Chapter 5
Using Geographic Information Science to Estimate Vulnerable Urban Populations for Flood Hazard and Risk Assessment in New York City

Juliana Maantay, Andrew Maroko, and Gretchen Culp

Abstract The research presented in this chapter seeks to demonstrate a new method to more accurately estimate populations vulnerable to hazards, especially in densely developed mega-cities, and to characterize at-risk populations based on measures of social, physical, and health vulnerability. Emergency management and disaster preparation, planning, mitigation, and recovery requires accurate estimation of potentially at-risk populations and sub-populations. Census data alone, however, cannot provide sufficiently detailed knowledge of population location and distribution, particularly in large, hyper-heterogeneous urban areas like New York City. Additionally, specific sub-populations (i.e., racial/ethnic minorities) may be at higher risk, yet under-counted by existing methods of calculating potentially exposed or impacted populations. We discuss two new inter-related methods that employ Geographic Information Science (GISc) to assess and quantify risk and vulnerability: the Cadastral-based Expert Dasymetric System (CEDS) and the New York City Hazard Vulnerability Index (NYCHVI). CEDS uses an expert system and dasymetric mapping to disaggregate population and sub-population data to the property tax lot level. The analysis shows that compared to CEDS, conventional areal weighting of census data and centroid-containment selection methods under count at-risk population for floods by 37 and 72%, respectively. We found that minorities and other vulnerable sub-populations are disproportionately underestimated using traditional methods, which impairs preparedness and relief efforts. NYCHVI provides a straightforward way of assigning a vulnerability rating to populations in potentially impacted areas, and incorporates locally significant factors that are not captured using national models. Used in tandem, CEDS and NYCHVI are effective in characterizing the vulnerable populations and areas subject to flooding and other hazards, enabling significant improvements in estimating vulnerability over prevailing methods.

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P.S. Showalter, Y. Lu (eds.), *Geospatial Techniques in Urban Hazard and Disaster Analysis*, Geotechnologies and the Environment 2, DOI 10.1007/978-90-481-2238-7_5,

Keywords Flood hazard · Dasymetric mapping · CEDS · Vulnerability · Cadastral · NYCHVI · HVA

5.1 Flood Hazard and Vulnerable Populations in New York City

Emergency management and disaster preparation, planning, mitigation, and recovery require accurate estimation of potentially at-risk populations and sub-populations, yet census data alone do not necessarily yield sufficiently detailed knowledge of population location and distribution, particularly in large, hyper-heterogeneous urban areas like New York City (NYC). Additionally, specific sub-populations (i.e., racial/ethnic minorities) may be at higher risk (Blaikie et al. 1994; Cutter 2006; Fielding and Burningham 2005; Fothergill et al. 1999; Mitchell 1999), yet minority sub-populations remain under-counted by existing methods of calculating potentially exposed or impacted populations. New York City, most of which is at or only slightly above sea-level, is at risk from flooding due to storm surge from hurricanes, "nor'easters," and the effects of sea-level rise from global warming, as well as from other natural and technological disasters (Bloomfield et al. 1999; Coch 1994; Gornitz et al. 2002).

This chapter demonstrates the benefits of developing new geomatic methods to more accurately estimate populations vulnerable to hazards, especially in densely developed mega-cities, and to characterize the at-risk populations based on measures of social, physical, and health vulnerability. Geomatics (geospatial technologies) is the discipline of gathering, storing, processing, and delivering of geographic information, or spatially referenced information, and it encompasses the tools and techniques used in land surveying, remote sensing, geographic information systems (GIS), photogrammetry, geodesy, global navigation satellite systems, and related forms of earth mapping. We introduce two new geomatic methods that employ Geographic Information Science (GISc) and models loosely-coupled with the GIS. These two methods, the Cadastral-based Expert Dasymetric System (CEDS) and the New York City Hazard Vulnerability Index (NYCHVI), represent inter-related ways to assess and quantify risk and vulnerability.

