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A method for creating high resolution maps of social vulnerability in the context of environmental hazards

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ABSTRACT

The availability of demographic information from census data has enabled the development of indices that describe the relative social vulnerability of populations at different locations. These indices are often used in conjunction with models of physical exposure to environmental hazards, such as flooding and hazardous waste emission, to identify populations at greatest risk. However, using standard census areal units to calculate social vulnerability can lead to significant underestimation of vulnerable populations as environmental hazards typically occur on a finer spatial scale than census units such as block groups. This paper describes and illustrates a hybrid method for creating a social vulnerability index (SVI) at a tax parcel level by utilizing supplementary information about tax parcels to link cadastral dasymetric mapping techniques and established social vulnerability indexing methods. This high resolution social vulnerability index may be used for planning at the municipal level to address existing or potential environmental justice issues.

1. Introduction

1.1. Motivation

In May of 2010, Middle Tennessee and more specifically, the greater Nashville area (Davidson County), experienced catastrophic flooding following a record setting rainfall event in which more than 13 inches (330 mm) of rain fell within a 48 h period (NOAA, 2011). At least eleven fatalities occurred due to flash flooding of streams and tributaries of the Cumberland River, many of them senior citizens, and more than 11,000 buildings were damaged at an estimated cost of at least $2 billion (NOAA, 2011).

As with many natural hazards, the 2010 flood prompted inquiries into social vulnerability (i.e., the ability of individuals to cope with and rebound from physical, emotional, and economic burdens) induced by the flood (Burton, 2010; Cutter, Boruff, & Lynn Shirley, 2003; Maantay & Maroko, 2009; Myers, Slack, & Singelmann, 2008). A study of social vulnerability, flood inundation, and locations of emergency response shelters in Davidson County conducted at a spatial scale of census tracts suggested that areas with higher social vulnerability were more likely to be flooded and had disproportionately limited access to emergency services (Padgett, 2013). While this study addressed issues relevant to social vulnerability and the distribution of harms produced by an environmental hazard by offering a social vulnerability index (SVI) as a measure for addressing environmental justice issues, the use of census tracts for the analyses provided a level of precision insufficient for identification of significant disparities in flood exposure and emergency shelter access for high and low vulnerability populations.

The study described herein attempts to overcome these spatial mismatches between identification of environmental hazards and socially vulnerable populations that can hinder identification of environmental justice issues by developing a methodology, using Davidson County as a test bed, which allows for assessment of social vulnerability at high spatial resolution. The approach taken in this study combines a social vulnerability indexing method and a dasymetric population mapping method via disaggregation logic based on supplementary information within a cadastral dataset. The result is an SVI at the tax parcel spatial scale (to be referred to as parcel level in the remainder of the paper) that can be overlaid with environmental hazard boundaries for precise identification of spatial coincidence between socially vulnerable populations and exposure to harm from environmental hazards. While

Abbreviations: SVI, Social Vulnerability Index; BGSVI, Block Group Level Social Vulnerability Index; PSVI, Parcel Level Social Vulnerability Index.

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development of the methodology was motivated by the Nashville flood case, the parcel level SVI produced is broadly applicable to many environmental hazards that affect the built human environment.

1.2. Social vulnerability in the context of environmental hazards

The concept of social vulnerability to environmental hazards has gained increasing interest with many studies proposing composite indices for comparative analysis of vulnerability across spatial extents (Chakraborty, Tobin, & Montz, 2005; Cutter et al., 2003; Krishnamurthy & Krishnamurthy, 2012; Shepard et al., 2012). The social vulnerability indices often utilize a hazards-of-place framework, which implies that only human environments, spaces containing human populations, are considered vulnerable, and are often mapped to show spatial relationships between social vulnerability and biophysical vulnerability to environmental hazards such as flooding (Azar & Rain, 2007; Cutter, 1996). These indices have been created as planning tools and metrics that can be used to inform policy development, funding allocations and educational efforts, to assist municipal and emergency planners in identifying populations at risk during evacuation scenarios, and to identify potential or existing environmental justice concerns (Burton, 2010; Chakraborty et al., 2005; Cutter et al., 2003).

In the natural hazards literature social vulnerability indices are typically based on a definition of vulnerability that posits that social stratification and local infrastructure factors are the primary contributors to the vulnerability or resilience of a population (Chakraborty et al., 2005; Cutter, 1996; Cutter et al., 2003; Rygel, O'Sullivan, & Yarnal, 2006). The vulnerability indicators (such as age, gender, socioeconomic status, living arrangements, access to medical care, and race/ethnicity) used in construction of most social vulnerability indices are heavily based on socio-demographic information measured in census data and are generally consistent from one study to another (Azar & Rain, 2007; Cutter et al., 2003; Rygel et al., 2006). However, choice of which specific census variable to use to represent a vulnerability indicator and the number of indicators and variables used for an index varies widely, with the number of variables used ranging from less than ten to more than fifty depending on the type of analysis and the index construction method (Chakraborty et al., 2005; Cutter et al., 2003; Fekete, 2009; Krishnamurthy & Krishnamurthy, 2012; Rygel et al., 2006; Shepard et al., 2012; Wilhelmi & Morss, 2013).

One widely accepted method for creating an SVI is the SoVI® [1] analysis method, in which principal components analysis (exploratory factor analysis) is used to reduce a large number of demographic variables to a smaller subset of vulnerability factors (Cutter et al., 2003). The vulnerability factors produced in the principal components analysis are linear combinations of variables that are highly correlated with each other, while the factors themselves are orthogonal to each other. In this way, each factor can be generally described as representing a certain unique characteristic of vulnerability. This methodology was recently adopted by the United States Army Corps of Engineers (USACE) for use in water resources planning (Dunning & Durden, 2013).

1.3. Environmental justice and associated analytical challenges and advances

Related to the concept of social vulnerability to environmental hazards is the idea of environmental justice. Derived from the idea of environmental racism, which was focused on discrimination against people of color in environmental policy-making, environmental justice has been generally described as a type of distributive justice concerned in particular with the distribution of benefits and burdens among a population that is affected by decisions and actions made in relation to the environment (Cutter, 2012; Wenz, 1988). As a form of distributive justice, environmental justice analysis involves an assessment of the geographical distribution of environmental hazard burdens among the population. Therefore, it is an inherently spatial problem, and one where scalar mismatches between populations of interest and environmental hazards often hamper precise characterization of the at-risk population (Chakraborty, Maantay, & Brender, 2011; Mennis, 2003).

