THE IMPACT OF HOMELESSNESS IN SOCIAL VULNERABILITY ASSESSMENT: A CASE STUDY OF AUSTIN, TEXAS

by

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FAIR USE AND AUTHOR'S PERMISSION STATEMENT

DEDICATION

To my family who stood by me through every stumbling block I have encountered in life. I am forever grateful.

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LIST OF ABBREVIATIONS

Abbreviation	Description
COA	City of Austin
FEMA	Federal Emergency Management Agency
PIT	Point-in Time Count
CDC	Center for Disease and Control
ACS	American Community Survey
LA	Los Angeles
NYC	New York
GIS	Geographic Information Systems
CD	Council District
BG	Block Group
SOVI	Social Vulnerability Index

ABSTRACT

Among existing research on social vulnerability, virtually no studies have considered homelessness as a variable in their vulnerability assessments. This study identified the relevance of homelessness as a key index in social vulnerability assessment to inform the public, policymakers and the broader body of literature of its impacts on shaping vulnerability patterns in cities. Homeless data for Austin in 2018 was first disaggregated from the council district level to block group level using dasymetric model in Geographic Information System (GIS). Principal Component Analysis was used to group highly correlated demographic and socioeconomic variables into factors, which were normalized and summed to model social vulnerability with (SOVI_H) and without homeless index (SOVI) for each BG in Austin. The result revealed significant differences in the geographic patterns between SOVI_H and SOVI. The former index, SOVI_H, showed hotspots of vulnerabilities in Downtown and East Austin neighborhoods, depicting a slight shift of social vulnerability westwards of the city. This finding is different from past results of social vulnerabilities in Austin where it used to be predominant in the East. This study shows that incorporating homelessness in identifying social vulnerability can better help researchers and other associated organizations identify the most vulnerable groups when conducting social vulnerability assessments. More importantly, a noticeable pattern in this study suggest that using SOVI variables alone without homeless would have underestimated the vulnerability distribution and thereby under-prepare for the severe disaster to hit those communities.

1. INTRODUCTION

Natural hazards pose challenges to major cities in the United States. The United States has experienced major transformations in population growth, economic conditions, development patterns and social characteristics. These changes have altered the American hazardscape in profound ways, with more people living in high-hazard areas than ever before as well as increasing frequencies in hazard occurrences (Cutter and Finch 2008). However, some communities are adversely impacted more than others are (Dwyer et al. 2004; Cutter et al. 2003). For example, extreme weather in Austin, Texas like the recent Memorial Day flood in 2015 have shown that some population groups, such as the poor, the elderly, female-headed households and/or recent migrants, are generally at greater risk throughout the disaster response.

In disaster research, communities are often characterized by their demography and their resilience to environmental hazards. Social vulnerability refers to how a population's demographic, socioeconomic and cultural characteristics may reflect their capacity to anticipate, respond and recover from a hazardous event (Center for Disease Control 2018; Cutter et al. 2006; Wisner et al. 1994). In the hope of effective disaster management, vulnerability assessment typically involves: 1) the identification of population groups vulnerable to disasters within affected communities, 2) and the evaluation of their circumstances and needs.

In light of global climate change, many cities around the world, such as the City of Austin (COA), are planning to prepare themselves to be climate-resilient that are adaptive to natural hazards. Thus, it is important to conduct a thorough social vulnerability assessment to identify socially at-risk communities and create policies that braces the resilience of such communities.

1.1 Homeless Population and Social Vulnerability

Among those who are affected by a natural hazard, homeless population are particularly vulnerable throughout disaster response, relief, recovery and reconstruction. Homelessness is "the condition of people without a regular dwelling because they are unable to acquire, maintain regular, safe, and adequate housing, or lack fixed, regular, and adequate night-time residence" (The Universal Declaration of Human Rights 1948). Although homelessness is a growing concern in the United States with about 554,000 people being homeless as at 2017 (HUD 2017), it hasn't gained much stance in social vulnerability or hazards literature. According to Statista (2019), about half of those experiencing homelessness are in the following five states - California, New York, Florida, Texas and Washington. In the United States, about 65% of the total homeless population can be found in shelters, including emergency shelters, safe havens, and transitional housing. Unsheltered homeless individuals, living in locations like wooded areas, cars, and abandoned buildings, account for 35% of the total homeless population. About 63% of homeless people live alone or not a part of an intact family, with about 67–77% of those single people are men, meaning that single males account for the largest portion of the total homeless population (U.S. Department of Housing and Urban Development 2014).

Homelessness is often a by-product of rapid urbanization, in which the poorest urban dwellers suffer from an increasing living cost that has become unaffordable to them (Ballal 2011). About 31.5% of US households spend more than 30 percent of their total income on housing, a standard recommended by the U.S. Department of Housing and Urban Development (American Community Survey 2017). Not only is this a socio-economic issue, ethnic minorities in the United States experience homelessness at higher rates than Whites, and therefore make a disproportionate share of the homeless population. During a disaster, vulnerable populations, especially the homeless are subjected to higher risk of displacement, loss of possessions and/or human lives.

Despite a dramatic rise in the number of homeless people across the United States since the 1980s, homelessness is hard to quantify given their dynamic mobility, the lack of administration incentive to count them, the unavailability of resources and appropriate measurements. According to Chamberlain (2008), a person is homeless if the only housing to which the person has access to is damaged, or is likely to be damaged; or threatens the person's safety; or marginalizes the person through failing to provide access to adequate personal amenities; or places the person in circumstances which threaten or adversely affect the adequacy, safety, security and affordability of that housing. Based on the reports of key informants located in the nation's largest cities, advocates for homeless people have claimed that the number of homeless people in the United States is as high as 2 to 3 million (Link et al. 1994). However, surveys that try to count people who are currently homeless usually produce much smaller estimates (Ending Community Homelessness Coalition or ECHO 2018). Critics suggests that the underestimation could be a result of inadequate survey planning among other possible political reasons (Curbed 2019).

Social vulnerability is apparent after a hazard event has occurred, especially when geographic disparity of disaster impact and recovery are observed among certain population groups (Tapsell et al. 2010). In disaster research, poverty is a key factor in social vulnerability as it may affect housing (e.g., homelessness) and education level (Fothergill 2004). The homeless lack the resources needed to follow emergency preparedness instructions, like stockpiling of supplies. By identifying the homeless and other vulnerable groups ahead of time, disaster management (e.g. evacuation) can be more effective and efficient.

Prior to a disaster, existing vulnerabilities and the extent of resources available to individuals and groups to recover after a disaster mean that marginalization, and the structures that create and sustain marginalization, will continue to exist after a disaster. People who were rich before will still be the most well-off after the event while the poor are likely to remain poor (Blaikie et al. 1994). In other words, marginalization does not stop with disasters as disasters do not have equalizing impacts or outcomes (Gaillard 2009). Instead, post disaster aid and relief are often unfairly distributed to the benefit of the most affluent segments of the society (Middleton et al. 1997). Therefore, disasters frequently lead to status quo or even intensifies marginalization in which the marginalized population whose livelihoods have been affected are less likely to recover from the impacts (Wisner 1993).

1.2 Purpose Statement and Research Objectives

The purpose of this study is to quantify the homeless population and examine its impact in vulnerability analysis. With the use of Geographic information systems (GIS), this research attempts to visualize the spatial distribution of vulnerable populations in Austin, Texas and incorporates the homeless populace in the context of vulnerability assessment. To achieve this purpose, the next chapter examines the literature on social vulnerability and small area geography of homeless population to identify the major demographic and socio-economic variables that contribute to the risk factor of vulnerable populations.

In order to incorporate homeless population in the vulnerability assessment, the specific objectives of this study are:

1. To quantify and map out homeless population in Austin, Texas.

2. To incorporate homelessness in developing a composite social vulnerability index.

By identifying and locating the homeless population, this study examines the effectiveness of disaster management to engage the most vulnerable and marginalized group in disaster planning and response. Some marginalized groups have received significant attention in the disaster literature and disaster risk reduction policy, e.g. women (e.g. Phillips et al. 2008), children (e.g. Anderson 2005; Peek 2008), elderly (e.g. Ngo 2001; Wells 2005), people with disabilities (e.g. Alexander et al. 2012), ethnic minorities (e.g. Bolin et al. 1986; Perry et al. 1986). However, homeless people have stirred much less academic and policy interest. This study can assist local emergency planners, policy-makers and first responders in planning adequately for vulnerable populations during emergencies. The identified social vulnerability index will improve mitigation efforts to be targeted at the most vulnerable groups and areas.

2. Literature Review

This section starts with an overview of previous studies focusing on social vulnerability. Latter part of this literature review explores the identification and quantification of homeless population as it relates to vulnerability assessment.

2.1 Factors affecting Social Vulnerability

Social vulnerability is partially attributed to social inequalities, which includes social factors that shape the susceptibility of population groups to various harms and also their ability to respond and recover from them. There has been a consensus in previous vulnerability literature about major factors influencing social vulnerability, including the lack of access to resources (e.g. information, knowledge and technology), limited access to political power and representation, social capital, beliefs and customs, type and density of infrastructure (Cutter et al. 2003; Blaikie et al. 1994). These factors may be closely associated with the demographics (e.g. age, gender, race, etc.) and socio-economic status of individuals (Cutter et al. 2003)). Other socially vulnerable populations include those with special needs in disaster recovery, such as the physically or mentally challenged, non-English-speaking immigrants, and the homeless. Given their general acceptance in the literature, a list of variables that capture these characteristics is summarized below (Table 1):

Authors	Criteria				Hazard Type	Method/Approach	Study Area
	SES	Demographical	Medical	Built Environment			
Blaikie et al. (1994)	Income	Age, race and ethnicity, gender	Medical disability	-	Natural and biological hazards	Explained root causes of disasters, risk and vulnerability using a disaster pressure and release model	General
Bolin and Bolton (1986)	Social class	Race and ethnicity, age, religious affiliation	-	-	Flood, tornado, hurricane and earthquake hazards	Multiple regression for explaining data factors without any weight assignment	Texas, Utah, Hawaii and California.
CDC (2017)	Poverty, income, unemployment, education	Household composition, minority status, language age	Disability	Housing and transportation	General hazards and diseases	Percentile ranking with an equal weight assumption	USA
Cutter et al. (2003)	Income, employment	Age, gender, race and ethnicity		Housing, commercial and manufacturing facilities	Environmental Hazards	Factor analysis with an equal factor weight assumption	All Counties in USA
Fothergill et al. (2004)	Income, poverty	-	-	Housing	Natural disasters	Explained SOVI through a literature synthesis of past studies	USA
Gaillard (2010)	-	Political power, ethnicity, religion	-	-	Natural hazards and disasters	Explained the role of religion in disaster vulnerability.	General

Gladwin et al. (2000)	Income	Race and ethnicity, gender	-	-	Hurricane hazard	Logistic regression with an equal weight assumption	Miami, Florida
Mason et al. (2007)	Occupational status	Gender, age	Health status	Location: urban, suburban and rural	Flood hazard	Cross-sectional survey, Logistic regression with an equal weight assumption	United Kingdom
Nkwunonwo (2017)	Poverty	Gender, age	Medical disability	Housing	Flood hazard	Regression analysis with an equal weight assumption	Lagos, Nigeria
Roder et al. (2017)	Education, employment, income, SES	Age, race and ethnicity, gender	-	Housing	Flood hazard	Principal Component Analysis (PCA), Local Moran I with an equal weight assumption	Italian Municipalitie s
Schmidtlein et al. (2008)	Employment, poverty, education.	Gender, age, race and ethnicity	-	Housing	Hurricane Katrina	Principal Component Analysis (PCA), Correlation analysis with an equal weight assumption	South Carolina, California, Louisiana
Wisner et al. (2004)	Social class, poverty	Race and ethnicity, age group, gender	Physical disability	-	Hazards and disasters	Explained selected vulnerability factors through a Literature synthesis	General
Wu et al. (2002)	Income	Age, gender, race	-	Housing	Natural hazard: se-level rise	Weighted Linear Combination (WLC) to assign weights to factors	May County, New Jersey.
Zahran et al. (2008)	Poverty, income	Race and ethnicity, population density	-	Dams, impervious surfaces	Flood hazard	Ordinary least squares regression	Texas, USA

