freedman, 2008; Lawrence & Baker, 2009; McGranahan, 2008; Moore, et al., 2008), and the ability for emergency food assistance programs to meet the growing needs (Needles Fletcher, 2008; Winne, 2008).

Climate change, economic crisis, and increased oil prices are interconnected threats that place the U.S. and the world at great risk (Conceicao & Mendoza, 2009; Harvie, et al., 2009; Lang, 2009; McBeath & McBeath, 2009; Needles Fletcher, 2008). These risks underscore the importance of exploring how community food security can be achieved and how programs and policies based on this model can move beyond global economic-based models to help communities create planned social change. Understanding community-specific risk and protective factors associated with food security is thus a vital scientific and social endeavor.

Findings

This study explored a number of different variables hypothesized to be related to community food security. The analysis shows that, of the top 10 community food uncertain counties, only one is in an urban county (St. Louis City). County-level data limitations exist in the annual USDA CPS Food Security Supplement, which has limited research, over-representing urban areas. This research is important because it provides a better understanding of community food uncertainty in understudied rural communities.

In Missouri, community food uncertainty is a major problem for rural communities. While Bernell, et al (2006) found that moving to rural areas in Oregon reduced the likelihood of food insecurity, this study suggests this is not true in Missouri. Other resources and support systems that may be protective against community food uncertainty may be considered in subsequent studies (Bernell, et al., 2006). Grussing

(2007), on the other hand, used multilevel modeling to estimate food insecurity and found higher rates of food insecurity in rural areas with high unemployment and extensive poverty.

The following section discusses the original research questions related to community food security, emphasizing the non-sociodemographic predictors found to explain community food security. Particular attention is paid to differences between rural and urban counties.

Q1: What are the most important parts of a sustainable non-metropolitan food system that impact food security?

Q2: Which identified community-level risk and community-level protective factors are predictive of food security rates in non-metropolitan areas?

Q3: What significant differences in community-level risk and community-level protective factors exist between non-metropolitan areas and metropolitan areas?

Availability and Affordability (WCS6)

The regression analysis of the data (N=106) indicates that four of the six components determined by the PCA accounted for 58.7% of the variance and was statistically significant. The most influential component was "availability and affordability." Areas where there were a higher number of Farmers' Markets and SNAP-authorized stores were related to higher levels of community food uncertainty. This was an unexpected result. Although not directly related to the food environment, this component included a measure for homeownership affordability; indicating that community food insecure areas have more people paying more than 30% of their income towards their mortgage.

An interesting finding is that rural counties had a positive mean Weighted Component 6: Availability and Affordability (WCS6), while urban areas had a negative mean WCS6. Since nine counties were excluded from the analysis because of outliers, another independent samples t-test was conducted to determine if all three indicators were significantly different from one another to see which differences contributed to the differences between urban and rural areas. Rural areas had a significantly higher number of SNAP-authorized stores per 1000 people, a significantly higher number of Farmers' Markets per 1000 people, and a significantly higher percent of households paying more than 30% for their mortgage.

The independent samples t-test between the 10 counties with highest percentage of food uncertainty and the 10 counties with the lowest percentage of food uncertainty indicates that a negative overall WCS6 indicates a more community food certain county. Two indicators are statistically significant. Areas with the highest community food uncertainty had a significantly higher number of SNAP-authorized stores per 1000 people, and areas with the lowest community food uncertainty had a significantly lower percentage of households paying more than 30% of their income on mortgage. Thus, housing affordability is can be considered a protective factor against community food uncertainty. This is consistent with other studies showing that high housing costs are related to food insecurity (Bartfeld, 2003; Biggerstaff, et al., 2003; Gross & Rosenberger, 2005; Rose, 1999).

The difference between the mean number of farmers' markets per capita was not significant, and the number of SNAP-authorized stores per 1000 people is higher in community food uncertain areas.

Program Usage (WCS4)

The second highest predictor of community food uncertain was program usage (WCS4). Areas with higher amounts of WIC and SNAP redemptions per store indicated areas with higher levels of community food uncertainty. Housing affordability for renters was an important aspect. In counties where a high percentage of the population is paying more than 30% of their income for rent, there is greater community food uncertainty. Rural counties had a positive mean WCS4, while urban areas had a negative mean WCS4. However, differences between groups were not significant for any of the indicators. Rural areas had a slightly higher percentage of households paying 30% or more for rent, while urban areas had a slightly higher amount of SNAP redemptions per SNAP-authorized stores.

A negative overall WCS4 indicates a more community food certain county. Housing affordability alone differed significantly between the groups. Again, for the most community food uncertain counties, an average of 51.55% paid more than 30% of their income for rent. Areas with rents considerably high, especially in relation to income and available jobs are at risk for community food uncertainty. This was consistent with findings that high rent counties are more likely to have higher food insecurity (Bernell, et al., 2006), as are areas with high overall housing costs (Bartfeld, 2003; Biggerstaff, et al., 2002; Gross & Rosenberger, 2005; Rose, 1999). Other studies have found that households that pay rent, rather than a mortgage, are predictive of food insecurity (Olson, et al., 2004).

Areas with the highest community food uncertainty had lower WIC redemptions per store, but higher SNAP redemptions per store.

Accessibility (WCS2)

Accessibility was an important predictor of community food uncertainty. Counties with high percentage of community food uncertain households had higher percentages of households without transportation living more than one mile (short) or more than 10 miles (long) from a food store. They also had higher percentages of low-income households living short or long distances from a food store. Both transportation and distance to food stores appears to be risk factors, i.e. factors that increase, for community food uncertainty.

Rural counties had a positive mean WCS2, while urban areas had a negative mean WCS2. There were significant differences for all five indicators. Rural areas had a significantly higher percent of households without vehicles living short or long distances from a food store. Urban areas had significantly less of their low-income households living short or long distances from a food store. Rural areas had a significantly higher number of grocery stores per capita.

The independent samples t-test between the 10 counties with highest percentage of food uncertainty and the 10 counties with the lowest percentage of food uncertainty indicates that a positive overall WCS2 indicates greater community food uncertainty. Three indicators are statistically significant. Areas with the highest community food uncertainty had a significantly higher percentage of low-income households and households without transportation living more than one mile from a food store. The most community food uncertain counties also had more grocery stores per capita.