The analytical problems associated with coincidence analysis of hazards and populations have been well documented to show that scale does matter, particularly when examining the intersection of two or more areal units of different scales and spatial extents (Chakraborty et al., 2011; Mennis, 2003). Different interpretations of intersection or overlap of census units with hazard zones have been shown to have a large influence on the results of hazard risk analysis, leading to both overestimation and underestimation of at-risk populations, an issue referred to as the Modifiable Areal Unit Problem (MAUP) (Maantay, Maroko, & Herrmann, 2007; Mennis, 2002). In particular, the use of census data, which is heavily relied upon for social vulnerability and environmental justice studies, restricts spatial interpretation of socio-demographic data to areal units (e.g., census tracts) that may not correlate well with the spatial scale of the hazard of interest (e.g., floodplains), or with the actual boundaries of spaces in which people are located (e.g., residences).

Dasymetric mapping techniques have recently received attention as a valuable tool for environmental justice analyses as they provide a way to disaggregate socio-demographic data to a finer scale which may be more representative of the area affected by a hazard (Chakraborty et al., 2011; Maantay et al., 2007; Mennis, 2003). Dasymetric mapping is a form of areal interpolation that utilizes an ancillary dataset containing supplementary information that can be used to redistribute data to smaller areal units. Land use classification raster data sets are commonly used as an ancillary dataset for this purpose, allowing census data to be redistributed to raster grids of 30 m–100 m in edge length by attributing a population density to different land use classifications (Mennis, 2002, 2003). An alternative to land use classification rasters as a supplementary dataset is cadastral (tax parcel) data (Maantay et al., 2007; Tapp, 2010). Using cadastral data as an ancillary dataset allows population data to be redistributed to individual parcels, a spatial unit highly relevant to municipal planning.

Dasymetric mapping techniques that make use of density of development categories in land-use classification rasters as a proxy measure of population density were utilized by Mennis (2002) for analysis of environmental justice risk. In an analysis of the proximity of 'disadvantaged' populations (minorities and those living below the poverty line) to a hazardous facility, Mennis found that the percentage of the population that could be considered 'disadvantaged' peaked at a distance from the hazardous facility that is several times smaller than the length of many block groups and census tracts. Without disaggregation of the population to higher resolution sub-units, the relative increase in the percent of the population residing near hazardous facilities that are 'disadvantaged', and the environmental justice risk associated with this disproportionate population distribution, would likely not be recognizable.

Cadastral-based dasymetric mapping techniques have also been applied to analysis of environmental justice issues. Maantay and

[1] The SoVI social vulnerability index is a product of the Hazards and Vulnerability Research Institute and a registered trademark of the University of South Carolina.

Maroko (2009) investigated the distribution of populations according to racial/ethnic group in New York City in relation to flooding risk. Their analysis found that the use of standard methods for evaluating flood affected populations using census block groups underestimated the at-risk population by as much as 72% when compared with a cadastral-based dasymetric mapping technique. They also found that while minority racial/ethnic groups did not disproportionately reside in high flood risk areas, they were disproportionately undercounted using standard methods for evaluating flood affected populations, indicating that decision-making tools that lack sufficient spatial resolution may provide faulty information that leads to the underestimation of 'disadvantaged' at risk populations. Tax parcel data, while less widely available than land-use classification data and not nationally standardized, is available in most urban areas and frequently includes zoning information, property size, and living area (or number of dwelling units) (Maantay et al., 2007; Tapp, 2010). Cadastral data also often includes information such as property value and land use information (i.e., designated nursing home, single family dwelling, boarding house, etc …) that can provide insight into the makeup of the population within a parcel (Maantay & Maroko, 2009).

Both of the aforementioned environmental justice studies utilized dasymetric mapping to improve the precision of spatial distribution estimates of various populations relative to an environmental hazard, but examined only a few variables that describe 'disadvantaged' populations to assess environmental justice risk (Maantay & Maroko, 2009; Mennis, 2002). These 'disadvantaged' populations are groups that are believed to have higher degrees of social vulnerability than the population at-large, and are identified by variables that are often used in the construction of social vulnerability indices (Azar & Rain, 2007; Chakraborty et al., 2005; Cutter, 1996; Cutter et al., 2003; Rygel et al., 2006). As the concept of environmental justice commonly used today suggests that all people, regardless of socioeconomic or demographic character, should bear an equitable proportion of the burdens of both man-made and natural environmental hazards, and have equitable access to environmental benefits, and it is commonly accepted that a number of variables such as race, socioeconomic status, and cultural beliefs may interact to increase or decrease the overall extent of the vulnerability of specific sub-groups (Chakraborty et al., 2011; Cutter et al., 2003; Maantay & Maroko, 2009), a tool that provides a more comprehensive characterization of the social vulnerability of populations at high spatial resolution should prove valuable in the assessment of environmental justice risk (Padgett, 2013).

2. Methods

The methodology described herein attempts to provide high spatial resolution social vulnerability information relevant to a hazards-of-place model by combining cadastral-based dasymetric mapping techniques with selective socio-demographic variable disaggregation logic and SVI creation techniques to create a parcel level SVI. Davidson County, Tennessee, shown in Fig. 1, was used as a test-bed for development and application of the hybrid method.

Census block groups from the American Community Survey (ACS 2012 5-year estimates) were used as the original socio-demographic data to be disaggregated to the parcel level, as they are the smallest census unit for which the detailed demographic information needed for construction of social vulnerability indices is available on an annual basis (United States Census Bureau, 2012). Detailed parcel data (2013) for Davidson County, Tennessee, was used as the ancillary cadastral dataset. The parcel dataset included information at the parcel level such as property type, building type, living area, dwelling units, and assessed property value. Geoprocessing necessary for dasymetric mapping and selective demographic variable distribution, as well as mapping of social vulnerability indices, was facilitated by ESRI's ArcGIS. The statistics package SPSS Statistics 22.0 was used for principal components analysis of demographic data in order to construct social vulnerability indices at both the block group and parcel levels.

Fig. 1. Location of Davidson County, Tennessee, (36.1667° N, 86.7833° W).

Analyses necessary for construction of the parcel level SVI and evaluation of the hybrid method included:

- disaggregating total population from block groups to parcels using cadastral-based dasymetric mapping techniques,
- identifying relevant social vulnerability indicator variables in the area using principal components analysis of block group census data and creating a block group level SVI (BGSVI),
- disaggregating the identified relevant social vulnerability indicator variables from block groups to parcels using cadastral-informed selective disaggregation logic,
- conducting a principal components analysis of the parcel level social vulnerability variables and constructing a parcel level SVI (PSVI), and
- comparing the value of BGSVI and PSVI at parcels.

2.1. Population disaggregation

Cadastral dasymetric mapping techniques were adapted from the Cadastral-based Expert Dasymetric System (CEDS) developed by Maantay et al. (2007). This system ensures that the sum of the population of all parcels in a census area is equal to the total population of the census area as defined by the original census data, also referred to as the pycnophylactic property (Mennis, 2002). The system also selects which of two types of ancillary data, living area or number of dwelling units, to use for disaggregation of census data on a block group by block group basis, by determining which data type minimizes errors in aggregation of parcel populations to census tracts (Maantay et al., 2007). Although living area and/or dwelling unit values were missing for some of the parcels, these values were modified in the parcel data only where supporting information was available, implying that the accuracy of the dasymetric mapping is limited by the accuracy of the ancillary parcel data.