Table 1. A summary of social vulnerability indices

Existing literature has addressed various hazards and their associations with social vulnerability, including age, race and ethnicity, as well as gender (Bolin and Bolton 1986; Blaikie et al. 1994; Gladwin et al. 2000). Other indices like income and poverty have been used to study vulnerability in hurricane scenarios (Peacock et al. 2000; Fothergill and Peek 2004). Built-up environment indicators like housing, commercial facilities have been used in studies to measure the density of development and to predict areas prone to structural losses in disasters (Zahran et al. 2008; Wu et al. 2002; Cutter et al. 2003). Those affected by the harmful effects of hazards are disproportionately drawn from the segments of society which are chronically marginalized in daily life (Wisner et al. 2004). Such people are marginalized geographically as they tend to live in hazardous places; socially and culturally as members of minority groups (e.g. ethnic minorities, people with disabilities); economically because they are poor (e.g. homeless or jobless); and politically because their voice is disregarded by those with political power (e.g. women, gender minorities, children, and elderly) (Gaillard 2010). Cutter et al. (2003) and Wu et al. (2002) used similar variables in their studies to examine social vulnerability of populations living in hazard zones of South Carolina and New Jersey respectively. In contrast, Zahran et al. (2008) used only three variables as a proxy to assess social vulnerability. These Social vulnerability indices across the literature has been shown to be subjectively selected by researchers in regard to the context of their studies. Based on previous literature, this study identifies and reviews the following common criteria generally accepted in social vulnerability indices:

Socioeconomic status:

Socioeconomic status (SES) is one of the key factors of social vulnerability. It includes employment, income, housing, and education attainment. People with lower SES often lack the resources needed to follow instructions of emergency preparedness. They might be unable to stockpile food, unwilling to stay home from work in losing a day's pay, and/or cannot leave their home during an emergency. By identifying at-risk groups ahead of time, one can plan more efficient evacuation and target specific groups of people who need transportation or special assistance (e.g., those without a vehicle). Other subsets of SES are discussed below.

a.) Poverty: this is directly associated with access to resources which affects both vulnerability and coping from the impacts of extreme events. Because of affordability, poorer people tend to live in more remote and hazardous areas with a higher marginal cost of access to resources (e.g., government aid), and poorer housing susceptible to flood damage (Adger 1999). Poverty also affects housing (e.g., homelessness) and education attainment.

b.) Education: education has been recognized as a key to alleviate poverty and enhance adaptive capacity (Muttarak and Lutz 2014). Directly, education is considered as a primary way people acquire knowledge (e.g. hazards, risk perception) and skills (e.g. problem solving) that can enhance their adaptive capacity (Mileti and Sorensen 1990; Spandorfer et al. 1995). Moreover, lower education constrains the ability to understand warning severity (Cutter et al. 2003). Highly educated people have a greater advantage of having better access to useful information and enhanced social capital where less-educated individuals may not have such access (Cotton and Gupta 2004; Neuenschwander et al. 2012). Indirectly, education improves SES (Psacharopoulos et al. 2002) with greater lifetime earnings, more resources (e.g. purchasing costly disaster insurance), better living options (e.g. quality housing), and thereby enabling them to implement disaster preparedness measures and make decision at critical times (e.g. when to evacuate).

Demographic:

c.) Age: children and elderly are the two demographic groups most affected by disasters. Aging is likely to cause medical or chronic health problems that put them at an increased risk during a disaster (Cutter et al. 2003). They might also have limited sight, hearing, cognitive ability or mobility that compromise their capacity to follow instructions especially during disaster evacuations (Cutter et al. 2000). Reduced income, social isolation and limited mass media use also contributes to poor risk communication with this group and hence an increased risk (Morrow 1999). On the other hand, young children are also more at risk because they have not yet developed the resources, knowledge, or understanding to effectively cope with disaster, and they are more susceptible to injury and disease. Young children also are more vulnerable when they are separated from their parents or guardians (e.g. at school or in daycare).

d.) Gender: during a disaster, females might be more vulnerable because of differences in employment, lower income, and family responsibilities, as most single-parent households are single-mother families (Morrow 1999). However, females are more responsive in mobilizing to a warning and more likely to be effective communicators through active participation in the community. Hence, they might know more “neighborhood information” that can assist emergency managers. While a family often evacuate together, it is not uncommon for males to stay behind to safeguard the property or to continue working as the family provider. Males are also more likely to be risk takers and might not heed warnings (Blaikie et al. 1994).

e.) Race and ethnicity: in general, minorities have fewer resources and face more barriers to recovery than Whites (Fothergill et al. 1999). Racial minorities have increased risks for environmental injustice, which can place them in closer proximity to environmental hazards (Stretesky and Hogan 1998). For example, African Americans remain a substantial constituent in the U.S. vulnerable population (HUD 2015). Social and economic marginalization contributes to the vulnerability of this race. African Americans also made up 48.7 percent of homeless families, according to HUD's 2015 Point-in-Time (PIT) estimates of homelessness (HUD 2015). An analysis of 2010 homeless data indicated that members of African American families were seven times as likely as members of white families to spend time in a homeless shelter (Institute for Children, Poverty, and Homelessness 2012). Hispanic persons, in contrast, are disproportionally underrepresented in the homeless population, despite having poverty rates comparable to African Americans (Krogstad 2014). This may be an effect of their strong family and social networks.

f.) English language proficiency: in the U.S., people with limited English proficiency (LEP) are less competent to read, speak, or write in English. LEP groups might have trouble understanding the public health directives if language barriers are not addressed when developing emergency preparedness messages (Derose et al. 2007). LEP populations include those who speak English as a second language, as well as native English speakers who have difficulty reading, interpreting, and calculating from written materials. Race/ethnicity, SES and immigration status are additional drivers of flood-related social vulnerability since these may impose cultural and language barriers that affect residential locations in hazardous areas, pre-disaster preparation, and access to post-disaster resources for recovery (Blaikie et al. 1994). For example, Vietnamese migrants were adversely affected by Hurricane Katrina due to their lack of acculturation and English proficiency (Rufat et al. 2015).

Built environment:

Built environment is typically measured by the quality and quantity of manufacturing and commercial establishments as well as housing units, this factor depicts areas where significant structural losses might be expected in a hazard event (Cutter et al. 2003).

h.) Housing: the quality and ownership of housing is an important component of vulnerability. The nature of housing stock (e.g. mobile homes), ownership (e.g. renters), and the location (urban-ness) combine to be a part of the social vulnerability constituents (Cutter et al. 2003). Property ownership affects the level of control a resident has over the adoption of protective measures and access to post-disaster assistance, leading to differences in flood susceptibility among owners, renters, squatters, and the homeless (Rufat et al. 2015). The homeless population is perhaps the most vulnerable from this perspective as they have no place they can call home. Chronically homeless individuals often have extensive health, mental health and psychosocial needs that pose barriers to obtaining and maintaining affordable housing.

Medical:

i.) Medical issues and disability: persons with medical needs and/or a disability include those with cognitive, physical or sensory impairments featuring limited sight, hearing, or mobility, as well as their dependency on electric power to operate medical equipment (Morrow 1999). Because of such medical conditions and disabilities, their ability to respond to a warning is compromised. This category also includes individuals with access and functional needs, irrespective of diagnosis or status, and persons who are diagnosed with chronic disease and need regular medical treatments (e.g., cancer, diabetes, etc.).

In summary, many studies have applied vulnerability assessment in the decision-making process of disaster management (e.g. emergency response and relief, shelter location, routing, evacuation, etc.). But few studies have acknowledged and incorporated homeless people, who are perhaps the most vulnerable population in vulnerability assessment. The Center for Disease and Control (CDC 2017) uses U.S. Census data to determine the social vulnerability of every census tract in the U.S. CDC's Social Vulnerability Index (SOVI) ranks each tract on 15 socioeconomic factors, including poverty, lack of vehicle access, and minority population, and groups them into four related themes; socio-economic status, household composition and disability, housing and transportation, minority status and language. Each tract receives a separate ranking for each of the four themes, as well as an overall ranking. Ben Wisner (1998) attempted to discuss broadly the concept of homelessness in Tokyo, Japan and the problems which homeless population face but did not incorporate it into the vulnerability assessment. Shier et al. (2011) conducted interviews in Calgary, Canada to identify women experiencing homelessness to gain better understanding of their pathways from homelessness. Strategies to address social vulnerability should also consider this vulnerable group, as well as other major factors that influence individuals' and families' pathways into homelessness in the context of social vulnerability. A major challenge to incorporate homeless population in social vulnerability is the lack of good quality data (i.e. count and spatial distribution).

2.2 Quantifying and Mapping Homeless Population

It is difficult to ascertain the number and characteristics of persons experiencing homelessness due to the transient nature of the population, although attempts to count and describe homeless individuals have been made in recent decades. Beginning in the mid-1990s, the Department of Housing and Urban Development (HUD) required its grant recipients to provide information about the homeless clients they served. In addition, comprehensive attempts to count homeless individuals were made in both the 1980s and 1990s, first via Census data and then through a national collaborative survey called the National Survey of Homeless Assistance Providers and Clients.

There are two ways of counting the homeless population (Freeman and Hall 1987; Jencks 1994). The first is a census count (or 'point prevalence' count) which tallies the number of homeless people on a given night. The second method estimates the number of people who become homeless over a year. These are called 'annual counts' (or 'annual prevalence') and welfare agencies usually gather statistics in this way. In most cases, homelessness is a temporary circumstance and not a permanent condition. A more appropriate measure of the magnitude of homelessness is the number of people who experience homelessness over time, not the number of "homeless people" at a specific snapshot (National Coalition for the Homeless 2009).

Some US cities attempt to count their homeless population annually. For example, New York City and Los Angeles (LA) rank first and second in terms of homelessness rate in the U.S. (Ranker 2019). LA estimates its homeless population by extrapolating data obtained from street counts of the unsheltered population. The Los Angeles Homeless Services Authority (LAHSA) conducts a street count every January. The street count is a Point-in-Time (PIT) visual-only tally of people experiencing unsheltered homelessness and the number of cars, vans, recreational vehicles (RVs), tents, and makeshift shelters assumed to be housing people. The 2018 street count of homeless adults was conducted at the census tracts (CTs) level. Besides, a demographic survey (DS) was also conducted during this street count to 1) collect characteristics of unsheltered homeless adults to aid the estimation of overall homeless population across the city of Los Angeles, and 2) determine the multiplier for the number of people living in the cars, vans, RVs, tents and transient shelters captured in the street count. A two-stage stratified random sample was used for the demographic survey. Analytic weights were computed according to CTs sample selection probabilities. A total of 12,385 individuals and 8,036 households were counted during the shelter count while there were 10,747 individuals and 38 households with 118 members during the street count in 2018.

In 2018, the New York City Homeless Outreach Population Estimate (HOPE) deployed over 2,000 volunteers to areas where homeless individuals are known to stay (i.e. “high density areas”) to count. For other areas that were less populated by the homeless (i.e. “low density”), a random sample was taken to estimate the number of homeless individuals in areas not surveyed (NYC HOPE 2018 Report). From the report, a total of 3,675 people was estimated to be unsheltered on January 22nd of 2018.

2.3 Knowledge Gaps in the Literature

While the literature has explored many variables to assess social vulnerability and presented various methodological approaches and indices to quantify as such, there have been virtually no studies that have incorporated homelessness in their studies on social vulnerability Also, up-to-date spatial data of homelessness are rarely used, if any at all, in social vulnerability assessment. Homeless population has special needs that should be accounted for in social vulnerability assessments mainly because of the following:

a. Vulnerability assessment using Census data accounts for only household populations but not homeless population.

b. Homeless population is relatively mobile and unstable, and therefore, they are hard to be quantified and hence have been omitted in most existing framework of vulnerability assessment.

c. Homeless population often locate themselves in hazardous areas (e.g. floodplains, riparian zones, low water crossings, underpasses, transitional homes, etc.).

Despite there were a couple attempts in LA and NYC to enumerate homelessness in practice, no studies have produced risk maps to depict areas that are prone to homelessness prevalence based on salient demographic attributes. Moreover, there has been a lack of relevant research in the methodological development of homelessness enumeration and addressing any related challenges. Therefore, this directed research attempts to answer the following questions:

1. Using Austin, Texas as a case study, what is the spatial pattern and distribution of homeless population at the block group level?

2. Are there any significant differences between vulnerability assessment with or without homelessness in terms of:

   a. spatial pattern and distribution?

   b. social vulnerability indices?

This study enriches the vulnerability literature by incorporating homeless population as key stakeholders of vulnerable population during a disaster. By taking into consideration of relevant social and physical vulnerability indicators which are representative to the homeless people, this research creates a framework extending existing vulnerability indicators commonly used by researchers in the field.

3. Methodology

To answer the presented research questions, this study utilizes dasymetric modeling, a disaggregation technique to derive homeless count at a fine spatial resolution, and an additive method of vulnerability assessment to calculate SOVI (Figure 1). Most data for this research was collected in Austin at the block group level to be analyzed at the finest scale possible. By examining the role of homelessness into vulnerability assessment, the results can aid planners and emergency managers in targeting socially vulnerable populations more effectively.