Access issues are an important consideration for people working to improve community food uncertainty. People usually purchase food within 2 miles from where they live (Eisenhauer, 2001). Transportation may limit food choices leading to consumers purchasing food at non-food stores (Drewnoski & Specter, 2004; Morland, Wing, Diez-Roux, & Poole, 2002; Nayga & Winberg, 1999; Paez, et al., 2010; Winne, 2008).

Agricultural Production (WCS3)

Agricultural production was an indicator of community food uncertainty. Counties with high percentage of community food uncertain households tended to have larger average size farms, higher average sales per farm, but a lower percentage of farmland and crop sales.

Rural counties and urban counties had a negative median WCS3. Rural counties had significantly larger farms. However, the difference between urban and rural areas concerning average farm sales, the percentage of total land designated as farmland, and the amount in crop sales was not significantly different.

The independent samples t-test between the 10 counties with highest percentage of food uncertainty and the 10 counties with the lowest percentage of food uncertainty indicates that a positive overall WCS3 indicates lower community food uncertainty. Two indicators are statistically significant. Counties with the highest community food uncertainty had larger farms and higher sales.

Food Programs (WCS1)

WCS1 did not significantly predict community food uncertainty. A lower WCS1 was associated with higher community food uncertainty but there were no significant differences between the 10 highest and 10 lowest community food uncertain areas. While no significant differences existed for each indicator, community food certain counties distributed more food, had more Community Supported Agriculture (CSA) programs, and greater WIC redemptions. However, counties with high percentage of households considered community food uncertain had more Summer Program Feeding sties and higher SNAP benefits.

Both metro and non-metro counties had a negative WCS1, while metropolitan counties had a significantly higher median. Metro areas had more CSA's, higher total SNAP benefits, higher WIC redemptions, and more pounds of food distributed. The number of Summer Feeding Program sites did not differ significantly between urban and rural areas.

Direct Farm Sales (WCS5)

WCS5 did not significantly predict community food uncertainty. However, counties that were more community food uncertain have fewer farms and less direct farm sales. Rural counties had a negative WCS5, while urban counties had a positive score. The difference was significant. Rural counties actually had significantly less farms that urban areas and less direct farm sales. While the difference between direct farm sales per capita was not significant, rural areas had a higher mean.

Appendix 3 shows selected risk and proactive factors, and Appendix 4 shows selected differences between rural and urban communities.

Usefulness of Study

Policy makers, program developers, social workers, and other agents of change will find several aspects of this study useful. First, it offers a way to consider multiple, possibly interacting, variables at the same time, while also providing a method for reviewing significant factors related to community food uncertainty.

Second, the study enables CFS designers to conceptualize the systems components. This offers a way for practitioners to determine areas over which they may have greater control. The food system includes food production, processing, distribution, retailing, and eating. CFS interventions may consider how to intervene within the food system at the community-level addressing outcomes related to economic development, individual and public health, environmental stewardship, community viability, or regionalized agricultural production. By reviewing the results of the PCA, regression, and individual indicators, change agents can determine whether proposed interventions will impact economic development, public health, and/or environmental stewardship.

Third, the study's results can help multi-disciplinary teams consider long-term sustainable solutions to improving the community's health and well-being in conjunction with governmental and private emergency food assistance programs that meet the immediate needs of households and individuals. These community food security goals and strategies are models of social development because of their promotion of social welfare through multidisciplinary groups that reflect efforts to improve community well-being (Midgley, 1995).

Fourth, it is also important for community workers to acknowledge the interconnected elements of the food environment when seeking funding for intervention projects. Community workers have the opportunity to evaluate the food environment. The goal of intervening in a way that promotes sustainable, economic, and equitable processes is consistent with models for social development (Midgley, 1995). As an example, President Obama's Administration has proposed the Healthy Food Financing Initiative that is interested in improving access to healthy foods for those living in "food deserts." The food desert definition is being used in conjunction with other data, in part, as a way to determine if communities can receive funding (http://www.ers.usda.gov/Data/FoodDesert/about.html). The method used in this study allows communities to gain a greater understanding of disparities in food access, which may or may not match directly with the GIS-Food Desert Locator mapping tool offered by the USDA.

Comparing Food Uncertainty and Community Food Uncertainty

The most valuable contribution of this study is the extension of a method of measuring food uncertainty at the community level. Existing food uncertainty measures are helpful for estimating county level food insecurity using well-known predictors related to income, poverty, and related sociodemographic variables. The model developed in this study includes food environment variables that are increasingly being studied for their connection to community food insecurity and for their potential as intervention points. The community food uncertainty model allows researchers to use food environment components as predictors in a regression equation in which the dependent variable, food uncertainty, accounts for the known sociodemographic predictors, and all components may be considered in relationship to one another.

This study moves inquiry beyond the original food uncertainty variable to a community level food uncertainty model. Counties, used in this study as surrogates for communities, allow researchers and food intervention specialists to study other 'communities' by locating or developing data at the appropriate level of aggregation.

This study has provided a useful and important method of calculating community food uncertainty that can be used by practitioners and policy makers to determine what are changeable aspects of the food environment that may improve the ability for all households to obtain food in an equitable and sustainable way. The study's contribution to improving analysis can be seen when it is applied to a specific situation.

Counties with highest community food uncertainty. The follow section show the changes in county level food insecurity by comparing the previous prediction method with the one developed here. How the improved prediction can be used for intervention is shown through one example.

Counties are ranked in order of 1 (best) to 115 (worst) on all indicators, all components, and two models (county food uncertainty and community food uncertainty. A Spearman's rank correlation (Spearman's rho) was calculated between "food uncertainty ranking" and the "community food uncertainty ranking," rho=.789, p=.000.

Table 33 shows the 10 counties that were rated as being most food uncertain using the original modeled estimation technique, while Table 34 highlights the 10 counties that were rated as being most community food uncertain. Both tables also include the rankings for the food uncertainty and community food uncertainty models.

One practical application for this tool is look at differences in rankings and counties in which discrepancies appear. For example, a county that has an original estimation of food uncertainty that is higher than the measure of community food uncertainty, we might consider that there is some protective variable related to community food uncertainty. See Appendix 4 for a side-by-side comparison.