Unlike the original CEDS, in the adapted version, no adjustments were made to residential areas or number of dwelling units beyond the cases described below due to lack of relevant adjustment information at the parcel level in the tax data (Maantay et al., 2007). The majority of parcels with designated property type "mobile home" or "mobile home park" were missing both living area and dwelling unit values; for these cases, both dwelling unit and living area values were manually added following examination of current satellite imagery of the parcels. A few block groups contained no parcels with residential property type designations or contained no parcels with residential property type designations that also had dwelling unit or living area information. In these cases, parcels in the block group that clearly contained residential areas, such as universities with an on-campus population, or that were identified as residential by their property type designation, were assigned a proportion of the block group population relative to the parcel area. Validation of population disaggregation was carried out using the method described by Maantay et al. (2007) in which the disaggregation procedure is replicated for an alternate spatial scale, such as census tracts, and the resulting dasymetrically estimated parcel populations are aggregated back to the original scale (block groups) for comparison with census populations.

2.2. Identification of relevant social vulnerability indicators and construction of a block group level social vulnerability index

To identify demographic and physical variables relevant to social vulnerability in Davidson County, a principal components analysis was conducted on a set of 64 variables derived from ACS 2012 5-year block group estimate census data. This initial set of variables was composed of social vulnerability indicators commonly utilized in principal components construction of social vulnerability indices (Cutter et al., 2003; Kleinosky, Yarnal, & Fisher; Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008). The principal components analysis was conducted following the method generally outlined by Cutter et al. (2003). Block groups with no population values were removed from the dataset and cells with missing values were assigned a value of 0.

An iterative process involving use of different normalization schemes and elimination of variables with low commonality scores, low component loading scores, and/or low measured sampling adequacy scores was applied to reduce the number of variables used in the principal components analysis and increase the amount of variance explained by the extracted components (Cutter et al., 2003; Rygel et al., 2006; Wood, Burton, & Cutter, 2010). A composite BGSVI was created using a weighted sum method where the percent variance explained by each component was used as the weighting factor for each component (Schmidtlein et al., 2008; Wood et al., 2010). As in the SoVI® method, directionality was assigned to each component in a manner that leads to high vulnerability being represented by highly positive index scores (+if significant variables increase vulnerability, − if significant variables decrease vulnerability, or absolute value if the significant variable loadings produce mixed vulnerabilities). The z-scores of the raw BGSVI score were calculated to create a standardized index score and were mapped in ArcGIS as standard deviations.

2.3. Sub-population disaggregation

Sub-populations and physical variables relevant to social vulnerability in the area, as determined from the principal components analysis of social vulnerability indicators at the block group level, were joined with data at the parcel level based on block group identifiers (GEOID). The sub-populations were then disaggregated to residential parcels in order to create an SVI at the parcel level.

Due to lack of related ancillary information, many of the sub-populations were distributed to parcels as a proportion of the total population at the parcel equal to the ratio of the sub-population value at the block group level to the total population of the block group. Certain sub-populations (age 5 and under, age 65 and older, women, those living in group quarters) were selectively assigned to, or excluded from, certain parcels based on descriptive building type and land use information associated with each parcel (Appendix A, Table A.1). In addition, parcel information was utilized to provide parcel-level resolution for other physical and economic characteristics such as property value, residence type (i.e., mobile home, rental, or owner occupied), and access to medical care.

Disaggregation logic for sub-populations was developed to retain the pycnophylactic property whereby the sum of all parcel sub-population values in a block group is equal to the block group sub-population value. Using the disaggregation logic, an excluded property (EP) was considered a parcel where none of the sub-population is expected to be found, therefore the sub-population at that parcel was assigned a value of zero. An assigned property (AP) was considered a parcel where nearly the entire population of the parcel was expected to belong to the sub-population. In order to maintain the pycnophylactic property, the sub-population at APs was calculated as follows:

$$\begin{aligned}
&\text{If} && \sum TPop_{AP,BG} \leq SPop_{BG}, \\
&\text{then} && SPop_{AP} = TPop_{AP}. \\
&\text{Else if} && \sum TPop_{AP,BG} > SPop_{BG}, \\
&\text{then} && SPop_{AP} = TPop_{AP}\left(\frac{SPop_{BG}}{\sum TPop_{AP,BG}}\right).
\end{aligned}$$

where $SPop_{AP}$ is the designated sub-population at an assigned property, $TPop_{AP}$ is the total population at an assigned property, $SPop_{BG}$ is the sub-population value at the block group level, $TPop_{BG}$ is the total population value at the block group level, and $TPop_{AP,BG}$ is the total population of an assigned property in a specified block group. Similarly, the sub-population at all properties that are not EPs or APs was calculated as:

$$SPop_{Parcel} = TPop_{Parcel}\left(\frac{SPop_{BG} - \sum SPop_{AP,BG}}{TPop_{BG} - \sum TPop_{EP,BG} - \sum TPop_{AP,BG}}\right)$$

where $SPop_{Parcel}$ is the sub-population at a parcel which is not an excluded or assigned property, $TPop_{Parcel}$ is the total population at a parcel which is not an excluded or assigned property, $SPop_{AP,BG}$ is the sub-population at an assigned property in a specified block group, and $TPop_{EP,BG}$ is the total population at an excluded property in a specified block group. Here, the numerator represents the sub-population that is available for distribution to parcels that are not EPs or APs, and the denominator represents the total population in a block group among which the remainder of the sub-population may be proportionally distributed.

2.4. Construction of a tax parcel level social vulnerability index and comparison to the block group level social vulnerability index

Following sub-population disaggregation of all social vulnerability indicator variables identified as relevant in the principal components analysis of census data at the block group level, a principal components analysis of the parcel dataset was conducted using the same methodology as described in Section 2.2. The variables used in the parcel level principal components analysis were normalized as described in Table A.3 (this normalization means that values for variables for which selective assignment logic was not used are the same for each parcel in the block group). The resulting PSVI scores were also standardized using z-scores and mapped in ArcGIS as standard deviations. In order to compare the distribution and impact of the BGSVI and PSVI, dasymetrically estimated parcel total population, BGSVI values, and PSVI values were joined to parcels by parcel and block group identifier. Numbers of slightly vulnerable (index score greater than 0.5), moderately vulnerable (index score greater than 1), and highly vulnerable (index score greater than 2) parcels, as well as the expected total population at these parcels, were extracted for comparison.

3. Results

3.1. Cadastral-based dasymetric mapping

Produced dasymetric maps of Davidson County total population were tested for disaggregation errors by aggregating parcel populations to the block group level. Comparison of aggregated values to block group populations from census data confirmed that the pycnophylactic property was retained, indicating that any errors in disaggregation are confined within block groups. While direct validation of data disaggregated from block groups to parcels is generally not feasible, disaggregation from census tracts to block groups was found to be accurate within 13 percent (based on the sum of the absolute differences between dasymetrically assigned census tract populations and block group level census populations) (Maantay et al., 2007).