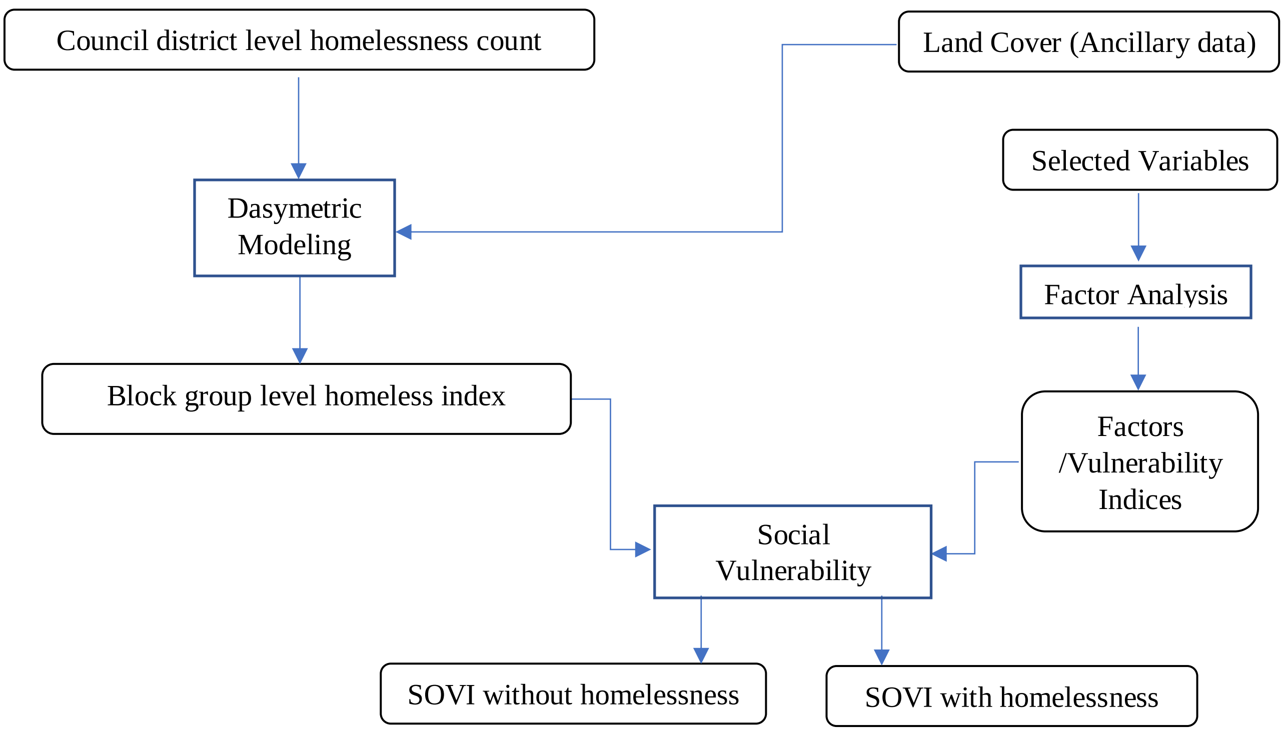


Figure 1. Conceptual framework

3.1 Study Area

In 2018, the Ending Community Homelessness Coalition (ECHO) found 2,147 people to be homeless in the city of Austin (COA), a five percent increase than 2017. Despite rapid urbanization and increasing gentrification in Austin, surprisingly, the reported number of homeless population has remained relatively the same over the past decade. This is probably due to inadequacies in financial resources and practical approaches to counting the homeless. On January 27, 2018, the city conducted its annual "Point-In-Time" count to document the number of people who are unsheltered and homeless in Austin, including people not just on the street but also those inhabiting in cars, tents, parks and under bridges. The derived numbers were combined with the count of people staying in transitional housing. Specifically, the number of people in 2018 sleeping unsheltered on the streets was 1,014— the highest in the last 8 years (ECHO 2018).

As a legacy of the early 20th-century segregation policy and discriminatory practices (Plessy v. Ferguson 1867), Austin’s socio-economically disadvantaged populations are largely concentrated on the east side of the City. Moreover, inequitable housing practices and racial-restrictive covenants persisted beyond the policy, resulting in a geographic isolation of minorities in East Austin (Busch 2015). Today, Austin has one of the nation’s highest levels of income segregation; nearly all census tracts with above-median numbers of families in poverty are situated on the east side (Census Bureau 2010). The COA has identified those living in poverty as a “special needs population” in its 2016 Hazard Mitigation Plan Update. According to the 2010 Census, nearly 800,000 people reside in the city. Among the work force, over 32,000 earn an income less than $20,000 per year (COA Hazard Mitigation Plan 2016). Austin is vulnerable to a variety of hazards (e.g. flash flood, wildfire, etc.) that threaten its communities, businesses and citizens, therefore, it is part of the city's responsibilities to prepare adequately for these hazards.

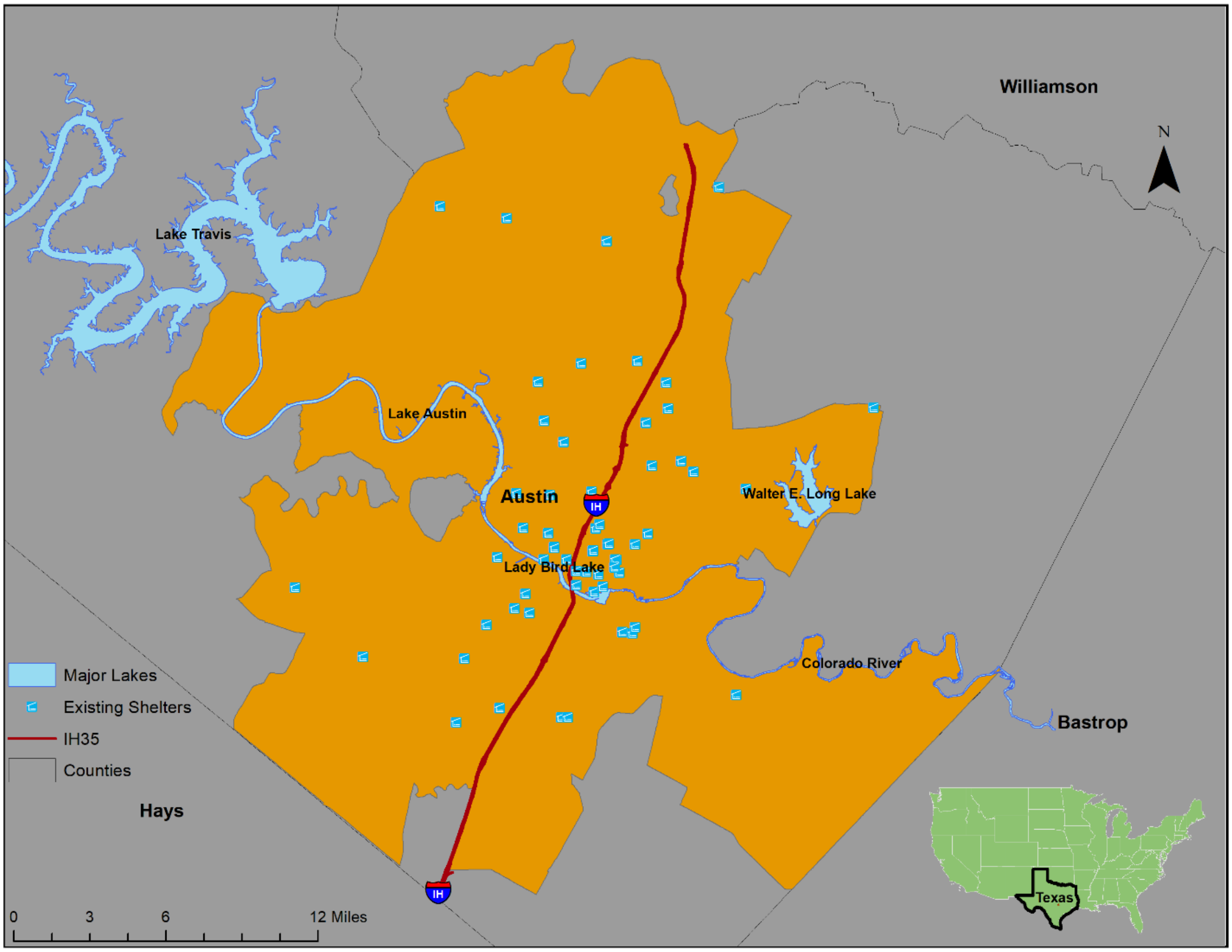


Figure 2. Map of the study area (data source: TNRIS)

3.2 Data and Methods

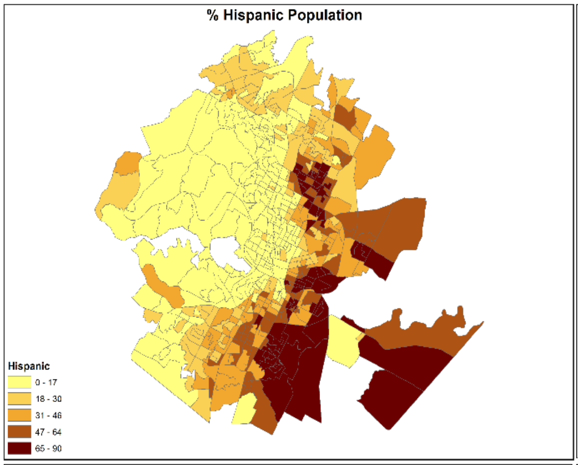
To examine the social vulnerability of COA, 21 relevant socioeconomic data shortlisted from the literature was collected for Austin (Table 2). In multivariate statistics, many socioeconomic and demographic indicators are inter-correlated with one another. The variables were grouped into composite factors to mitigate multicollinearity and reduce data redundancy. Data on the state of homelessness in Austin/Travis County is collected mainly by homeless service providers. Due to the sensitivity of this population group, the best available data on homeless population was that of unsheltered persons at the Council District (CD) level. In this study, dasymetric modeling was conducted to disaggregate homeless population at the block group level. This disaggregated result was then presented as a predictor in creating a composite social vulnerability index (SOVI) for the study area. Specific variables from 2013-2017 American Community Survey (ACS) data were acquired from U.S. Census Bureau to characterize the dimensions of social and physical vulnerability are identified in Figure 3.

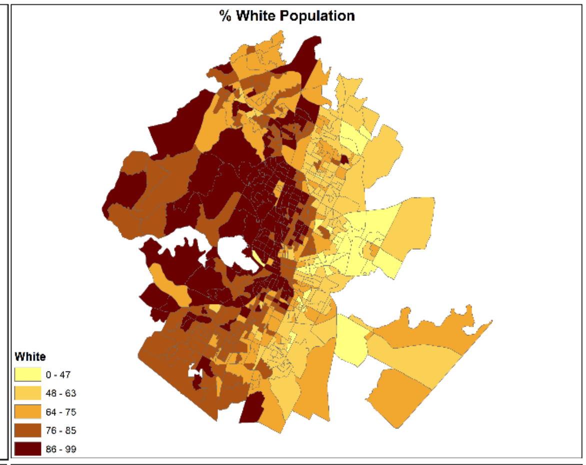
Overall Vulnerability	Variables	Literature Source (s)
	Demographical	
	% of Hispanic population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	% of White population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	% of American Indian and Alaska native population	Bergstrand et al. (2015); CDC (2017)
	% of Black population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	% of Asian population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	% of Hispanic non-White population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	% of female-headed households with children less than 18years	Blaikie et al. (1994); Cutter et al. (2003); Fothergill and Peek (2004)
	% of population aged 65 years and older	Cutter et al. (2003); Nkwunonwo (2017);
	% of population aged 0 to 5 years	Cutter et al. (2003)
	% of population aged 6 to 11 years	Cutter et al. (2003)
	% of population aged 12 to 17 years	Cutter et al. (2003)