The subsequent section explores one county that had a much higher estimate of community food uncertainty than food uncertainty. A closer look at indicators and components helps show how this method may be useful for people working in communities to address potential changeable aspects of the food environment.

Table 42.

Comparison of Community Food Uncertainty Model With Ten Most Food Uncertain Counties

County	*Food Uncertainty %*	*Food Uncertainty Ranking*	*Community Food Uncertainty %*	*Community Food Uncertainty Ranking*
Pemiscot	24.28	115	22.88%	115
Wright	21.88	114	16.97%	86
Scotland	21.83	113	17.57%	96
Mississippi	21.34	112	20.54%	112
Dunklin	21.22	111	20.39%	110
Shannon	20.51	110	18.14%	99
Carter	20.47	109	18.30%	103
Washington	19.88	108	17.53%	95
Ripley	19.81	107	18.93%	107
Oregon	19.74	106	18.42%	104

Table 43.

Comparison of Food Uncertainty Model With 10 Most Community Food Uncertain Counties

County	*Food Uncertainty %*	*Food Uncertainty Ranking*	*Community Food Uncertainty %*	*Community Food Uncertainty Ranking*
Pemiscot	24.28%	115	22.88%	115
New Madrid	19.26%	105	21.19%	114
St. Louis City	19.23%	104	20.94%	113
Mississippi	21.34%	112	20.54%	112
Ozark	15.11%	49	20.43%	111
Dunklin	21.22%	111	20.39%	110
Putnam	15.47%	55	19.98%	109
Butler	18.98%	101	19.10%	108
Ripley	19.81%	107	18.93%	107
Hickory	17.08%	90	18.58%	106

A closer look: The case of Ozark County. Ozark County, which was estimated to have 15.11% food uncertainty respectively, was estimated to have around 20% of households considered *community* food uncertain. Ozark County's population of persons over the age of 65 (21%) was well above the mean (16.44%). A closer look at the community food uncertain indicators and components reveals that Ozark may have several risk factors for community food uncertainty.

Component 1 (Food Programs): Component 1, Food Programs, includes five indicators. Ozark County has no CSA distribution sites. The one Summer Feeding Program site serves an average of 4397 meals. Ozark County distributed around 132,000 pounds of food or 67 pounds per capita of people living at or below 100% of the poverty level. This was below the mean for all counties (M=101.14), as well as for rural counties (M=119.50). It was well below the mean amount of food distributed (M=526,004).

The total SNAP benefits (in $1000's) for Ozark County ($1945) was well below the overall average (M=$7321) and the average for rural counties (M=$3112). Around 65.94% of eligible Ozark County residents participated in the SNAP program, which was above the mean percent of participation overall (M=64.11%) and in rural counties (M=62.47%).

WIC redemptions were well below the average. Ozark County redeemed $126,437 in 200 0 which was well below the average in rural areas (M=$102,497) and for all counties (M=$107,899). It may be of some help to review other WIC indicators. In Ozark County, there were an estimated 65% of eligible people participating in WIC, which was well below the overall average of 70.65% and 75.07% in rural counties.

Component 2 (Access): Component 2, Accessibility, includes indicators related to transportation, distance to food stores, and the availability of traditional grocery stores in each county. Ozark had three grocery stores in 2008. This is below the average for rural areas (M=4.62) but actually slightly above the average of 0.26 grocery stores/1000 people. Knowing this, the other indicators may help understand the potential risk for community food uncertainty, especially for Ozark County, which is rated as the 7th highest overall WCS2, indicating a high percentage of households with accessibility concerns.

Since both Ozark is considered rural, it is most useful to first look at the indicators that use a 10-mile distance (Ver Ploeg, 2009). In Ozark County, 2.70% of the population does not have a vehicle and lives more than 10 miles away from a food store (long). Around 26% of low-income households live a long distance from a food store. This indicates a major concern for accessibility since the average percent of households without a vehicle living a long distance to a store is 1.08% in rural areas, and the percent of low-income people without a vehicle living a long distance to a food store is 7.81%. While VerPloeg (2009) uses the 10-mile radius, it is worth noting that over 48% of low-income people in Ozark County live a short distance from a food store, which is above the average for rural counties (M=29.26%). Ozark County was slightly above the mean percent for households without vehicles living a short distance from a food store in rural areas (M=4.27%).

Component 3 (Agricultural Production: Component 3 relates to agricultural production. Ozark County had a lower percentage of their land designated for farming (52.17%) compared to all rural counties (M=68.11%). Ozark County's 742 farms was below the average for rural counties (M=861.07). While the average farm size in Ozark County (334 acres) is near the mean for rural areas (M=337.98, crop sales in Ozark County ($817,000) were well below the mean for rural counties (M=$32,902,000). Overall, average farm sales amounted to $42,372 in Ozark County, which was far less than the mean of $85,061.40 in rural areas and $76,509.95 overall.

Component 4 (Program Usage): Program usage includes indicators related to the amount of WIC or SNAP redemptions per authorized stores. It also includes an indicator that has to do with non-food budget costs and the related housing affordability context in each county. In Ozark County, a very low percentage of people are renters (15%). The average percent of renter-occupied units in all counties is 24.86%, while it is slightly higher in non-metro counties (25.23%). Housing affordability for renters seems to be problematic, with around 56% of renters paying more than 30% of their income for rent. This is well above the mean around 42% for all counties, and 43% for rural counties.

WIC redemptions were discussed in the section pertaining to Component 1. However, it is also important to consider the number of authorized stores. The average number of WIC-authorized stores in rural areas is 3.46 or 0.22 stores per 1000 people. However, in Ozark County, there is only one WIC-authorized store, or 0.11 stores per 1000 people. Since Ozark County has only one WIC-authorized store, the overall amount of redemptions is equivalent to the amount per store. This means that the denominator, the number of stores, is actually the driver to having a larger overall dollar amount per store. .

On average, there are around 17.46 SNAP-authorized stores in rural counties. These may include convenience stores, Farmers' Markets, specialty stores, supermarkets, supercenters, discount stores, and tobacco and liquor outlets. Ozark County has 16 SNAP-authorized stores. When the number of participants was considered, this amounted to 8.50 stores per 1000 Ozark County. Ozark County had information on 11 of the stores in four different towns. This included three partial markets, four convenience stores, one supermarket, and two discount grocery stores. The overall amount of SNAP benefits redeemed per store for Ozark County ($94,856) was below the mean amount in rural areas ($207,219) and in all counties ($219.030).