3.2. Principle components analyses

The principal components analysis of 64 block group census variables at the block group level produced a reduced dataset of 37 variables (Appendix A, Table A.2) and yielded 10 components with eigenvalues greater than 1.0 that explain 71 percent of the variance. Based on the loading of the variables, these components can be generally described as representing: 1. Race/Class (14%), 2. Economic Status (12%), 3. Foreign Born (9%), 4. Elderly (8%), 5. Women (7%), 6. Group Living (6%), 7. Families (5%), 8. Housing Quality (4%), 9. Hospice Care (3%), and 10. Rural (3%).

The principal components analysis of the social vulnerability indicator variables distributed to parcels reduced the number of relevant variables from 37 to 30 (Appendix A, Table A.3) and yielded nine components with eigenvalues greater than 1.0 that describe 66 percent of the variance. These nine components are similar in composition to the components extracted from the block group data analysis and generally represent: 1. Economic Status (11%), 2. Foreign Born (10%), 3. Race/Class (10%), 4. Elderly (8%), 5. Women (8%), 6. Families (7%), 7. Group Living (5%), 8. Renters/Population Density (4%), and 9. Mobile Homes (3%). In this case, the Rural component from the block group level analysis drops out as the variability in population density within an analysis unit that is captured by this component is already fully explained by the Renters/Population Density component, the Housing Quality component from the block group level analysis which included both low value housing and mobile homes is relabeled as Mobile Homes as the number of mobile homes is the only variable that significantly contributes to this component, and the Hospice Care component drops out as the significant variables in this component are incorporated into the Group Living, Race/Class, and Renters/Population Density components. Each component, with the exception of Foreign Born, includes at least one selectively assigned variable with a significant loading. The standardized BGSVI and PSVI scores for central Davidson County are shown in Fig. 2.

3.3. Comparison of BGSVI and PSVI

When BGSVI are applied to parcels, it was observed that fewer occupied parcels in the county are considered vulnerable than when the PSVI is used (Table 1). The difference between parcel vulnerabilities using the BGSVI and PSVI in terms of a percent of all parcels in the county is misleadingly small. Using the BGSVI, approximately 2% of all parcels in Davidson County are classified as highly vulnerable. This percentage increases to only 3% when the PSVI is used to identify highly vulnerable parcels. However, as the degree of vulnerability (as indicated by the index score) increases, the proportional difference between the numbers of parcels identified using BGSVI and PSVI increases, with the PSVI ultimately identifying nearly twice as many highly vulnerable parcels than the BGSVI.

Of greater note are the population trends associated with parcels classified as vulnerable (see Table 1 for details). While an estimated 3% of the total population in Davidson County is expected to reside in parcels that the BGSVI identifies as highly vulnerable, more than 22% of the total population is expected to reside in parcels that the PSVI identifies as highly vulnerable. As with the proportional differences between numbers of parcels, the proportional difference between estimated population numbers using the BGSVI and PSVI increases with increasing index score. The proportional difference between estimated resident populations in parcels identified as slightly vulnerable to highly vulnerable using the BGSVI and PSVI increases from a factor of approximately 1.7 times for slightly vulnerable parcels to 7.5 times for highly vulnerable parcels.

As the PSVI is derived primarily from block group level information and disaggregated block group information, the two indices are expected to be highly consistent. That is, it is expected that most parcels that are identified as vulnerable using the BGSVI will also be identified as vulnerable using the PSVI. The Pearson's correlation coefficient for BGSVI and PSVI is 0.906 (significant at the 0.01 level for a 2-tailed test), indicating that the two indices are highly correlated, and thus consistent.

The co-occurrence of slightly vulnerable, moderately vulnerable, and highly vulnerable parcel identifications using both PSVI and BGSVI was also examined (see Table 2 for details); the differences between the two indices increases with increasing index score. All but 7% of parcels that are identified as at least slightly vulnerable using the BGSVI were also identified as at least slightly vulnerable using the PSVI (i.e., 7% of parcels with a BGSVI of 0.5 or more have a PSVI less than 0.5). This percentage of failure of vulnerability identifications to co-occur increases to 36% for parcels identified as highly vulnerable using the BGSVI. However, much of this variance between the BGSVI and PSVI can be attributed to the establishment of analytical cutoff points for differing severities/levels of vulnerability identifications. Nearly all parcels identified as moderately or highly vulnerable using the BGSVI have a PSVI vulnerability identification that is one level removed or less (i.e., more than 99% of parcels with BGSVI of at least 2 have a PSVI of at least 1 and more than 99% of parcels with a BGSVI of at least 1 have a PSVI of at least 0.5). An example of parcels with consistent vulnerability identifiers using PSVI and BGSVI is shown in Fig. 3.

The percent of PSVI identified vulnerable parcels that are also BGSVI identified vulnerable parcels is less than the previously described reverse relationship, as the BGSVI identifies a smaller number of vulnerable parcels overall, but the trend is the same, with co-occurrence decreasing with increasing index score. However, while nearly all BGSVI vulnerable parcels had a PSVI within 1