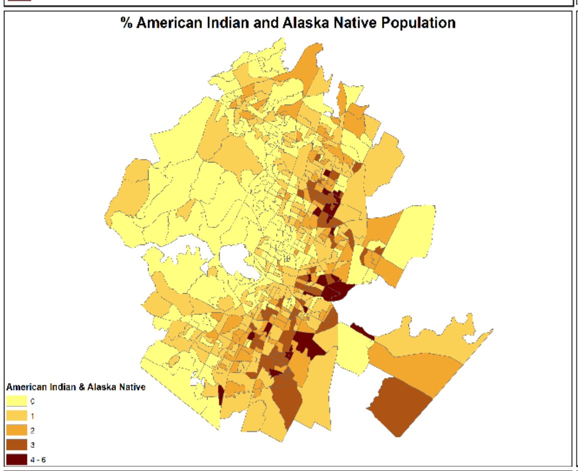
	% of Spanish speaking population	Blaikie et al. (1994); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000)
	Medical	
	% population with disability	Blaikie et al. (1994); CDC (2017); Nkwunonwo (2017); Wisner et al. (2004)
	SES	
	% of population living in Poverty	Schmidtlein et al. (2008); Zahran et al. (2008)
	% of population with income less than $25,000	CDC (2017); Cutter et al. (2003)
	% of population dependent on public assistance	CDC (2017); Cutter et al. (2003)
	% of renter occupied housing	Cutter et al. (2003)
	% of households with no vehicle	CDC (2017); Cutter et al. (2003);
	% of population without health/life insurance	CDC (2017); Cutter et al. (2003); Mason et al. (2007)
	% of population with no high school diploma	CDC (2017); Roder et al. (2017); Schmidtlein et al. (2008)
	% of Unemployed population	Bolin and Bolton (1986); CDC (2017); Cutter et al. (2003); Gladwin and Peacock (2000); Mason et al. (2007)
	% of population living in mobile homes	CDC, (2016); Cutter et al. (2003)
	PIT Unsheltered homeless population data	

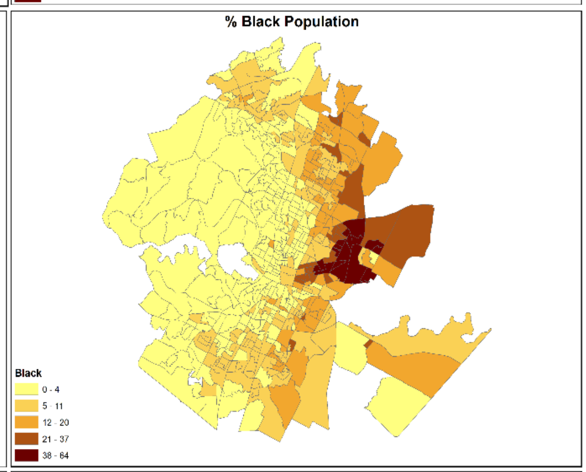
Table 2. Selected data and sources

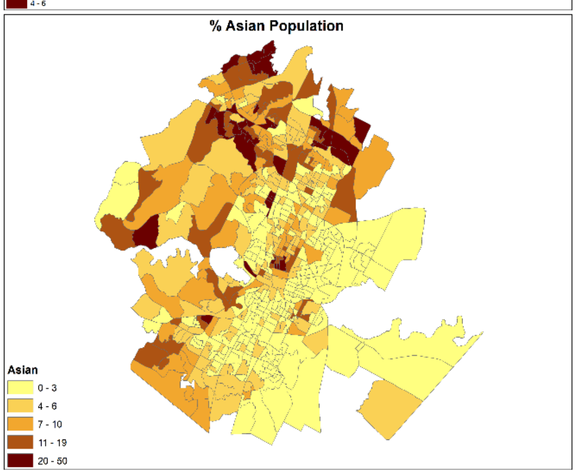
The 22 selected individual variables are mapped out below:

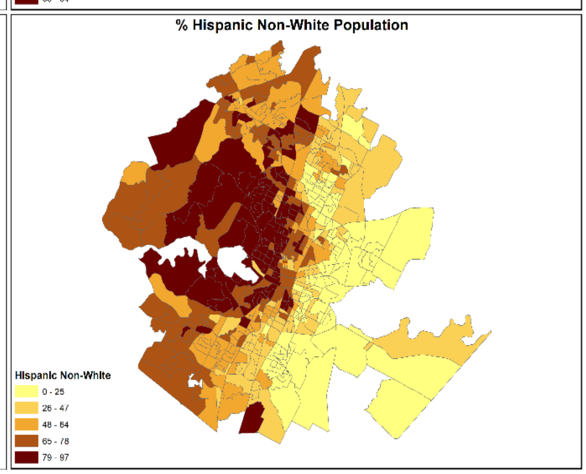


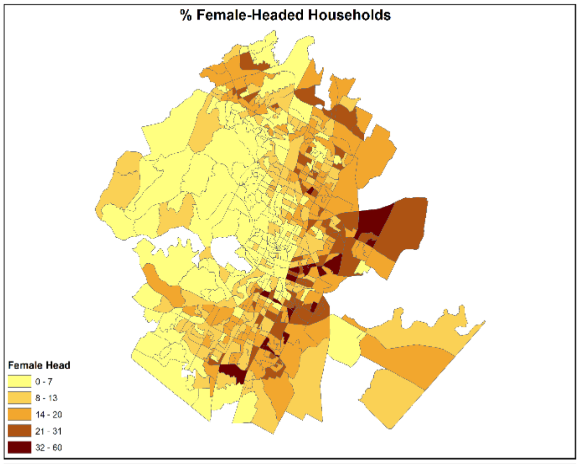


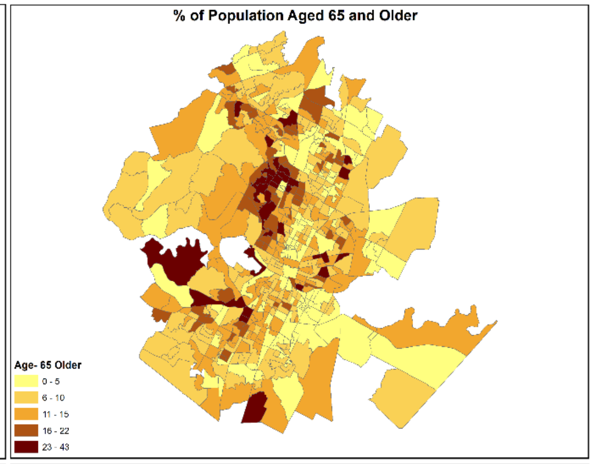


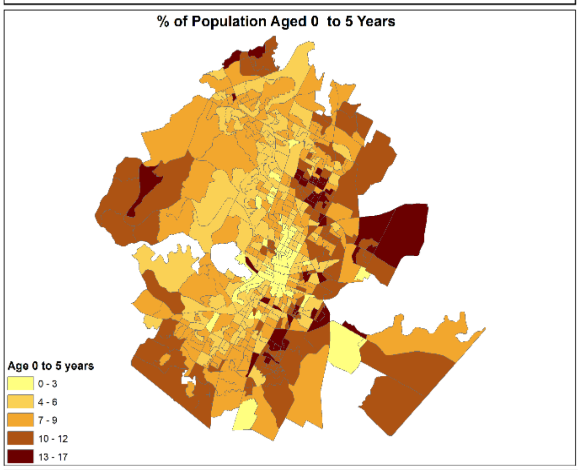


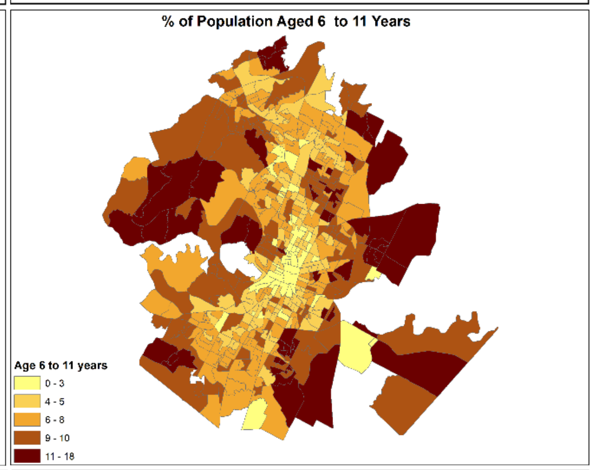


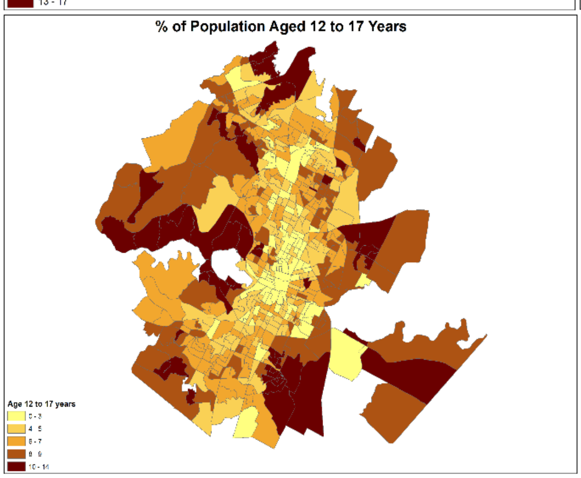


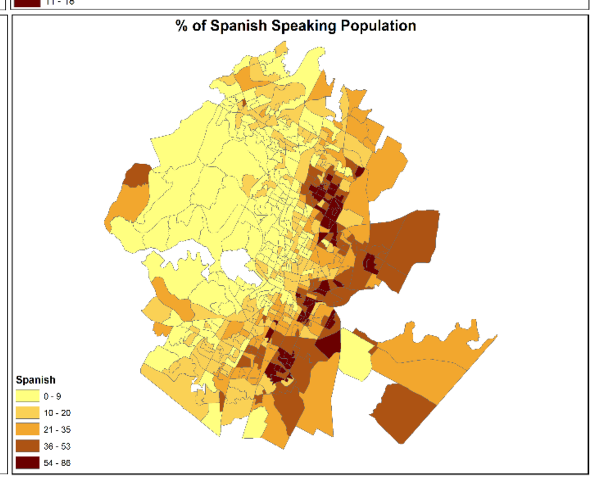

% Female-Headed Households
Female Head
0 - 7
8 - 13
14 - 20
21 - 31
32 - 60


% of Population Aged 65 and Older
Age- 65 Older
0 - 5
6 - 10
11 - 15
16 - 22
23 - 43

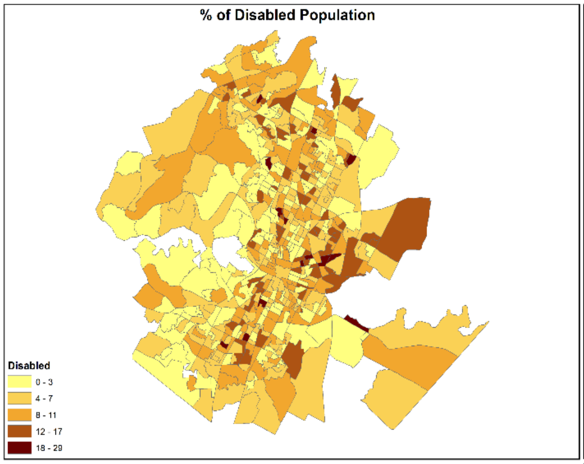

% of Population Aged 0 to 5 Years
Age 0 to 5 years
0 - 3
4 - 6
7 - 9
10 - 12
13 - 17


% of Population Aged 6 to 11 Years
Age 6 to 11 years
0 - 3
4 - 5
6 - 8
9 - 10
11 - 18

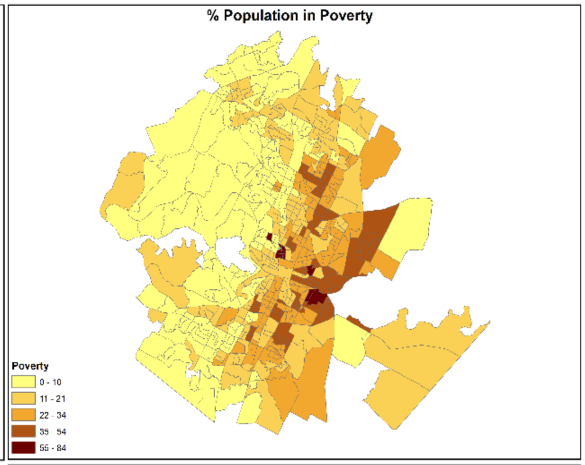

% of Population Aged 12 to 17 Years
Age 12 to 17 years
0 - 3
4 - 5
6 - 7
8 - 9
10 - 14