5.1.1 FEMA 100-Year Floodplain

Flooding has been, and continues to be, a concern not only in the New York City region, but across the country. Nationally, according to the United States Geological Survey, floods annually average 140 deaths and $6 billion in property damage.

A common way to delineate the extent of the flood hazard is with what is termed the "100-year floodplain." This designation represents areas with a 1-percent-annual-chance for flooding and was created as a standardized measure among federal, state, and local agencies involved with floodplain management. The Federal Emergency Management Agency (FEMA) estimates that nearly 150,000 square miles of the United States (over 4% of the total area) are within the 100-year

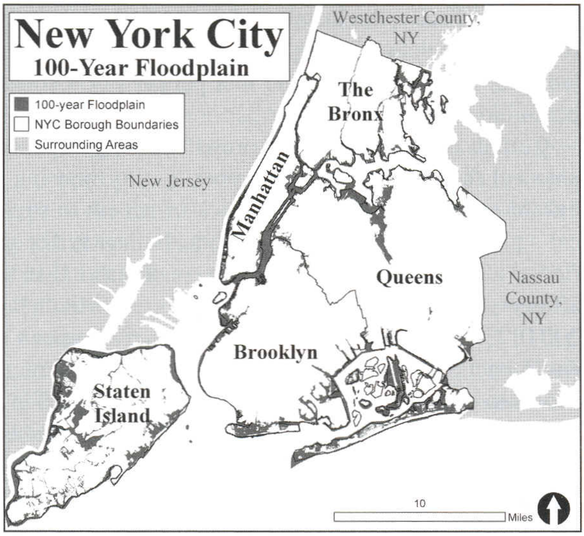

Fig. 5.1 FEMA Q3 100-year floodplain in New York City Source: FEMA 1996

floodplain (FEMA 1983). Approximately 15% of NYC's land area is within this floodplain. As one of the nation's most densely populated metropolitan regions susceptible to flood hazards, the City would be particularly difficult to evacuate because it is a city of islands surrounded by water – oceans, rivers, tidal straits, estuaries, and bays – with nearly 600 miles of coastline and numerous inland waterbodies (Bloomfield et al. 1999; Fig. 5.1).

Given the high density of NYC's built environment, encompassing both residential and commercial development, there is enormous potential for damage to life and property from flooding. New York City experiences frequent and destructive "nor'easters", and the occasional hurricane, and the storms' strength and potential for devastation are magnified by the unique configuration of Long Island's land mass in relation to the mainland – it sits at nearly a 90-degree angle to the eastern seaboard of the US. Hurricane experts state that even a Category 3 hurricane here could have devastating consequences (Coch 1994).

Further exacerbating the situation, it is predicted that global warming and accelerated sea level rise could greatly increase flood risk. Gornitz (2000) claims that the "...vulnerability of the Metropolitan East Coast Region to coastal hazards, such as more frequent storm flooding, beach erosion, submergence of coastal wetlands, and saltwater intrusion, will intensify as sea level rises" (p. 45) and that due to accelerated sea level rise "...the return period of the 100-year storm flood could be reduced to 19–68 years, on average, by the 2050s, and 4–60 years by the 2080s" (p. 61).

5.1.2 Vulnerable Populations

It is of particular importance in risk assessment of floods and other natural and technological disasters to determine what portion of the population is vulnerable, and more specifically, the location of these potentially vulnerable populations. Vulnerability may be defined using several criteria, each of which serves as a "vulnerability indicator" that can contribute to a person's or a community's overall vulnerability potential.

Certain people may be disproportionately exposed to hazards not only due to physical factors (i.e., living in poor quality housing that inadequately withstands hazard events), but also due to lack of access to strong social, financial, or political support structures. Such individuals thus suffer greater relative loss and experience a longer recovery time after a disaster than those populations considered affluent, mainstream, or socially supported (Mitchell 1999; Marandola and Hogan 2007). Consequently, identical physical phenomena can have dramatically different impacts on those who are socially and economically vulnerable, and/or whose access to a social support structure is limited (Blaikie et al. 1994).