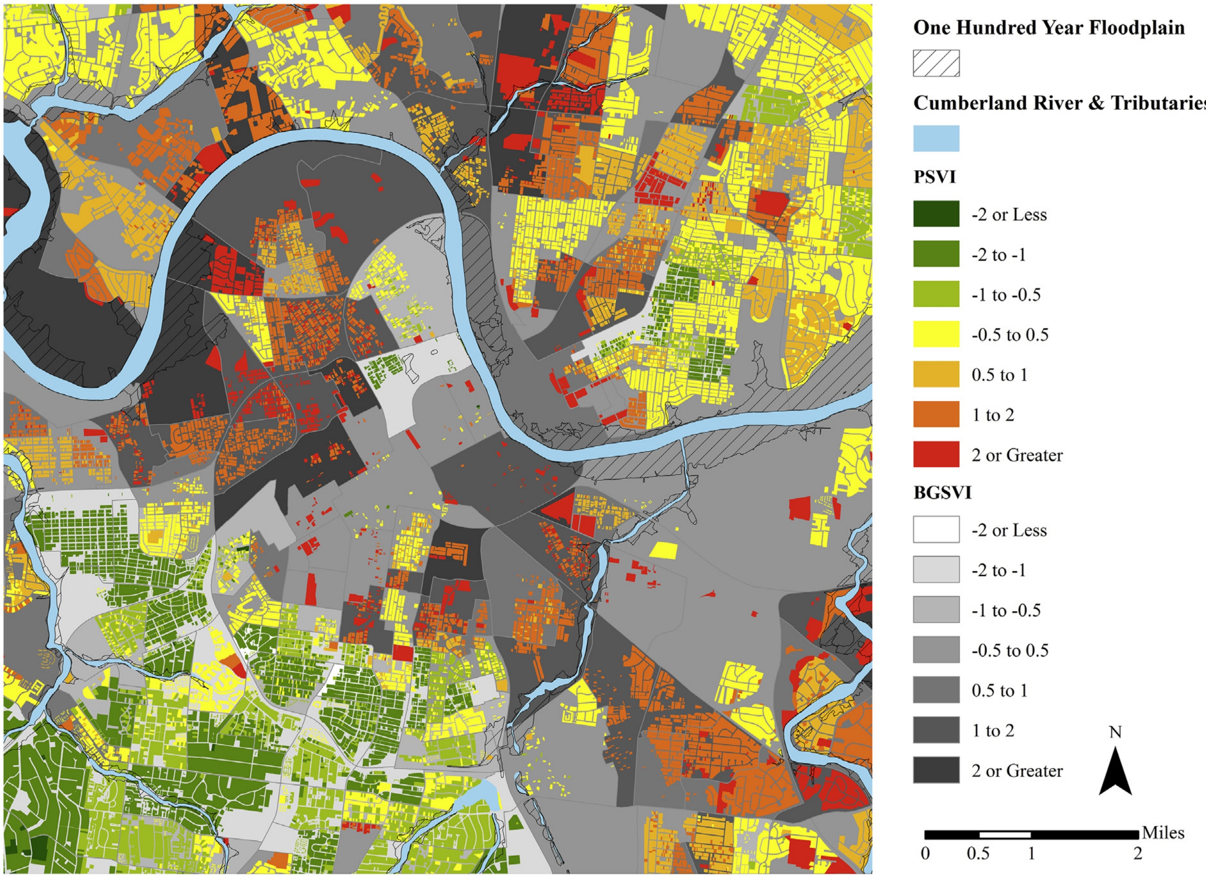

Fig. 2. PSVI and BGSVI for the Nashville area illustrating the non-homogeneity of the spatial distribution of social vulnerability among resident parcels across census block groups, and the spatial discontinuity between census units and an environmental hazard, the 100 year floodplain.

Table 1
BGSVI and PSVI comparison for Davidson county.

Vulnerability based on index score	Number of parcels		Percent of all parcels in county		Proportional difference in parcel count (PSVI/BGSVI)	Estimated resident population		Percent of total population in county		Proportional difference in estimated population (PSVI/BGSVI)
	BGSVI	PSVI	BGSVI	PSVI		BGSVI	PSVI	BGSVI	PSVI	
Slightly vulnerable (Index score > 0.5)	40,665	52,574	22	29	1.3	176,567	297,785	28	47	1.7
Moderately vulnerable (Index score > 1)	18,905	30,026	10	16	1.6	91,863	234,190	15	37	2.5
Highly vulnerable (Index score > 2)	3075	5863	2	3	1.9	18,754	141,250	3	22	7.5

level of the BGSVI, the reverse does not hold true. While 100% of parcels identified as highly vulnerable using the BGSVI were identified as at least moderately vulnerable using the PSVI, only 94% of the parcels that the PSVI identifies as highly vulnerable are also identified as at least moderately vulnerable using the BGSVI. In fact, more than 2% of parcels identified as highly vulnerable using the PSVI are identified as not vulnerable using the BGSVI (see Fig. 4 for an example), indicating that boundary conditions in the vulnerability scale are only part of the picture, and suggesting that the PSVI incorporates additional vulnerability attributes that are sensitive to parcel level spatial resolution and thus not considered using the BGSVI.

Table 2
Co-occurrence of BGSVI and PSVI vulnerability identifications at the parcel level.

Vulnerability based on index score	Number of parcels	Percent of all parcels in county	Percent of BGSVI parcels with same level PSVI	Percent of BGSVI parcels with PSVI within 1 level	Percent of PSVI parcels with same level BGSVI	Percent of PSVI parcels with BGSVI within 1 level
Slightly vulnerable (Index score > 0.5)	37,754	21	93	–	74	–
Moderately vulnerable (Index score > 1)	17,004	9	90	99	59	96
Highly vulnerable (Index score > 2)	1956	1	64	100	36	94

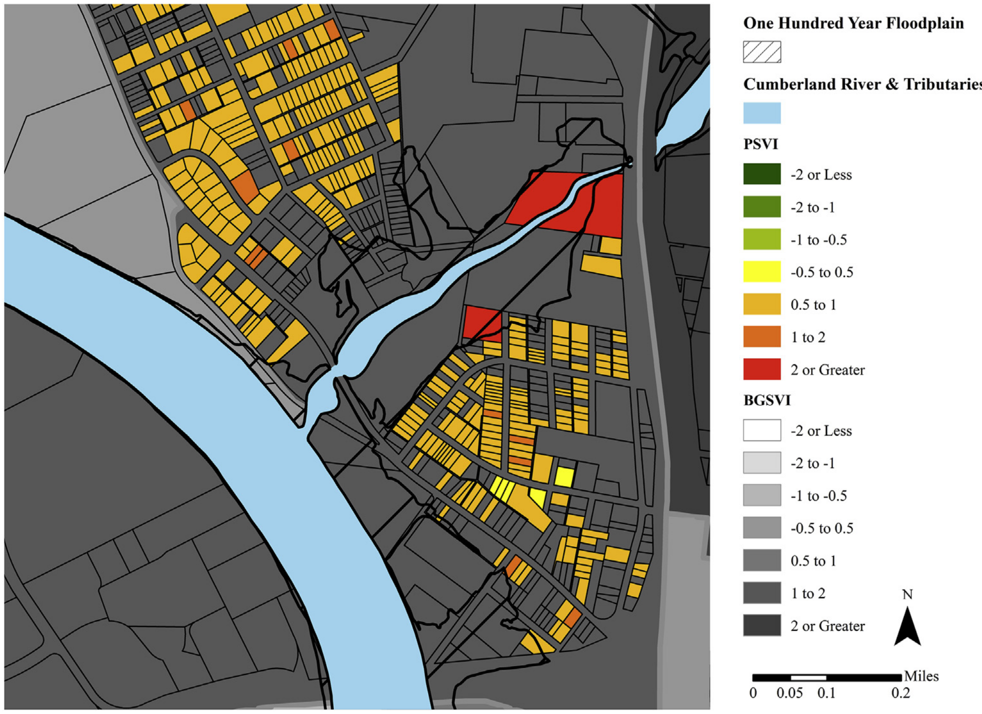

Fig. 3. PSVI and BGSVI along the Cumberland River where PSVI and BGSVI vulnerability identifications are consistent. Highly vulnerable parcels (red) are a mobile home park and a nursing home, while moderately vulnerable parcels (dark orange) are primarily duplexes (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