% of Spanish Speaking Population
Spanish
0 - 9
10 - 20
21 - 35
36 - 53
54 - 86

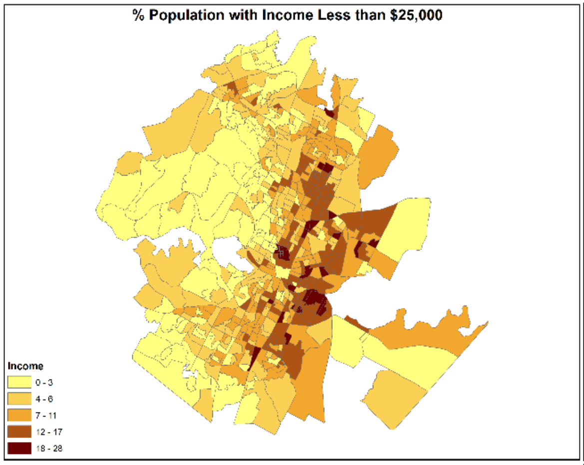
% of Disabled Population



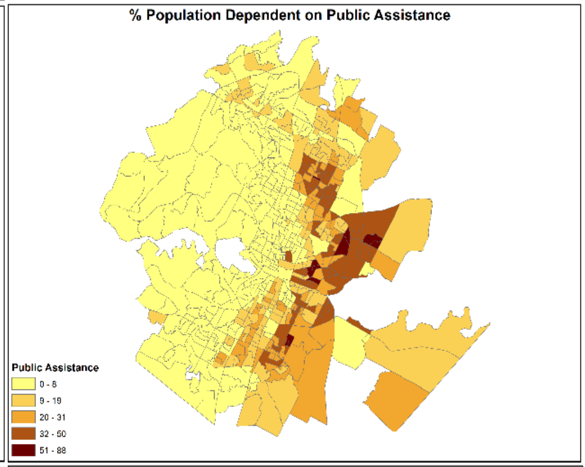
% Population in Poverty



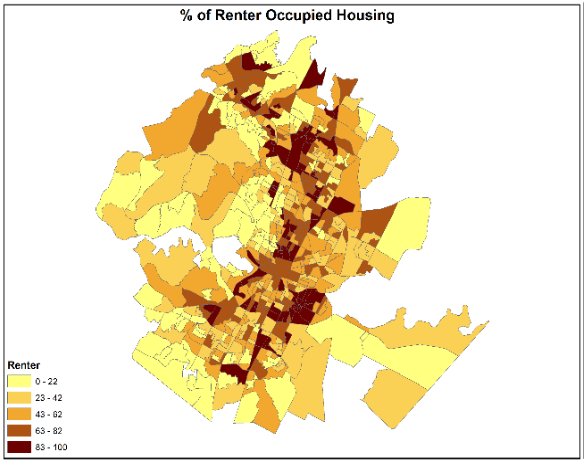
% Population with Income Less than $25,000



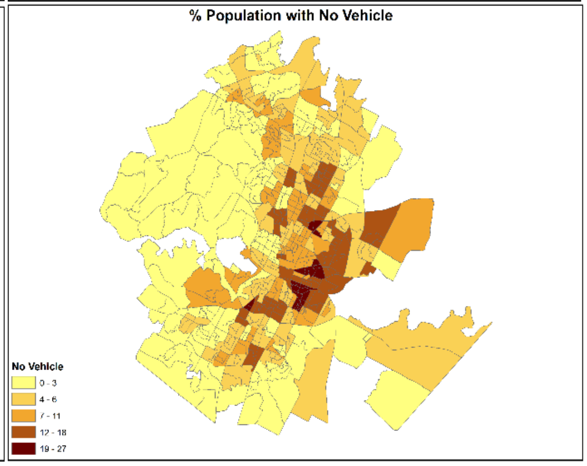
% Population Dependent on Public Assistance



% of Renter Occupied Housing



% Population with No Vehicle



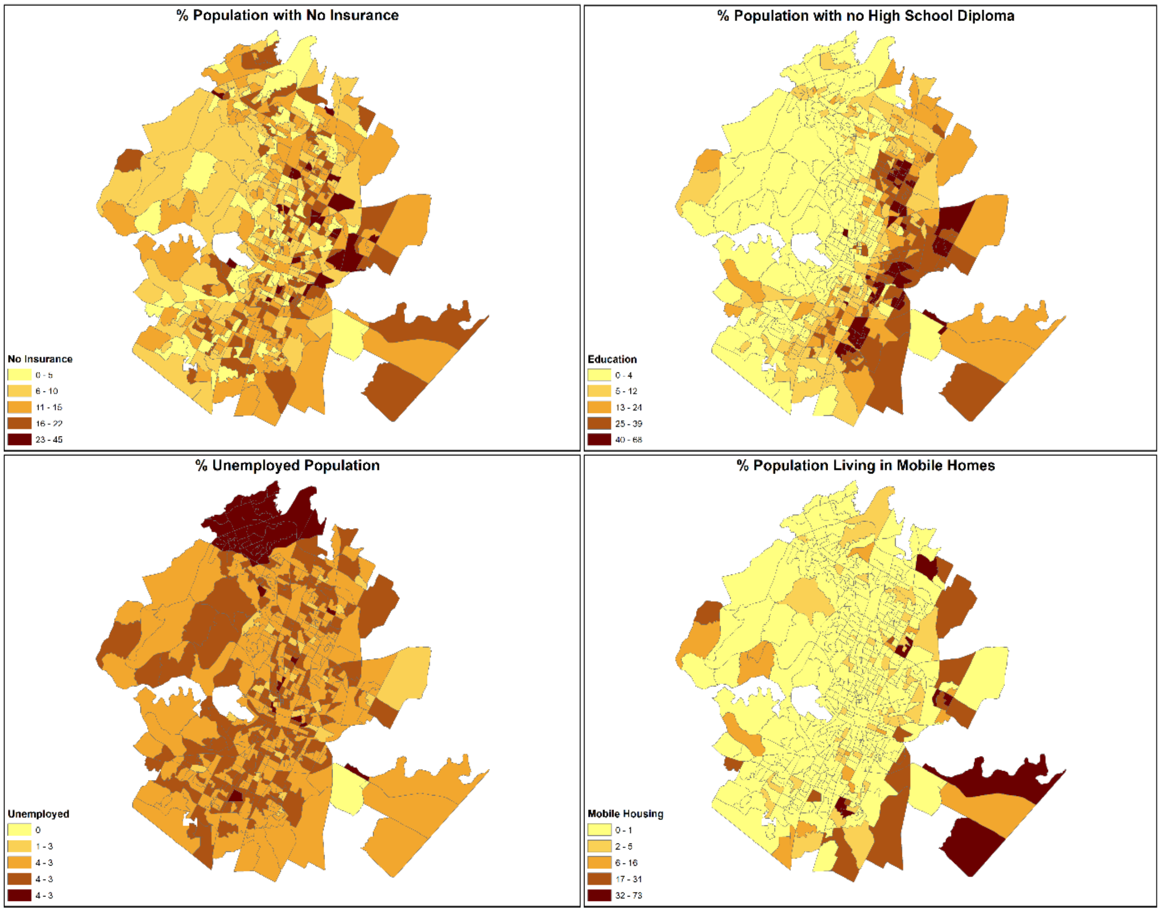


Figure 3. Variables of social vulnerability

3.3 Mapping Homeless Population

The PIT unsheltered homeless count data for 2018 at the CD level was derived from ECHO (1,014 total unsheltered spread over 10 CD's). As mentioned, dasymetric modeling technique was used to disaggregate the CD level data into Block Group (BG) in consistence with other independent variables to present a composite SOVI index map. Dasymetric mapping has been used by researchers to estimate population distribution using ancillary data like land cover or nighttime light (Li et al. 2018). Requia et al. (2018) also compared dasymetric and choropleth methods of mapping population distribution in terms of exposure to air pollution. These researchers reported reasonably high accuracies in their results.

In this study, the dasymetric process utilizes the 30 m land cover data in 2011 was acquired from the National Land Cover Database (NCLD) to serve as ancillary data. Land cover data are valuable because they serve as proxy for socioeconomic characteristics through a chain of indirect links that tie together land cover, land use, housing type and density. Each land cover pixel was reclassified into five land use classes: four of which represent potential areas for temporary shelters for the homeless (these are used as related ancillary variables) and one non-homeless class (i.e. water and wetland areas class is unlikely to have any residential/homeless potential). The four land use classes used as related ancillary variables are low and high density residential, agricultural, commercial and industrial (Figure 4).

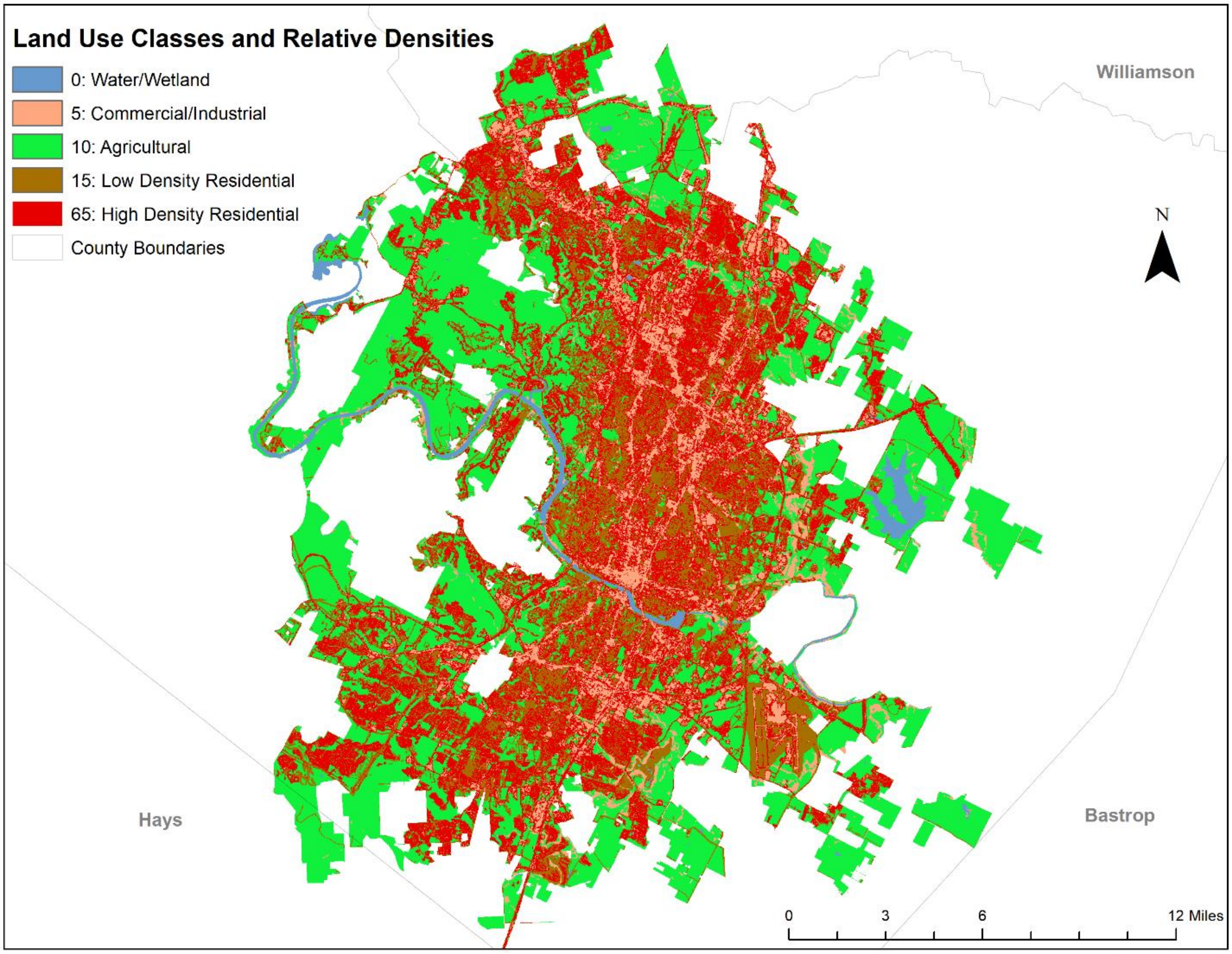


Figure 4. Land cover/use classification scheme and relative densities

This research replicates the dasymetric mapping equation from Holloway et al. (1997) to calculate homeless population for each land cover cell (pixel). The equation below was used:

$$P = (R_A)*(N/E)/A_T \qquad \text{(Equation 1)}$$

where P is the population of a cell,

-R_A is the relative residential density of a cell with land-cover type A,

-N is the actual population of enumeration unit (i.e., census block group)

-E is the expected population of enumeration unit calculated using the relative densities. E equals the sum of the products of relative density and the proportion of each land-cover type in each enumeration unit.

-A_T is the total number of cells in the enumeration unit.

The relative density (R_A) values used in this research relies solely on tested assumptions for dasymetric mapping and was refined based on the knowledge of social workers familiar with homeless population distribution in COA. The values of R_A for different land-cover types are given in the table below.

Land Cover Code	**Description**	**Relative Density ($R_{A)}$**
1	Low density residential	15
2	High density residential	65
3	Commercial/Industrial	5
4	Agricultural	10
5	Water/Wetland	0

Table 3: Land cover/Land use and relative densities

As previously stated, the dasymetric model disaggregates the homeless population and allocates each land cover cell a population count value. Using GIS to calculate the population for each land cover cell, the CD homeless polygon data was first converted into raster with homeless count as the input field. Next, to derive 'E', which is decided by the proportions of land-cover types in each BG, a raster map of the BGs' FIPS codes was created, which was tabulated to calculate the areas of different land-cover types present in each BG. The proportions for each landuse classes at BG level was then multiplied by its corresponding R_A to solve for 'E'. The tabulated table was joined to the BG polygon layer and converted into a raster layer to derive the number of homeless population per cell. To derive A_T, the area of the enumeration units was divided by the cell area (i.e. 900 m^2). After deriving all required values, they were evaluated using Equation 1 to derive the cell population raster (Figure 5). Finally, the BG layer was combined with the cell population raster by zonal statistic to derive the final count of unsheltered homeless population for each BG in Austin.