Component 5 (Direct Farm Sales): Ozark County had a lower percentage of farms that sold direct to consumers than both the overall average (3.85%) and the average for rural counties (3.31%). Ozark County has 20 farms that reported that they sell direct to consumers, which accounts for 2.7% of their total farms. In 2007, Ozark County reported $45,000 in direct farm sales, which amounted to $4880 per capita. Ozark was well below the average for direct farm sales in all counties ($158,696) and non-metro counties ($125,778).

Component 6 (Availability and Affordability): Component 6 includes two indicators concerning unique types of food sources and an indicator of housing affordability that may contribute to community food uncertainty. While a large percentage of housing stock is owner-occupied, 36.12% of Ozark County homeowners pay more than 30% of their income towards their mortgage payment. This is well above the average for nonmetro counties (28.54%) and all counties (28.17%). Ozark County has one registered farmers' market. When population was considered, Ozark was higher than the county average of 0.06 markets/1000 people and 0.07 markets/1000 people in rural areas. When population was considered, Ozark had 1.72 SNAP-authorized stores per 1000 people, which was above the average for all counties (0.91) and for rural counties (1.01). It was above the overall average of 4.4 stores per 1000 participants. While the presence of both unique food source types may be a protective factor, but that the high housing costs burdens may account for the higher estimate of community food uncertainty in Ozark County.

See Appendix 5 for a summary of selected Ozark County indicators that reveal possible intervention points. A person working in Ozark County may look at the selected indicators that significantly differed from the mean for all Missouri counties and for all rural counties. The table is presented in descending order of the contribution to food security. Housing affordability is a major risk factor for Ozark County. Transportation and distance to stores is problematic, and there is only one WIC-authorized store. Another major area of concern is the pounds of food distributed per capita, which is well below the average. Although Ozark County is not an agricultural area due to its geography, CSA distribution sites from nearby counties for meat, produce, or dairy may be piloted as one example of a way to improve access to healthy foods since there are no sites at this time.

Limitations

Although the study contributes to knowledge about food uncertainty, community food security, and community food uncertainty, there are several limitations. The first limitation is that is an exploratory study which attempts to extend food insecurity measures from household based hunger analysis to a larger unit of analysis – that of the community. Since the goal is to add food security for communities and provide points of intervention by improving estimates, there is a need for a definition of community. This study used “counties’ as a surrogate for community. Another limitation is that the analysis is conducted for one state in the United States and thus the results may not be generalizable to other states or other countries.

Another limitation, which is hard to address, is that the majority of the data, while from reliable sources and intended for research and policy purposes is secondary data. However, secondary data may limit the research. The researcher is constrained by the available data, the way it is collected, and the times at which it was collected.

Another limitation is one peculiarity of the state of Missouri. The study was focused on county-level data which included s St. Louis City – an independent city with county level recognition and authority. The city is important but many of the predictors of food insecurity are considerably higher than other areas. However, data related to agricultural production was collected in combination with St. Louis County. Direct farm sales had to be estimated too. The major problem with this limitation is that St. Louis City and St. Louis County reflect extremely different socioeconomic populations. This may have impacted the results for community food security rankings and estimations of community food uncertainty.

Another limitation is that the study was based on a modeled dependent variable. No accepted measure for county food security is exists. This variable was validated would need updating since new ACS 06-10 data is available. The original formula used multiple one-year estimates of Census data with fixed effects while this study used the five-year estimates which were better suited for a largely non-metropolitan state. This study was careful to not include indicators on both sides of the regression equation.

Agricultural and local food production variables are limited. The Agriculture Census only takes place every five years. Many of the food-related variables in the USDA Food Environment Atlas are regional-level variables. Only recently better data sources are becoming available but only after the study's data cut-off. However, no reliable data exists for community gardening.

This study does not include some aspects of community food security. Food systems analysts have proposed environmental variables, but it may be challenging to find data at the county level. This study does not include food consumption or health variables. The findings may be linked with county-level health indicators in future studies. No considerations for other food provisioning strategies were included in this study.

Future Research

Addressing Excluded Variables

This study began with 46 indicator variables. The PCA data reduction strategy retained twenty-three. Future research should consider the other indicator variables, as well as variables used in similar studies (see Bletzacker, et al., 2009; Gruzzing, 2007; Lopez, et al., 2008; Tchumtchoua & Lopez, 2005, Bernell, et al., 2006). Table 35 provides Spearman's Rank Correlations for excluded variables that were statistically significant. These may be starting places for further research concerning the food environment and community food uncertainty.

Table 44.

Spearman's Rank Correlations for Selected Excluded Variables and CFU Ranking

Variable	*Spearman's Rho*
Estimated foreclosure rate	.384***

Variable	*Spearman's Rho*
Ratio of Renter-Occupied to Owner-Occupied Units	.243**
Full-service restaurants/1000 people	-.191*
Average # meals served at Summer Feeding Program sites	.320**
Average monthly SNAP benefits	-.238*
% WIC participating, of income eligible	.427**
# of Food Distribution Sites/1000 people <100% FPL	-.196*

*p<.05, **p<.01, ***p<.001

Geographic Considerations

Future studies should be conducted in other geographic areas at the county-level for comparison. This may be neighboring states, states with similar agricultural and geographical landscapes, or similar population and socio-demographic characteristics. GIS-modeling techniques may be used to specify communities of various sizes that are different from geographic boundaries. This is especially useful for policymakers or practitioners who may want to focus on targeted area (e.g, Congressional Districts).

Economic Considerations

The study was less concerned with the impact of the economic recession. However, a comparison should be conducted if data is available for isolated years prior to the recession. The study showed the importance of housing costs and it would be useful to have samples of counties in diverse areas with differing cost burdens. Studying areas that have increased poverty levels due to natural disasters or unemployment may provide additional understanding of protective factors.

Urban and Rural Designations

As stated in Chapter 3, various definitions exist for rural and urban designations. Future research may use different definitions of rurality to see whether differences in the defining of communities, impacts the analyses done when mean differences were considered. Researchers should try include equivalent sample sizes to improve their data analysis.