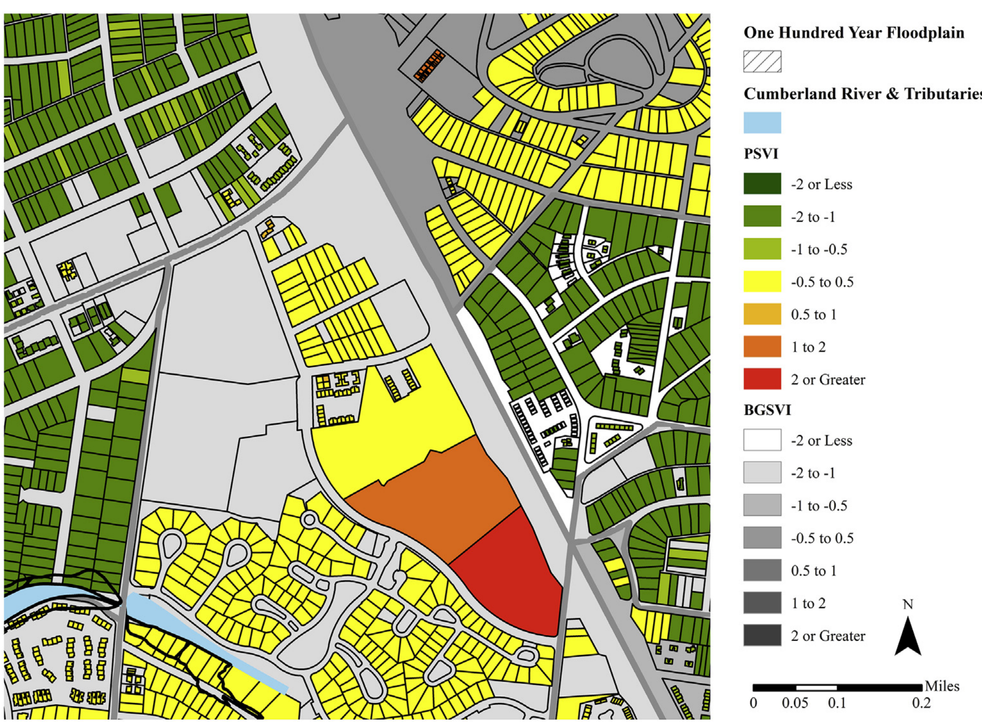

Fig. 4. PSVI and BGSVI in central Nashville where discrepancies are seen between the vulnerability identifications of PSVI and BGSVI. The three large parcels located in the lower-middle area of the image illustrate progressing levels of vulnerability from not vulnerable to highly vulnerable as the parcel residence type changes from owner occupied condominiums to renter occupied apartments to elderly housing.

This conclusion that discrepancies between the PSVI and BGSVI occur due to spatial sensitivity of certain vulnerability attributes is corroborated by examination of the parcel descriptions and associated social vulnerability indicator variables. All of the parcels identified as highly vulnerable using the PSVI and not vulnerable using the BGSVI are residences that are classified as apartments, mobile homes, or some form of group-living quarters, such as boarding houses or nursing homes. These residence classifications are contained within parcel descriptions and were all used in the selective distribution of social indicator variables. In comparison, only 25% of parcels that are identified as highly vulnerable using the PSVI and at least slightly vulnerable using the BGSVI have these same residence classifications.

Comparison of selectively distributed social vulnerability indicator variable values for parcels with discrepancies between PSVI and BGSVI, and parcels for which PSVI and BGSVI are consistent in identifying vulnerability, shows that total population, renter population, group quarters population, senior population, and the numbers of mobile homes are all significantly elevated for parcels with discrepant PSVI and BGSVI. Estimated senior populations at discrepant parcels are about 1.5 times higher than at consistent parcels, estimated group quarter populations are 4 times higher, the number of mobile homes is 15 times higher, estimated total population is more than 20 times higher, and estimated renter populations are more than 25 times higher.

This comparison of selectively distributed variables indicates that the PSVI is sensitive to parcel level population and to the heterogenous spatial distribution of different types of living arrangements and their associated resident populations. Such sensitivity may prove most useful for urban areas; particularly for areas with mixed residential types, where block group level analyses tend to dilute the effects of non-conformity to the mean within each block group.

4. Discussion

Application of the hybrid method to the Davidson County, Tennessee, test-bed found that a PSVI is consistent with a BGSVI constructed using standard principal components analysis methodology (Cutter et al., 2003). However, the high resolution PSVI is also sensitive to parcel level population and to residence type. These added sensitivities make the PSVI most useful for urban areas with mixed residential classifications and a high degree of local heterogeneity (Chakraborty et al., 2011; Maantay et al., 2007; Maantay & Maroko, 2009). As the PSVI is produced at a spatial scale that is, on average for the case study area, 80 times smaller than block groups, when overlaid with maps displaying exposure to environmental hazards, the PSVI can help to more precisely identify regions where biophysical and social vulnerabilities overlap, creating potential for environmental injustice to occur (Chakraborty et al., 2011; Maantay & Maroko, 2009; Mennis, 2003).

While the motivation of the study was based on issues related to flooding in the case study area, the hybrid method described in this work should be more broadly applicable to various hazards-of-place (Cutter, 1996; Cutter et al., 2003; Tate, Cutter, & Berry, 2010). By focusing the social vulnerability index construction on socially constructed vulnerabilities and basic infrastructural resources the constructed parcel index may be overlaid with any number of biophysical vulnerability indices or environmental hazard exposure scenarios (for examples see Fig. 5). These environmental hazard exposures could include: flooding, toxic substance releases, particulate matter emissions, and proximity to rail lines, heavy use freight corridors, or natural gas pipelines; and