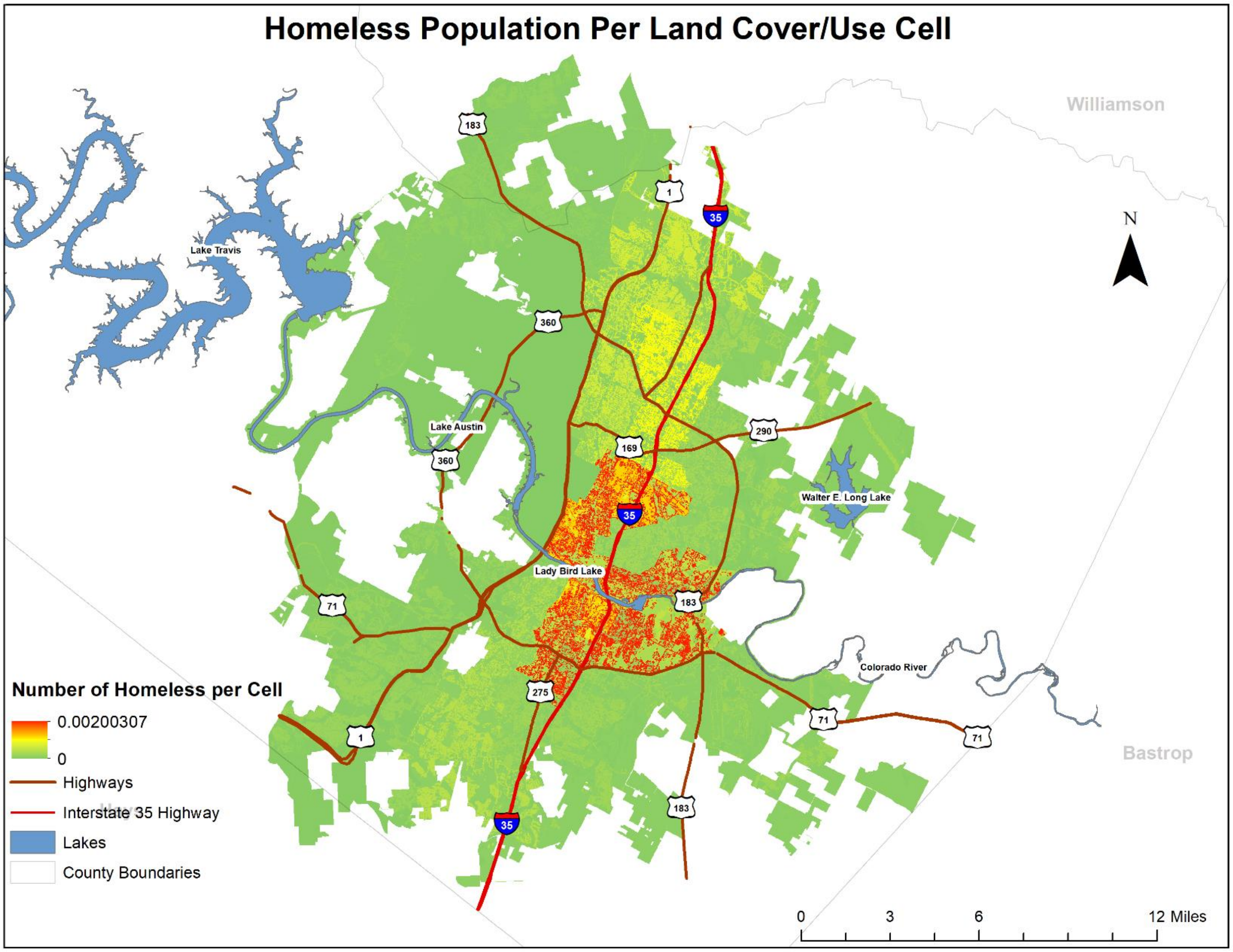


Figure 5. Homeless population per land cover cell

3.4 Social Vulnerability Assessment

To create a composite vulnerability index, homeless index generated from the dasymetric model was combined with factors generated from the 22 selected variables (Table 2). The literature encounters a crossroad with different approaches of factor weighting. Many researchers, such as Cutter et al. (2003), Mason et al. (2007), and Nkwunonwo (2017), used equal weighting to alleviate the burden of controversial weight assignment. Since weight assignment can greatly impact the resulting vulnerability assessment and there is no consensus for calculating vulnerability index, this study also adopts equal weight as well. Due to multicollinearity among the 22 chosen variables, Principal Component Analysis (PCA) was used to group highly-correlated variables to model SOVI. Based on the inter-correlation among variables, PCA combines the statistically-redundant variables into a component to generate a more robust set of social vulnerability factors. The PCA factors were then normalized and summed to obtain the relative measure of social vulnerability for each BG in Austin.

4. Results

4.1 Dasymetric Model

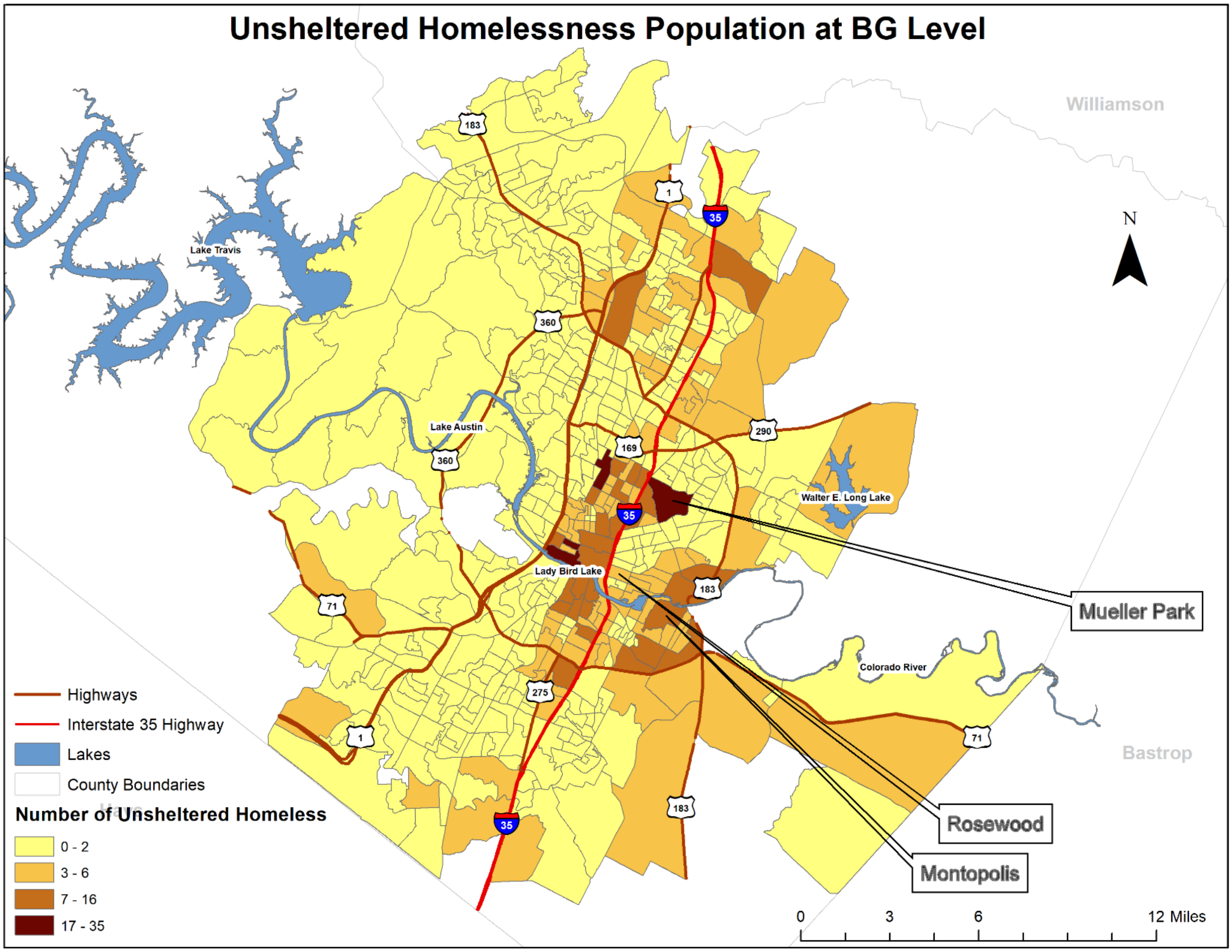


Figure 6. Unsheltered homeless count at BG level

The BG homeless count output (Figure 6) from the dasymetric model showed an agreement when compared with the CD homeless distribution (Figure 7). There were relatively higher numbers of homeless population spread across Austin downtown, along the major highways; Interstate-35, northwards along highways 183-North within Mueller park and in east

Austin along highway 183-South within Rosewood and Montopolis neighborhoods. There were smaller pockets spread around west Austin.

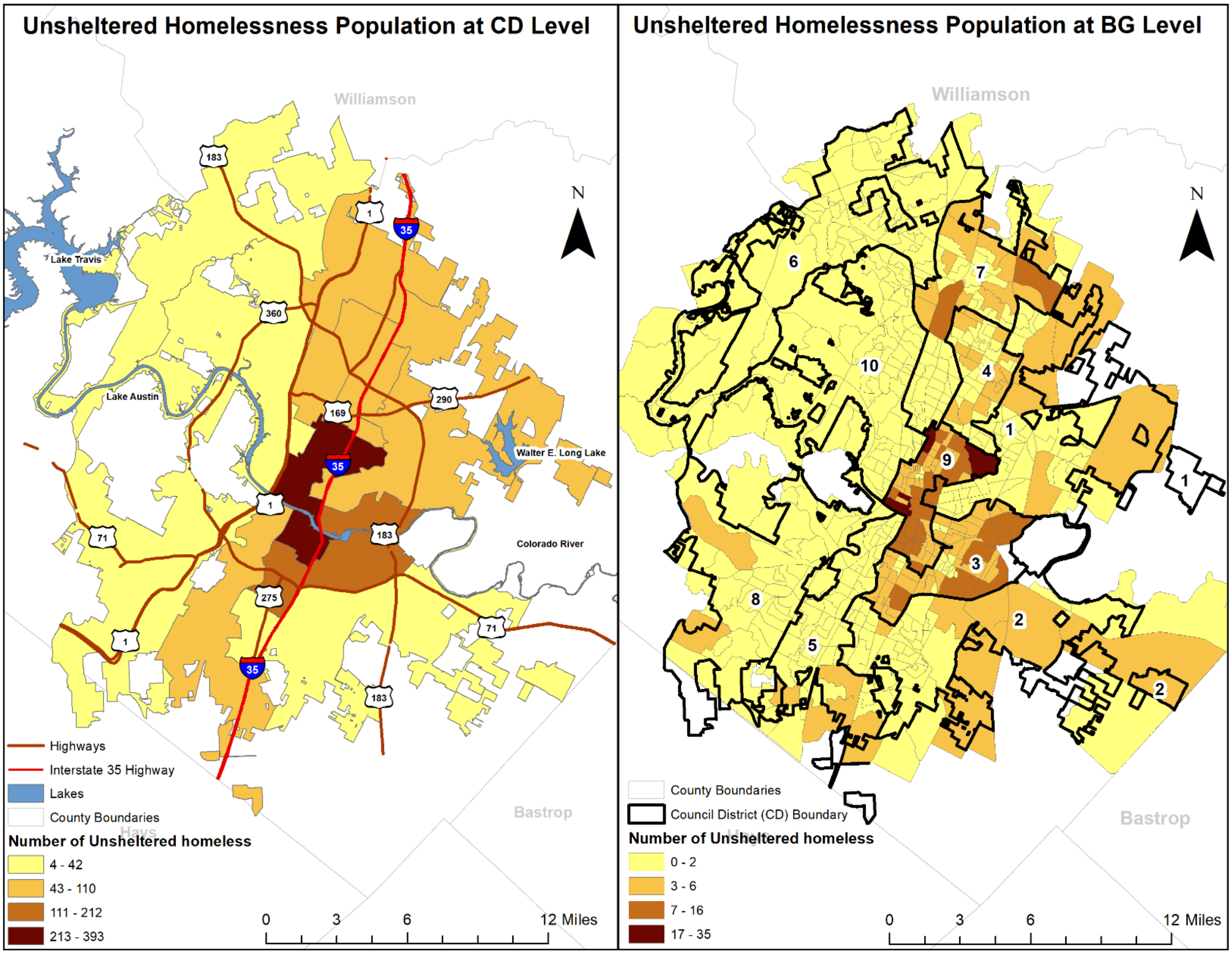


Figure 7. Unsheltered homeless population distribution at CD & BG level

The dasymetric approach to disaggregating homeless data produced some interesting patterns in terms of spatial distribution. A more realistic pattern of the homeless is observed in the BG homeless map. Due to the spatial heterogeneity of land cover/use data used, more precise estimates of population can be derived at smaller census levels (e.g. Census tracts, BG or at pixel level). For instance, CD's 2 and 8 in the CD homeless map (Figure 7) have the lowest counts (range 4 to 42) whereas these same districts house some BGs having a moderately low homeless count (range 3 to 6). This similar distribution pattern is seen across the other districts when compared with BG map. This result provides some level of precision and specificity especially for policy makers, social workers as well as shelters to be able to predict locations and concentration of homeless. It also allows for ease and speed in counting homeless population as service providers in Austin can better group volunteers by BGs instead of a more cumbersome and possibly ineffective method at larger census levels. The BG homeless count is incorporated as an index into the social vulnerability assessment in section 4.3.