Primary Data

A survey of farmers would be useful to supplement the data available through the Ag Census. It may help researchers gain a better understanding of the livelihood of farmers. This is especially important since this study did not address social justice elements related to people working within the food system (e.g., fruit pickers, processors, retailers). More information about what is produced, how it is produced, and the various hands that touch the food between the farm and plate, all contribute to a better understanding of the food system.

Access

Data is now available on the locations and names of SNAP and WIC-authorized stores. A cursory look at the data reveals that many authorized stores are convenience stores, discount stores, tobacco/liquor stores, and partial markets. These stores may provide improved access for low-income consumers and boost sales, but differences are likely to exist among the stores in terms of what types of food are available and how much they cost.

Other issues may relate to distance to the food stores. Even though community food uncertain counties have more grocery stores, no information has been collected or used that would indicate the average distance travelled (Apparicio, et al., 2007; Donkin, et al., 1999; Short, et al., 2007, any limitations on store hours (which affects people working third shifts), and differences in availability and affordability of different types of food (Chung & Myers, 1999; Freedman, 2008; Liese, et al., 2007; McEntee, 2009; Moore, et al., 2008; Wrigley, 2002 . Also, at the county level, it is difficult to account for public transportation or affordable transportation options, which may impact accessibility (Garasky, et al., 2004; Moreland, et al., 2002). The results of this study are consistent with Daponte, et al.'s (1998) study of food pantry clients that found that clients without vehicles and who were low-income were likely to be food insecure.

Program Usage

Further areas of study might consider how the WIC and SNAP-authorized stores might be able to handle an increase in the number of clients using the program. This is important since 14% of Americans participated in SNAP in 2011. Since 2000, the number of people in the U.S. participating in SNAP increased from 17.3 million to 46.2 million in 2011. This can be attributed to poor economic conditions but some of the increased participation may be related to changes at the policy level. The 2002 Farm Act (Farm Security and Rural Investment Act (PL107-171) and other legislation provided states with more programmatic flexibility. (Andrews & Smallwood, 2012). CFS Interventions might address reasons eligible people are not participating (Gorman, et al., 2006) and how to improve participation rates since links have already been shown to exist between WIC and SNAP participation and food insecurity (Bhattari, et al., 2005; Cassady, et al., 2007; Gross & Rosenberger, 2005; Kropf, et al., 2007; Needles Fletcher, 2008; Rose, 1999).

An area for further study may be a comparison of the types of SNAP-authorized stores, which include a range of stores that sell food as their main option or as part of a range of products. This includes convenience stores, liquor stores, tobacco outlets, grocery stores, and supermarkets. Differences of food availability and affordability at SNAP-authorized food stores is important, especially as it relates to healthy, nutrient dense foods (Dibsdall, et al.,, 2003; Freedman, 2008; Hendrickson, et al., 2006; Liese, et al., 2007; McEntee, 2009; Zenk, et al., 2009).

Localized Food Systems

CSA's are additional food sources, making them potentially viable options for improving availability of food, especially fresh and local produce (Brehn & Eisenhauer, 2008; Feenstra, 1997; Lass, et al., 2010). More research must be conducted about the use of CSA's in low-income households or emergency food assistance programs (Andreatta, et al, 2008). Additionally, great discrepancies existed in the amount of food distributed, as well as the amount of food per capita. More data should be collected that includes the types of food distributed, as well as best practices and barriers emergency food assistance programs face when trying to meet the food needs of their community (Jensen, Heflin, Hermsen, & Rikoon, 2011).

Agricultural Production and Environmental Sustainability

Interpretation of agricultural production is challenging. Analyses of the economic environment may be useful in helping understand the impact farming has on the overall livelihood of an area. For example, it would be useful to learn whether farmers have additional employment. Furthermore, it is important to consider the potential impacts the Farm Bill has on agricultural production (Lamb, 2003; Liliston, 2007; Putnam et al., 2002; Weiss & Smith, 2004) and look more in-depth at the amount of agriculture grown in the county that is edible, sold within the county, within Missouri, outside of the state, or even outside of the country. It may be that the crops that are grown are not directly consumed by humans or included in processed foods (Liliston, 2007; Wallinga, 2009). Further analyses of the environmental impacts, water consumption, and fossil fuel consumption from the agricultural production would assist in the exploration of public health and economic risks hypothesized to be part of community food security (Dimitri & Effland, 2005; Hoff & Polack, 1993; Hightower, 1972; Ikerd, 2002; Neff, Parker, Kirschenmann, Tinch, & Lawrence, 2011; Pirog & Benjamin, 2003; Winne, 2008).

Systems Models

Community food security interventions target various components of the food system and exist in a globalized context that includes multiple levels of policy, a variety of public and private food assistance providers, and the natural environment. Various methods of systems concepts may be used to both conceptualize the parts of the system that may be changeable and to evaluate targeted interventions (Midgley, 2006).

General systems theory is especially beneficial to determine whether an organization is performing well in the context of shocks on the system (Midgley, 2006). Thus, it may be useful to use in the analysis of the private and public food assistance program delivery in a community. Shocks that may impact the effectiveness of such programs may include limited community donations, legislation changes in eligibility, or increased need.

Many examples exist in which manipulating inputs of system components will impact other system components in positive and negative ways. Since community food security encompasses a social-ecological systems framework, contextual variables related to the environment must be considered. While some of those are not directly changeable, adjusting a component within the system may eventually diminish the impact of those variables (e.g., stricter pollution regulations from food processing plants may decrease the air pollution that is brought back to the ground where food is grown). Additionally, people are involved in all aspects of the system, from farm laborers, to truck drivers, to processing plant workers, to retail salespeople, to advertisers, to consumers. The reality of interventions is that people must interact and multiple potentially conflicting values (e.g., social justice vs. economic development vs. land preservation) come into play.

For example, food industry giants and retailers provide food to pantries as donations (e.g., foods past "sold by" date, items that did not sell well, test products, etc.) that provide emergency foods to immediately satiate hunger, but also may be negatively impacting the health of food pantry clients (Poppendieck, 1998). Interventions addressing pantry policies related to donations may have a reciprocal impact on food waste and may impact food companies' bottom line.