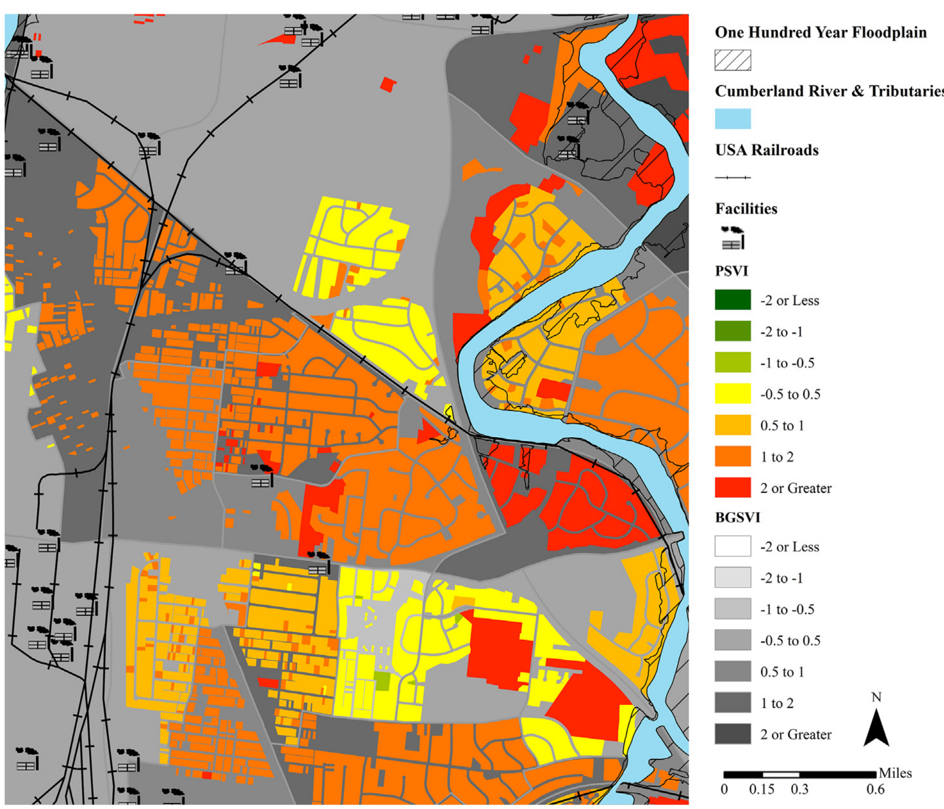

Fig. 5. Example of the PSVI and BGSVI overlaid with various environmental hazard exposure sources including railroads, U.S. EPA regulated facilities, and the 100 year floodplain.

together with the PSVI could be used to address environmental justice issues related to disparities in exposures to: asthma inducing emissions, pipeline ruptures and explosions, noise pollution, and flood inundation across vulnerable and non-vulnerable populations (Chakraborty et al. 2011; Maantay, 2007; Maantay et al., 2007; Maantay & Maroko, 2009). The general methodology used is also applicable to any metropolitan area in the United States for which census data and parcel information is available (Tapp, 2010). While specific social vulnerability indicators relevant to different municipal areas may differ, and specific selective disaggregation information on parcels may vary, the selective disaggregation logic structure may be adapted to fit the municipality of interest.

It should be noted that despite the high spatial resolution provided, this methodology is not intended to be used to evaluate the vulnerability of individuals. The social vulnerability indices described are composed primarily of aggregated data that represent different indicators of vulnerability within our social structure (Cutter, 1996; Cutter et al., 2003). As such, they are inherently descriptors of populations rather than of individuals. Even when demographic information is interpolated to smaller areal units, the base composition is aggregated data; individual choices and agency are not represented in the index and hence the index cannot accurately describe individuals' vulnerability (Cutter, 1996). Nor is this methodology immune to errors in assignment of vulnerability scores as the selective disaggregation logic makes use of generalized assumptions about sub-population locations and the influence of distributed vulnerability indicators, which may or may not hold true in all cases. Additionally, while areal interpolation is a powerful tool, validation at this scale is difficult, and all disaggregated population data should be utilized as estimates (Maantay et al., 2007).

Instead, this methodology should be viewed from a municipal planner's perspective as a tool that can provide information about the relative likelihood that the population residing at a particular parcel is more or less socially vulnerable than the average parcel population, and the respective level of social vulnerability that can be expected for residents of that parcel. This information may serve as supplementary justice-oriented information that can help planners locate areas where residents may lack the means to cope with and recover from the physical, emotional, and economic burdens associated with environmental hazards.

5. Conclusions

In this work we have adopted two well established methods for social vulnerability indexing and dasymetric mapping, and used supplementary data and basic logic functions as a bridge between them to create a hybrid methodology. To our knowledge this work is the first to propose a method for construction of a parcel level SVI. The produced high resolution SVI illustrates localized heterogeneity in social vulnerability and may be used for planning at the municipal level to address environmental justice issues resulting from non-equitable distribution of environmental hazard burdens among local populations.

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APPENDIX A

Table A.1
Selectively Distributed Variables

	Variable	Excluded properties	Assigned properties
Disaggregated sub-population	Age 5 and under	Nursing home, Elderly housing, Jail, Women's Jail, Dormitory/Boarding house, School or College, Sanitarium	N/A
	Age 65 and over	Dormitory/Boarding house (if not also elderly housing), School or College	Nursing homes, Elderly housing
	Age 65 and over in group quarters	Dormitory/Boarding house (if not also Elderly Housing), School or College	Nursing homes
	Women	Jail	Women's Jail
	Employed women	Jail	Women's Jail
	Population in group quarters	N/A	Nursing home, Dormitory/Boarding house, School or College, Orphanage/Charitable Service (unless also Single Family Dwelling), Sanitarium, Jail, Women's Jail
Parcel-specific economic or physical characteristic	Rental/Semi-permanent housing	All others	Duplex(s), Triplex(s), Quadplex(s), Nursing Home, Parsonage, Orphanage/Charitable Service, Dormitory/Boarding House, Apartment
	Owner occupied housing with value greater than $200,000	All others	Single Family Dwelling, Residential Condominium Unit, Residential Zero Lot Line, Mobile Home, Residential Combination, Mobile Home Park, Rural Combination where the total appraisal value was greater than $200,000
	Mobile homes	All others	Mobile Home, Mobile Home Park
	Rural	All others	Single Family Dwelling, Mobile Home, Duplex, Triplex, Combination where also designated as Rural
	Number of hospitals within 3 mile radius	N/A	All parcels within a 3 mile radius of a Davidson County hospital or medical clinic.
	Property total appraisal value	N/A	All properties