4.2 Principal Component Analysis (PCA)

Using an eigenvalue of one as the threshold, the multicollinearity among all 22 variables was examined using PCA and produced five composite factors.

	Component				
	1	2	3	4	5
Age (65 and Older)	-.145	.059	**.782**	.016	-.003
Black	-.011	.091	-.012	**.941**	-.144
Disabled	-.177	-.058	.261	.504	.285
Education < High School	**.824**	.050	.008	.198	-.103
Female Headed Household	**.767**	.063	-.154	.446	.252
Hispanic	**.878**	.083	-.053	.108	.051
Hispanic Non-White	-.614	-.104	.255	-.474	.092
Income < $25,000	.538	-.447	-.253	.096	.184
Mobile Housing	.483	.213	-.025	-.244	-.058
Uninsured	.122	-.049	-.012	.173	.295
No Vehicle	.395	-.507	.139	.226	.215
Poverty	.576	-.435	-.174	.147	.059
Public Assistance	.590	.069	.034	**.864**	.092
Renter	.182	-.633	-.457	.049	.245
Unemployed	-.133	.172	-.037	-.243	**.925**
White	-.293	-.101	.379	**-.716**	.183
Age up to 5 Years	.424	.627	-.162	.161	.242
Age 6 to11 Years	.252	**.881**	-.065	.120	.149
Age from 12 to17 Years	.123	**.903**	.031	.100	.093
American Indian and Alaska Natives	**.789**	.028	.046	-.049	.092
Asian	-.597	.060	**-.755**	-.002	.047
Spanish Speaking	**.875**	.089	-.026	.105	-.026

Table 4. The results of principal component analysis

Factor loading of 0.7 was used as the threshold for grouping and classifying the "loaded" variables for each factor. Factor one depicts race and ethnic minorities and the socio-economically disadvantaged. It explains about 39 percent of the variance with American Indians, Alaska Natives and Hispanic (Spanish speakers), female-headed households, less educational attainment and Spanish-speaking populations having high loadings on this factor. This result makes sense as these range of traits are often popular among minority populations (Bergstrand 2015; Cutter et al. 2003).

Children aged 6 to 17 years loads highest in factor two, explaining 16.4 percent of total variance and showing that young children are at risk because they lack the knowledge and understanding to cope in a disaster. This population group is also susceptible to injuries and diseases that may result from disasters. The third factor explains about 7 percent of the variance and suggests disability among older populations. Disability is commonly found among older populations which makes them highly vulnerable during disaster occurrence, whereas Asian population maybe attributed to be healthier at the same age and having high educational attainments which loads negatively on this factor. Factor four shows a high dependence of African American population on public assistance with both variables loading high on the factor while White population loads negatively which suggests that Whites have more access to resources and need not depend on public assistance. African Americans are a minority population group and lack access to resources which increases their social dependence. This factor explains 6.9 percent of the total variance. The last factor shows a high significance of unemployment on social vulnerability explaining 5 percent of the variance among BGs.

Overall, about 74 percent of variance was explained by the five factors. Variables that predicted highly on the factors can be seen in Table 4 (greater than + or - 0.7). These factors are then entered into the SOVI calculation presented below.

4.3 Calculating SOVI Using Additive Model

The factor scores derived from PCA alongside the homeless index were normalized using the min-max stretching formulae shown in equation 2 where y_α is the summed value of a factor, y_{min} is the minimum value in the range of a factor and y_{max} is the maximum value in the range for a factor:

$$x = \frac{y_\alpha - y_{min}}{y_{max} - y_{min}} \qquad \text{(Equation 2)}$$

The additive model equation used to calculate SOVI is shown below, z depicts individual factors added together to derive index I. By using this model, no weight was assigned as all factors were assumed to present equal relevance in the overall vulnerability model:

$$I = z_1 + z_2 + z_3 \ldots z_n / \mathrm{N} \qquad \text{(Equation 3)}$$

Finally, a social vulnerability map without homeless index was created using the 4 derived factors in the additive model. Likewise, another social vulnerability map with homeless index was created by adding the homeless index into the additive model. These maps are created at the BG level with classes ranging from low to high social vulnerabilities shown below in Figure 8. SOVI scores were mapped based on their standard deviations from the mean into five categories to determine the least and most vulnerable BGs respectively.

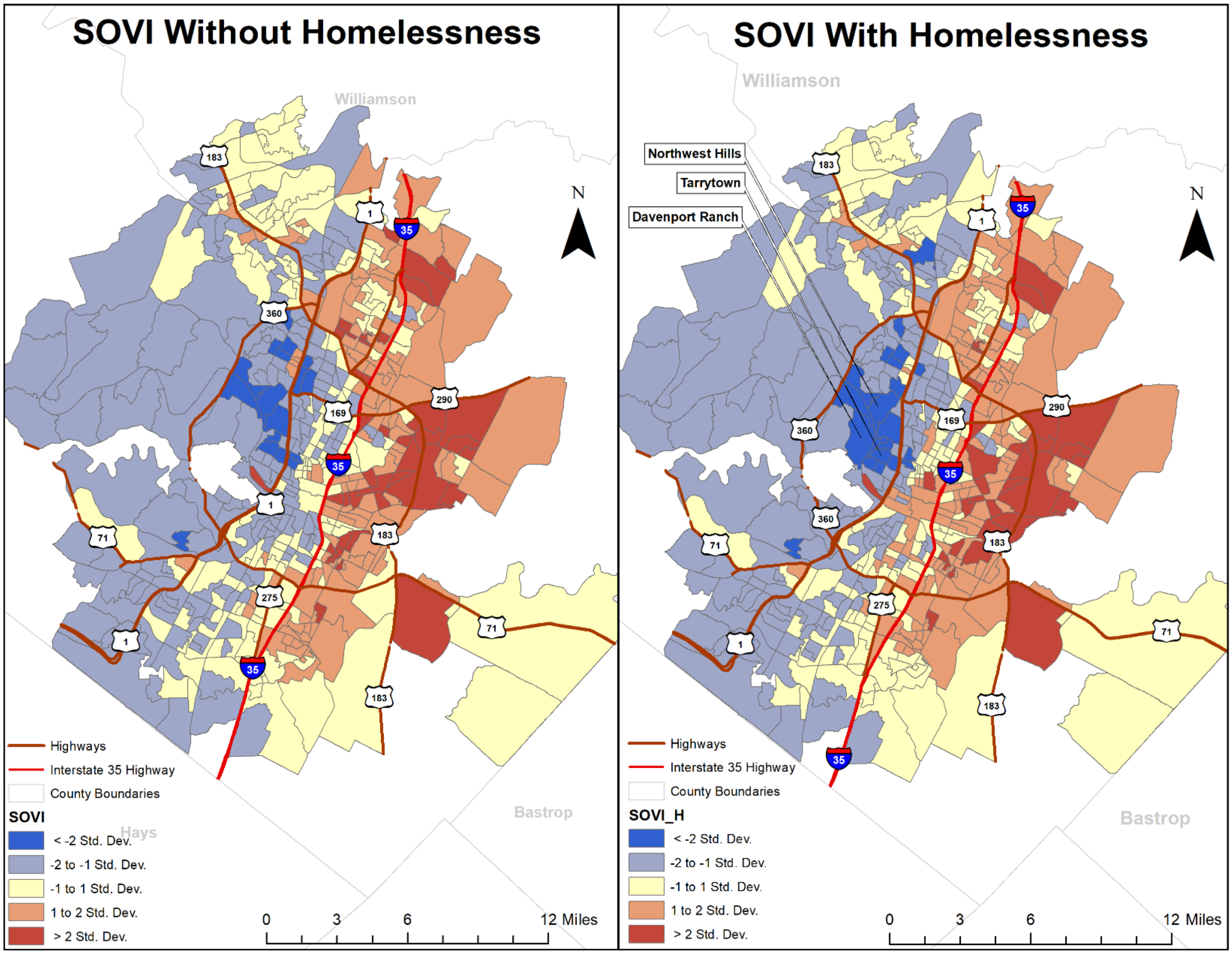


Figure 8. Social vulnerability map with and without homelessness

In general, Figure 8 show an east-west divide commonly reported in the social studies conducted in Austin. Inferring from these maps above, it is noticeable that the most vulnerable populations based on the selected variables are concentrated on the east side of the city where greater ethnic and racial inequalities as well as rapid population growth is prevalent.

A particularly interesting observation from the homeless SOVI map in Figure(s) 8 and 9 shows a significant concentration of vulnerable populations in BGs around downtown Austin. SOVI with homelessness showed 115 BGs (22%) have a medium high to high (> 0.5 standard deviations (S.D.)) social vulnerability, while SOVI without homelessness showed only 58 BGs (11%). The least vulnerable BGs (> -2 S.D.) are seen to be located in West Austin. Statistically speaking, BGs at (> ± 2 S.D.) have p value of < 5% assuming normal distribution. The frequency distribution of the two indices are plotted below (Figure 9).

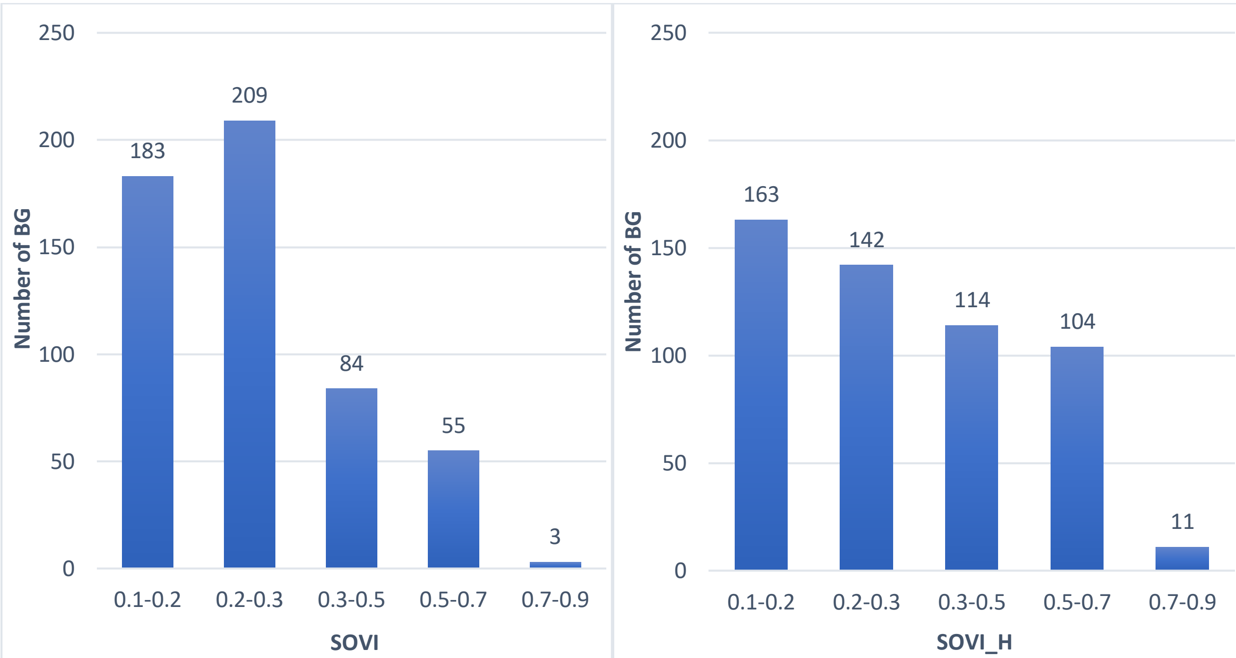


Figure 9. Frequency distribution of SOVI scores for SOVI (left) and SOVI_H (right).