Future research may use Ulrich's (2000) model of critical systems heuristics (CSH) as a tool in communities. This approach is useful for communities that begin working on community food security issues in order to ensure involvement of all people to address the desired needs of the community. Ulrich's (2000) model emphasizes various boundary categories (e.g., client, purpose, decision-maker, resources, expertise, world view) and boundary issues (e.g., sources of motivation, power, knowledge, and legitimation). The method allows community members to develop a shared vision, evaluate the current state, discuss contextual elements impacting stakeholders, and challenge participants to be transparent in their values and insights (Ulrich, 2005).

Appendix 6 provides an initial conceptual systems model showing inputs, outputs, and possible paths of intervention.

Other Statistical Methods

Originally, the methodology included a Hierarchical Linear Modeling technique looking at counties nested within Congressional Districts or another grouping variable. However, at least 10 groups are needed in HLM with much variance amongst them. It would be interesting to expand outside of the state to conduct a HLM model and find a way to model county-level food uncertainty using this method.

Structural Equation Modeling or path analyses might be useful too, especially if variables related to health outcomes were included. There are likely latent variables that are underlying some of the food environment variables.

Contribution to Social Work

The most vulnerable of the 14.7% of Americans who are food insecure are the elderly poor, people living in rural areas, single-parent households, African Americans, and Hispanics (Needles Fletcher, 2008; Nord, et al., 2010; USDA, 2009). Large numbers of food insecure households experiencing the effects of food insecurity threaten a community's health, social, and economic functioning (Hamelin, et al., 1999). Social workers, whose clients in multiple settings are the most vulnerable, have the ability to create change. This may be in terms of helping clients meet the immediate needs or helping agencies plan for sustainable solutions to increased participation. Or it may be in terms of providing leadership to interdisciplinary teams to organize communities around these important issues.

Social workers must become knowledgeable about the consequences of food insecurity and potential impacts of diet due to food hardships. Food uncertain households consume less fresh fruits and vegetables, report higher rates of fair/poor health, higher rates of obesity, higher chronic health problems leading to limited mobility, work impairment, mental depression, anxiety, health care costs (Adams, et al., 2003; Alaimo, et al., 2001; Cook, et al., 2004; Dietz, 1995; Hamelin, et al., 1999; McIntyre, et al., 2003; Tarasuk & Beaton, 1999; Vozoris & Tarasuk, 2003). High rates of diabetes, obesity, and high blood pressure are common in food uncertain individuals (Hamelin, et al., 1999; Vozoris & Tarasuk, 2003). Health outcomes resulting in low productivity and decreased social participation (Hamelin, et al., 1999) can negatively impact communities experiencing economic hardships.

This study provides a method for calculating community food uncertainty, a way to look at multiple indicators related to the food environment, and a way to compare counties. This is helpful for people who want to seek community-level change through multiple intervention entry points.

The goals of community food security stated in Hamm and Bellow's idealized definition are all important to social values and ethics. Equality, social and economic justice, and self-determination are integral to community food security. Unless social workers can identify variables which impact community food security over which communities have or can gain some control and only if they can help community members' understand the interdependent and sustainable aspects community food security will remain an unattainable dream at the mercy of extra community forces.

Appendix 1

COMMON MEASURES IN COMMUNITY FOOD SECURITY RESEARCH

	Literature	**Indicators**
Food Insecurity (Food Uncertainty) ***county-level**	Based on modeling of state-level data onto counties (Dawdy, et al., 2010) *Similar to Grussing, 2007; Gundersen, et al., 2011, Taponga, et al., 2004* Predictors in Holben & ADA, 2006; Gross & Rosenberger, 2005; Kaiser, et al., 2003; Olson, et al., 1997; Rose, 1999; Taponga, et al., 2004	-Citizenship -Age (% Elderly) -Race (Hispanic/African American) -Female-Headed Households -Poverty rate -Median Household Income -Unemployment Rate

	Literature	**Indicators**
Demographics	Lopez, et al., 2008; Tchumtchoua & Lopez, 2005 Olson, et al., 1997; Olson, et al., 2004; Rose, 1999	-Proportion of pop. < 65, Proportion of pop. <18 -Proportion of pop. ≥25 w/o h.s. diploma -Proportion of single female-headed households w/child < 18 -Proportion of female-headed households -# people/sq mile (Lopez, et al., 2008); Tchumtchoua & Lopez, 2005)
Poverty	Lopez, et al., 2008; Tchumtchoua & Lopez, 2005 Holben & ADA, 2006; Rose, 1999	- # renter-occupied housing units/total # households -Prop. of children < 18 living in poverty -Prop. of pop. w/income < poverty level -# people unemployed/# people >16 in labor force (Lopez, et al., 2008); Tchumtchoua & Lopez, 2005)

	Literature	Indicators
Income & Wealth	Lopez, et al. (2008); Tchumtchoua & Lopez (2005) Cohen, Andrews, & Kantor, 2002; Gross & Rosenberger, 2005; Rose, 1999; Taponga, et al. (2004)	-Property tax mil rate -Median hh income ($) -Income per capita ($) -Value of property per capita -Monthly gross rent -Monthly owner cost of owned housing units (Lopez, et al., 2008); Tchumtchoua & Lopez, 2005)
Access	Apparacio, et al., 2007; Caraher, et al., 1998; Cohen, et al., 2002; Donkin, et al., 1999; Drewnoski & Specter, 2004; Eisenhauer, 2001; Freedman, 2008; Garasky, et al., 2004; Gross & Rosenberger, 2005; Holben, et al., 2004; Morland, et al., 2002; Nayaga & Winberg, 1999; Paez, et al., 2010; Sharkey & Horel, 2008; VerPloeg, et al., 2009; Winne, 2008; Wright Morton & Blanchard, 2007	-percentage of households without a car living more than one mile from a food store (2006) -the percentage of low income households living more than one mile from a food store (2006) - the percentage of households without a car living more than 10 miles from a food store (2006) -percentage of low income households without a car living more than 10 miles from a food store (2006)
Availability of Food Stores	Apparaicio, et al., 2007; Chung & Myers, 1999; Cohen, et al., 2002; Dibsdall, et al., 2003; Donkin, et al., 1999; Freedman, 2008; Galvez, et al., 2007; Garasky, et al., 2004; Hendrickson, et al., 2006; Horowitz, et al., 2004; Liese, et al., 2007; Lopez, et al., 2008; Moore & Diez-Roux, 2006; Moore, et al.,	-number and percentage of supermarkets and grocery stores per capita -number and percentage of convenience stores per capita -number and percentage of supercenters per capita -number and percentage of specialty food stores per capita -number of stores that accept SNAP -number of stores that accept WIC -square footage of stores divided by population (Lopez, et al., 2008)