Table A.2
Block Group Social Vulnerability Index (BGSVI) Variables

Social dimension	Variable type	ACS 2012 5 yr block-group estimates variable/s short name	Variable normalization	Component variable loads on significantly
Age	Median age	B01002e1	None	Elderly
	Age under 5 years	B01001e3 + B01001e27	Total Population (B01003e1)	Families
	Age over 65 years	B09020e1	Total Population (B01003e1)	Elderly
Gender	Female	B01001e26	Total Population (B01003e1)	Women
	Female civilian employed, Age 16 and up	C24010e38	Total Civilian Employed, Age 16 and Up (C24010e1)	Women
Race/Ethnicity	African American alone	B02001e3	Total Population (B01003e1)	Race/Class
	Some other race/races	B02001e4+B02001e5+ B02001e6 + B02001e7+ B02001e8	Total Population (B01003e1)	Foreign Born
	Hispanic or Latino	B03003e3	Total Population (B01003e1)	Foreign Born
Employment	Unemployed in labor force, Age 16 and up	B23025e5	Total Civilian Labor Force (B23025e2)	Race/Class
	Participating Civilian labor force, Age 16 and up	B23025e2	Total Population, Age 16 and Up (B23025e1)	Institutional and Group Living
Occupation	Service workers	C24010e19 + C24010e55	Total Civilian Labor Force (C24010e1)	Race/Class
	Natural resources, Construction, Maintenance workers	C24010e30 + C24010e66	Total Civilian Labor Force (C24010e1)	Foreign Born
	Production, Transportation, Material moving workers	C24010e34 + C24010e70	Total Civilian Labor Force (C24010e1)	Economic Status & Housing Quality
Medical services	Healthcare workers	C24010e16 + C24010e20 + C240101e52 + C240101e56	Total Population (B01003e1)	Institutional and Group Living
	Number of hospitals	Not Available (Use Tax Info)	Total Population (B01003e1)	Hospice Care
Family structure	Population in occupied housing units	B25008e1	Total Occupied Housing Units (B25007e1)	Families
	Female householder, No husband present	B09002e15	Total Households with Children (B09002e1)	Race/Class
Housing quality	Number of mobile homes		Total Housing Units (B25001e1)	Housing Quality
Renters	Renter-occupied housing units	B25056e1	Total Occupied Housing Units (B25007e1)	Race/Class
	Median gross rent	B25064e1	None	Institutional and Group Living
Education	Over Age 25 with No High School Diploma	B15003e16	Population Over Age 25 (B15003e1)	Foreign Born & Rural
Special needs	Over Age 65 in Group Quarters	B09020e21	Population Over Age 65 (B09020e1)	Hospice Care
	With a disability, Age 16–64	C23023e3 + C23023e14	Population Age 16–64 (C23023e1)	Women
	Population in Group Quarters	B09019e38	Total Population (B01003e1)	Institutional and Group Living
Social dependence	Households with social security income	B19055e2	Total Households (B16002e1)	Elderly
	Households receiving food stamps/SNAP in past 12 Months	B22010e2	Total Households (B16002e1)	Race/Class
Immigrants	Households where no one Age 14 or older speaks English only or English “Very Well”	B16002e4 + B16002e7 + B16002e10 + B16002e13	Total Households (B16002e1)	Foreign Born
Wealth and Income	Per Capita Income (2012 Adjusted $)	B19301e1	None	Economic Status
	Household income > $100,000	B19001e14 + B19001e15 + B19001e16 + B19001e17	Total Households (B16002e1)	Economic Status
	Population below poverty level in the past 12 months	B17021e2	Total Population (B01003e1)	Race/Class
	Median home value	B25077e1	None	Economic Status
	Owner occupied housing units with value < $100,000	B25075e2 + B25075e3 +B25075e4+B25075e5+B25075e6+ B25075e7+ B25075e8 +B25075e9+ B25075e10 + B25075e11 + B25075e12 + B25075e13 + B25075e14	Total Owner Occupied Housing Units (B25075e1)	Housing Quality
	Owner occupied housing units with value $100,000–$200,000	B25075e15 + B25075e16 + B25075e17 + B25075e18	Total Owner Occupied Housing Units (B25075e1)	Economic Status
	Owner occupied housing units with value > $200,000	B25075e19 + B25075e20 + B25075e21 + B25075e22 + B25075e23 + B25075e24 + B25075e25	Total Owner Occupied Housing Units (B25075e1)	Economic Status
Transportation	Population using public transportation to get to work, Age 16 and over	B08134e61	Total Worker Population (B08134e1)	Race/Class
	Occupied housing units with No vehicle available	B25044e3 + B25044e10	Total Occupied Housing Units (B25007e1)	Race/Class
Rural	Land in farms/Rural use	Not available (Use Tax Info)	Total Population (B01003e1)	Rural

Table A.3
Parcel Social Vulnerability Index (PSVI) Variables

Social dimension	Variable type	ACS 2012 5 yr block-group estimates Variable/s Short name	Variable normalization	Component variable contributes to significantly
Age	Age under 5 years	B01001e3 + B01001e27	Total Population per Parcel	Families
	Age over 65 years	B09020e1	Total Population per Parcel	Elderly
Gender	Female	B01001e26	Total Population per Parcel	Women
	Female Civilian Employed, Age 16 and Up	C24010e38	Total Civilian Employed, Age 16 and Up per Parcel	Women
Race/Ethnicity	African American alone	B02001e3	Total Population (B01003e1)	Race/Class
	Some other race/races	B02001e4+B02001e5+ B02001e6 + B02001e7+ B02001e8	Total Population (B01003e1)	Foreign Born
	Hispanic or Latino	B03003e3	Total Population (B01003e1)	Foreign Born
Employment	Unemployed in labor force, Age 16 and up	B23025e5	Total Civilian Labor Force (B23025e2)	Families
	Participating Civilian labor force, Age 16 and up	B23025e2	Total Population, Age 16 and Up (B23025e1)	Elderly
Occupation	Service workers	C24010e19 + C24010e55	Total Civilian Labor Force (C24010e1)	Race/Class
	Natural resources, Construction, Maintenance workers	C24010e30 + C24010e66	Total Civilian Labor Force (C24010e1)	Foreign Born
	Production, Transportation, Material moving workers	C24010e34 + C24010e70	Total Civilian Labor Force (C24010e1)	Economic Status
Medical services	Healthcare workers	C24010e16 + C24010e20 + C240101e52 + C240101e56	Total Population (B01003e1)	Economic Status
	Number of hospitals in 3 mile radius of parcel	Davidson County Tax Info	None	Race/Class
Family structure	Population per tax lot/household	B01003e1	Tax Lot Footprint Area	Renters/Population Density
	Female householder, No husband present	B09002e15	Total Households with Children (B09002e1)	Race/Class
Housing quality	Number of mobile homes per parcel	Tax Info	None	Mobile Homes
Renters	Population in renter-occupied PARCELS	Tax Info	None	Renters/Population Density
Special needs	Over age 65 in Group Quarters	B09020e21	Population Over Age 65 per parcel	Institutional and Group Living
	With a disability, Age 16–64	C23023e3 + C23023e14	Population Age 16–64 (C23023e1)	Women
	Population in Group Quarters	B09019e38	Total Population per Parcel	Institutional and Group Living
Social dependence	Households with Social Security Income	B19055e2	Total Households (B16002e1)	Elderly
	Households receiving food stamps/SNAP in past 12 months	B22010e2	Total Households (B16002e1)	Race/Class
Immigrants	Households where no one Age 14 or older speaks English only or English "Very Well"	B16002e4 + B16002e7 + B16002e10 + B16002e13	Total Households (B16002e1)	Foreign Born
Wealth and income	Household income > $100,000	B19001e14 + B19001e15 + B19001e16 + B19001e17	Total Households (B16002e1)	Economic Status
	Population below Poverty level in the past 12 months	B17021e2	Total Population (B01003e1)	Race/Class
	Parcel value	Davidson County Tax Info	Total population per parcel	Economic Status
	Owner occupied housing with value > $200,000	Davidson County Tax Info	None	Economic Status
Transportation	Population using public transportation to get to work, Age 16 and Over	B08134e61	Total Worker Population (B08134e1)	Race/Class
	Occupied housing units with No vehicle Available	B25044e3 + B25044e10	Total Occupied Housing Units (B25007e1)	Race/Class

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