These patterns signify the impact of incorporating homelessness as an index in calculating vulnerability and can help direct the attention of COA toward the above identified vulnerable block group locations either with or without homelessness. The highly vulnerable BGs include a geographic mix of highly urbanized BGs, large minority and socially dependent populations, including those in poverty and lacking in educational attainments. The highly vulnerable BGs are spread across Austin downtown, along the major highways; Interstate-35, northwards along highways 183-North within Mueller park, Rosewood and Montopolis neighborhoods in the Eastern Austin neighborhoods. The least vulnerable BGs are seen in West Austin having Davenport Ranch, Tarrytown and Northwest Hills neighborhoods. It is observed that more BGs in SOVI_H distribution fall into the medium vulnerable and highly vulnerable categories when compared with the frequency distribution for SOVI.

For the first part of research question 2 (RQ2a), to spatially compare the derived SOVI maps with or without homelessness, a difference map and their mean centers and directional distribution ellipses were derived (Figure 10). Based on the difference map, there are more highly vulnerable BGs around downtown and not predominantly in the east as SOVI pattern shows. Also, the frequency distribution plot for SOVI_H in Figure 9 shows higher numbers of vulnerable BGs when compared with the distribution for SOVI. The directional distribution (Figure 10) was used to observe the pattern of SOVI and SOVI_H based on their scores. The pattern shows that SOVI_H shifts a bit more western than SOVI alone.

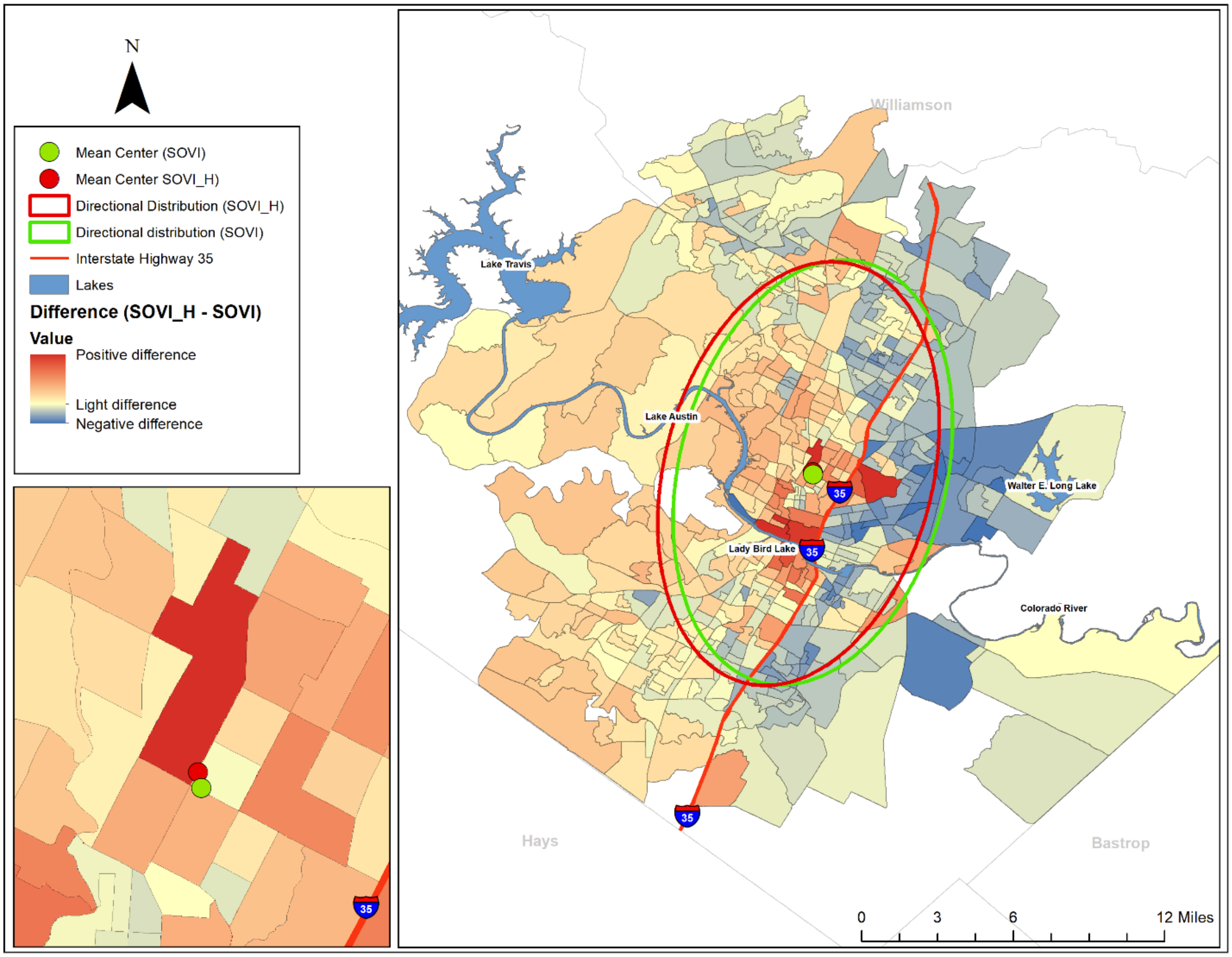


Figure 10. Map difference (SOVI_H – SOVI) and their spatial patterns (mean centers and directional distributions).

	Minimum	Maximum	Mean	Std. Deviation
SOVI	0.223	0.773	0.478	0.072
SOVI_H	0.213	0.710	0.393	0.062

Table 5. Descriptive statistic of SOVI and SOVI_H

A paired t-test was conducted to observe for any differences in the means of social vulnerability with homelessness (SOVI_H) or social vulnerability without homelessness (SOVI) in terms of their social vulnerability indices (part b of research question two) based on 534 BGs in Austin. From the t-test, the mean and standard deviation of SOVI and SOVI_H scores were

(0.478 and ±0.072) and (0.393 and ±0.062) respectively. Furthermore, the paired t-test conducted revealed that there was a significant difference between both indexes ($t = 92$, $p < 0.05$, $n = 534$). This result also confirms the result derived from the spatial pattern observation between both indexes for RQ2a.

5. Discussion and Conclusion

In many cities, Austin included, homeless population data are typically aggregated to the level of administrative units for many reasons (e.g. privacy, ease of administration). However, detailed information on the spatial distribution of the population within these units is masked. In this research, dasymetric mapping techniques was used to disaggregate population to a finer spatial scale using ancillary data (i.e. land cover/use data). Thus, the dasymetric model used in this study reveals a successful method for disaggregating population data at a desired scale.

This research has introduced the application and relevance of homelessness as a factor in social vulnerability literature and applies it to Austin, Texas as a case study. This study has also presented social vulnerability as a multidimensional concept that helps in identifying those characteristics and experiences of communities that enable them to respond to and recover from hazards. The major dimensions of the social vulnerability of the study area are clustered into specific locations, East and downtown Austin. At a general consideration, economic welfare, age, and ethnicity are the major social attributes affecting the residents of those locations. In contrast with many studies that report social vulnerability in Austin as being solely as a result of a classic divide, this study presents a slight change in perspective showing that not only is East-Austin predominantly vulnerable, its Downtown region is highly vulnerable as well. This shows the impact of homelessness in computing social vulnerability indices.

The methodology applied in this research has shown that incorporating homelessness into the broader range of social variables of vulnerability presents a significant difference when compared with SOVI with commonly used variables. This study also presents a framework for potential improvement and adaptation in the existing framework of social vulnerability assessment that have been widely adopted at various government levels in the U.S (Cutter et al.

2003). Besides mapping the SOVI with GIS, PCA was used to further explore the indicators with respect to their ranges of contribution to the overall SOVI. The factors identified in the statistical analysis are consistent with the broader hazard's literature (Blaike et al. 1994; Cutter et al. 2003) which reveals the geographic variability in social vulnerability and the fundamental causes of vulnerability. While the methods used in this study can be replicated in future studies of social vulnerability and risk assessment, the results obtained can also be useful for decision making and prioritizing plans and strategies with regards to building effective coping capacity in those areas with higher social vulnerabilities.

Furthermore, results from the social vulnerability assessments reveal the differences between the two social vulnerability assessments. The geographic patterns observed in the result for this study suggests a key to improving social vulnerability assessment. As seen in the SOVI map (Figure 8), there were only a few BGs around Austin Downtown with medium high to high SOVI, with more of the concentration in the East while a high concentration of vulnerable population is seen both in BGs around Downtown and East Austin. Beside the spatial distribution observed in the results section (Figures 9 and 10), it is interesting to note that more BGs in SOVI_H are categorized as being vulnerable when compared with BGs in SOVI. This finding stresses the relevance and importance of considering homelessness as one of the many social factors when evaluating social vulnerability indices for cities and considering the appropriate disaster management planning. Downtown Austin is a hub for many homeless individuals because of the presence of welfare and temporary shelter providers such as Salvation Army and Foundation for the Homeless. Most homeless population flock around to receive meals, donated clothing and other welfare resources. Homeless individuals are also known to be concentrated around major highways in Austin especially at road intersections and traffic lights (e.g. Mueller Park in North-east Austin). Often times, these individuals roam the streets begging for alms and putting themselves at high risk of being assaulted or hit by moving vehicles. Their whereabouts at road intersections, especially low water crossings, may also be susceptible to various natural hazards. Figures 8 and 9 reveal the pattern of social vulnerabilities in Austin which suggests that the most vulnerable BGs should be prioritized in disaster management. These neighborhoods (Mueller Park, Rosewood and Montopolis) have high potentials for losses during natural disasters and should therefore serve as priorities for disaster management officials during disaster emergencies. Hence, incorporating homeless distribution can better help researchers to identify the most vulnerable groups when conducting social vulnerability assessments. More importantly, a noticeable pattern in those figures (Figures 8 and 9) suggest that using SOVI variables alone without homeless would have underestimated the vulnerability distribution and thereby under-prepare for the severe disaster to hit those communities.

For both vulnerability assessments with or without homeless ((i.e. SOVI_H and SOVI respectively), the most vulnerable BGs are still predominantly in east Austin (Figure 8). The difference map (Figure 10) shows that the BGs with the most difference between SOVI and SOVI_H are in Downtown Austin, with a positive difference being mostly in the west (i.e. SOVI_H > SOVI) and the negative difference in the east (i.e. SOVI_H < SOVI). This result means western BGs could have been overestimated using the SOVI framework. For disaster management, this may not necessarily mean reversing the trend and investing more effort and resources in West Austin than East Austin (because the most vulnerable group are indeed in East Austin as indicated by Figure 8), but disaster managers may want to do targeted disaster planning in West Austin and consider the homeless population that are “hidden” in West Austin so that they are not being overlooked.

The t-test results also confirm the importance of incorporating homeless as a variable in assessing vulnerability with a high significance observed when paired with SOVI without homelessness. Incorporating this key index, homelessness, in vulnerability studies will go a long way in aiding COA and Travis County managers in their effort to implement effective strategies and programs targeted at improving living conditions and overall social capital of vulnerable populations within their jurisdictions. The results from this study have shown differences in spatial patterns when compared to the results from past studies. The spatial distribution and orientation of the overall vulnerable populations take a slight shift to the West (Downtown Austin) unlike previous studies that have reported it being predominantly in East Austin. This research provides useful insights for identifying the neighborhoods that can benefit most from direct resources to aid social and economic development. Also, future studies in hazards and social vulnerabilities should consider adding homelessness in their works to create a more socially significant and realistic interpretation of the spatial distribution of social vulnerability.

The sensitivity of homeless population presented some drawbacks in data availability. Since the best available homeless count data for COA was at the CD level, a finer scale level would have been preferred to validate the dasymetric modeling of homelessness at the BG level, and to aid the analysis with less uncertainties. A future direction of this study considers sampling homeless population and identifying salient factors that defines pathways into homelessness. Furthermore, the rather complex and lengthy dasymetric approach could be further refined by developers and incorporated into a simple toolbox in mapping software for efficiency. A future direction for this research is to include the likelihood of experiencing different hazards as an additional factor when mapping and identifying vulnerable areas. This would indicate whether areas with high vulnerability are also prone to threats or disasters, thereby increasing their level of risk even further. Morrow (1999) advocates for emergency planners and policymakers to use community vulnerability maps to identify and work with high-risk areas in disaster preparation and response. Thus, understanding which areas are most in need of assistance can be beneficial in deploying programs that help prepare communities and mitigate harm before disasters, as well as direct aid and resources to struggling areas after hazards

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