	2008; Short, et al., 2007; Zenk, et al., 2009	
Public Food Assistance	Bartfeld, 2003; Bhattari, et al., 2005; Cassady, et al., 2007; Gross & Rosenberger, 2005; Kropf, et al., 2007; Needles Fletcher,2008; Rose, 1999	-percentage of students eligible for NSLP -average number using WIC each month -percentage of pop. using SNAP -percent eligible for SNAP and participating in SNAP -percent eligible participating in NSLP -percent eligible for WIC and using WIC (Dawdy, et al., 2010; Foulkes, et al., 2008) -Farmers' Markets Accepting SNAP -Farmers' Markets Accepting WIC

Private Food Assistance	Bartfeld, 2003; Bhattari, et al., 2005; Biggerstaff, et al., 2002; Daponte, et al., 1998	-number of food pantries divided by the low income population -number of soup kitchens divided by the low income populations (Lopez, et al., 2008; Tchumtchoua & Lopez, 2005) -pounds per capita distributed by food pantries to food insecure (Dawdy, et al., 2010; Foulkes, et al., 2008)
Food Production Resources	Bedford, 2006; Bellows & Hamm, 2001; Burrows & Betz, 2011; Feenstra, 2009; Hamm, 2004; Hamm, 2009; Joseph, Tagtow & Roberts, 2011; Malhi, et al., 2009; Story, Hamm, & Wallinga, 2009; Winne, Joseph, & Fisher, 2000	-number of Farmers' Markets per capita -number of FM vendors per capita -number of preserved farm acres -number of CSA's per capita -proportion of total land areas in agriculture and farms -Direct Farm Sales -Vegetable Acres Harvested -local mapping of gardens -# farm to school programs
Affordability	Gunderson, et al. , 2011 Drenowski, 2007; Drewnowski & Specter, 2004 Putnam, et al., 2002	-Cost of Meal -Ratio of Food Prices -Average Cost of -Nutrient Density costs
Food		-Total Food Expenditures/per capita

Consumption		-Fast Food Expenditures/Total Food Expenditures -Restaurant Expenditures/Total Food Expenditures -Total Food Expenditures in County as % of Total County Earnings
Environment	Anderson, Feenstra, King, 2002; Cleveland, 2009; Cozad, King, Krusekopf, Prout, Feenstra, 2002; Ellsowrth & Feenstra, 2010	-acres of farmland converted to development -acreage in organic farming -well water pollution average nitrate -# farms using irrigation -total # of irrigated acres in county -use of state and subsidized water -pesticide use -expenditures on fuel, fertilizer, pesticides -% of total farm costs for inputs
Food Distribution	Anderson, Feenstra, King, 2002; Cozad, King, Krusekopf, Prout, Feenstra, 2002	-# food manufacturers -# food retailers -# food wholesalers
Labor	Feenstra, 2009	-Farm Labor wages -Farm Labor as % of Total Employment -Food Distribution System Wages -Food Manufacturer Wages -Food Wholesalers Wages -Food Retailers Wages -Food Servers Wages
Health	Dawdy, et al., 2010; Feenstra, 2009; many not listed here	-Prevalence of diabetes -Overweight and obese -Prevalence of high cholesterol -Prevalence of high blood pressure -% adults meeting fruit and vegetable guidelines

Appendix 2

SELECTED RISK AND PROTECTIVE FACTORS

	Indicators of Community Food Uncertainty (Risk)	Indicators of Community Food Certainty (Protective)
Availability and Affordability		Housing Affordability (mortgage)
Program Usage	Low WIC redemptions/store	Housing Affordability (rent)
Accessibility	Transportation Limitations Distance to Food Stores	
Agricultural Production	Large Farms High Agricultural Sales	
Food Programs		Higher Emergency Food Distribution More CSA's More WIC redemptions
Direct Farm Sales		Fewer Farms and Direct Sales

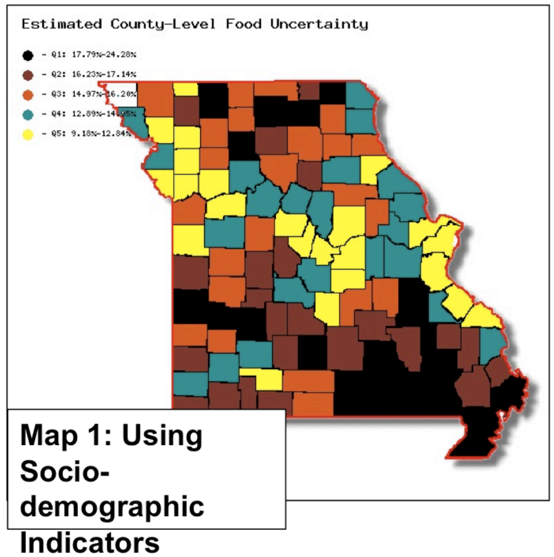
Appendix 3

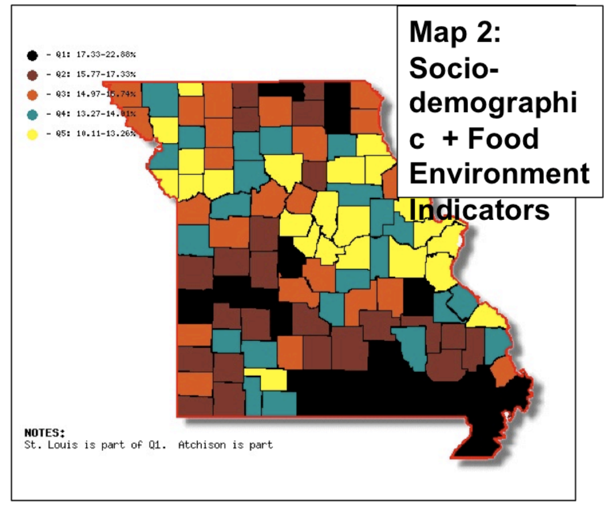
SELECTED RURAL AND URBAN DIFFERENCES

	Rural	Urban
Availability and Affordability	Higher # Farmers Markets/1000 people Higher % People Paying >30% on Mortgage Higher # SNAP-authorized stores/ 1000	
Program Usage	Higher % People Paying > 30% on Rent	Higher SNAP redemptions/ SNAP authorized stores
Accessibility	Higher Transportation Limitations Longer Distance to Food	Lower # Grocery Stores/1000 people
Agricultural Production	Larger Farms	
Food Programs		More Lbs. Food Distributed More CSA's More WIC redemptions Higher SNAP benefits
Direct Farm Sales	Less Farms Less Direct Farm Sales	

Appendix 4

SIDE-BY-SIDE COMPARISON OF FOOD UNCERTAINTY AND COMMUNITY FOOD UNCERTAINTY





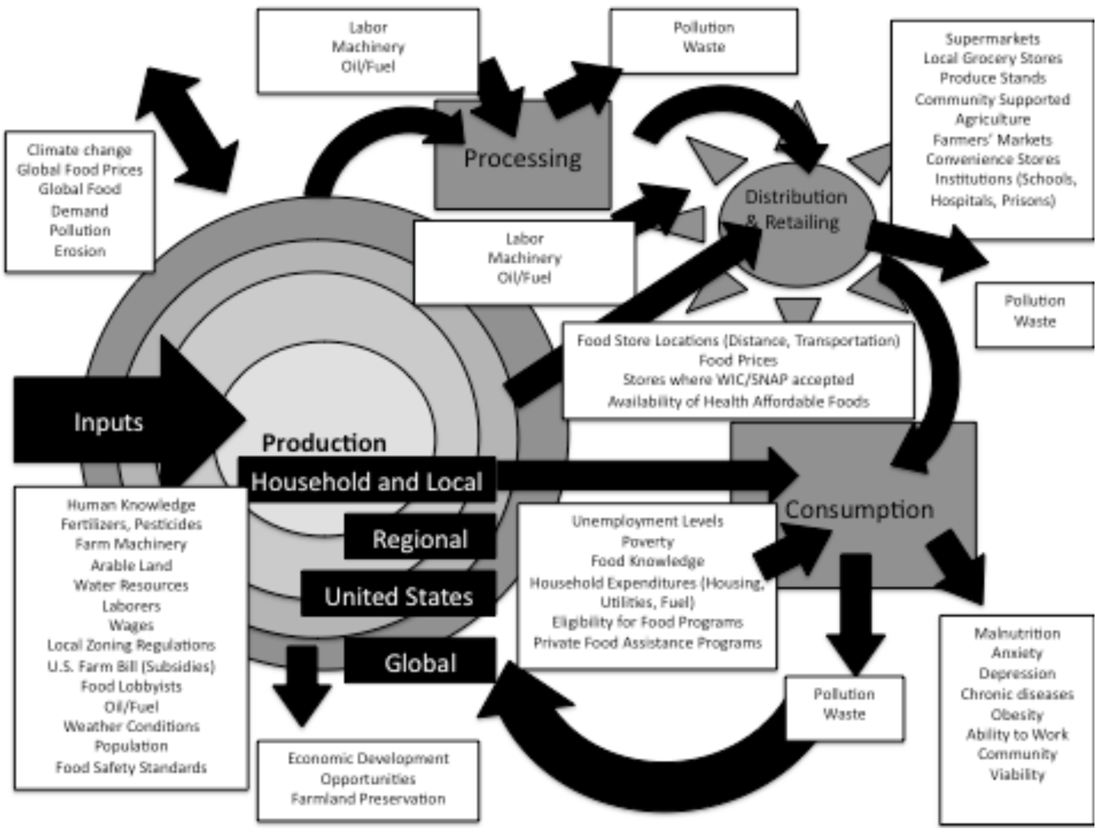
Appendix 5

SELECTED OZARK COUNTY INDICATORS FOR EXPLORATION

	Key Indicators
Availability and Affordability	36% pay > 30% mortgage (M=28%) Types of SNAP-authorized stores (4 convenience, 3 partial markets, 1 supermarket, 2 discount stores)
Program Usage	Below average WIC and SNAP $$ 56% pay > 30% rent (M=42%) Only 1 WIC-authorized stores
Accessibility	2.70% no transportation and > 10 miles to store (M_R=1.08%) 26% low-income > 10 miles to store (M_R=7.81%)
Agricultural Production	Lower agricultural production and sales
Food Programs	No CSA distribution sites Only 67 lbs food per capita (M=101)
Direct Farm Sales	No significant differences

Appendix 6

SYSTEMS CONCEPTUAL MODEL



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VITA

Michelle Lee Kaiser was born October 5, 1978. She graduated from the University of Iowa with a BA in Social Work in 2001. Michelle then moved to rural Eastern Kentucky to complete her social work internship with the Hazard-Perry County Housing Development Alliance and Community Ministries. She spent the next two years as the Kentucky Field Coordinator for the Appalachia Service Project, based out of Johnson City, Tennessee. Michelle enjoyed working with communities to develop partnerships for the emergency housing program, training staff to carry out the mission, and getting to know the families with whom they worked. Michelle then moved to Columbia, South Carolina, earning a Masters in Social Work in 2003. After that time, she moved back to the mountains and nestled in Asheville, NC. There, she worked as the Family Selection Coordinator for the Asheville Area Habitat for Humanity and then as Interim Assistant Dean of Service-Learning at Warren Wilson College. She also earned a graduate certificate from the University of North Carolina-Chapel Hill in Core Public Health Concepts. She completed her PhD (2012) and her MPH (2011) at the University of Missouri-Columbia. She has been involved with the Interdisciplinary for Food Security and the Center for Applied Research and Environmental Systems. Her next adventure is as an Assistant Professor at The Ohio State University College of Social Work, beginning in the July of 2012. Her research interests include community food security, health disparities among vulnerable populations, interdisciplinary research teams, community-based participatory research, and economic, environmental, and social justice.