Previous research in the United States has demonstrated increased disaster risk and vulnerability for communities of color (Fothergill et al. 1999). Additional factors, such as an individual's health status, can also result in increased vulnerability. People with reduced mobility, or who suffer from conditions such as heart disease, emphysema, asthma, AIDS, or cancer, as well as those who are blind or deaf tend to be more vulnerable and at increased risk from flooding (Kilbourne 1997; Sanderson 1997; Etzel and French 1997). Young children and the elderly are also considered to be more vulnerable than other age cohorts (Noji 1997).

Negri et al. (2005) note that by,

> analyzing census data with GIS tools, we can identify specific areas where people are at risk for floods and landslides. Some factors further increase social vulnerability, such as limited access to political power and representation, lack of access to resources (including information and technology), lack of social capital (like social networks), and poor health. Beliefs and customs, and the age, type, and density of infrastructure, buildings, and lifelines are also factors that affect risk and potential losses (p. 1245)

Different populations represent differing demographics, socio-economic characteristics, and health conditions for those at risk from floods, and therefore may require different strategies and approaches to disaster preparedness, emergency response, and disaster relief. In order to design appropriate warning communications, mitigation, and recovery planning efforts for implementation prior to or in the aftermath of a flood, it is not only necessary to determine the size and location of potentially affected populations, but also to know exactly which members of those populations are most vulnerable to a major natural disaster.

5.2 GeoTechnical Contributions to Flood Hazard Assessment: CEDS and NYCHVI

Geographic Information Science is a discipline which employs geomatic technologies such as Geographic Information Systems (GIS), remote sensing, Global Positioning Systems (GPS), geo-statistical analysis, and environmental modeling, to examine research issues. The technologies are used to assemble, create, store, display, analyze, edit, and map spatial and attribute data. GIS can convert "real world" information into constituent elements, creating data layers or themes, which can then be re-combined within the GIS to yield information that was unavailable when the data were separate. GIS, which combines specialized mapping software, spatial and attribute databases, is a powerful tool in the hands of the analyst/user who makes decisions about and interprets the datasets, the methodologies employed, the analyses, the output, and the results (Maantay and Ziegler 2006).

We developed two geographic information system tools to determine the "who" and "where" regarding the potentially most impacted and vulnerable populations. The first of the two tools is the Cadastral-based Expert Dasymetric System (CEDS), which is described in Section 5.2.1. The second tool is the New York City Hazard Vulnerability Index (NYCHVI) based on the Human Vulnerability Assessment (HVA) model, and is described in Section 5.2.2. Each data layer of vulnerability indicators can also be utilized independently of the compiled index, which can be very useful for many planning and management needs.

5.2.1 Disaggregating Population Data Using CEDS

The Cadastral-based Expert Dasymetric System (CEDS) is a model that uses both an expert system and dasymetric mapping to disaggregate population data (e.g., from the census) into much higher resolution data, giving a more realistic depiction of population locations and densities (Maantay et al. 2007). Dasymetric mapping uses ancillary datasets to refine and redistribute the locations of some phenomena (e.g., population) to reflect its distribution more accurately. CEDS, for instance, uses data sets that mask off the areas where people tend not to live (such as parks and waterbodies), then re-distributes the census populations throughout only the known inhabited areas, rather than throughout the entirety of the census unit area. CEDS then uses tax-lot (cadastral) data, which in NYC is on average 150 times finer resolution than the census block group data, to further disaggregate the census population data, as described below.

The expert system is a computerized decision-making program, which has been instructed to "decide", based on heuristic rules and expert judgment, which among several variables in the tax-lot data set to use for disaggregating the census data to calculate the optimally accurate tax-lot level population. Total populations, as well as sub-populations such as racial/ethnic groups, age cohorts, income/poverty status, and educational attainment levels, can be reliably disaggregated with CEDS.

5.2.1.1 Comparison of Three Methods: CEDS, FAW, and CCM

There are a few commonly-used methods to estimate at-risk populations. The Federal Emergency Management Agency (FEMA) uses a model called HAZUS (FEMA 2006). HAZUS employs the centroid containment method (CCM) to select only the

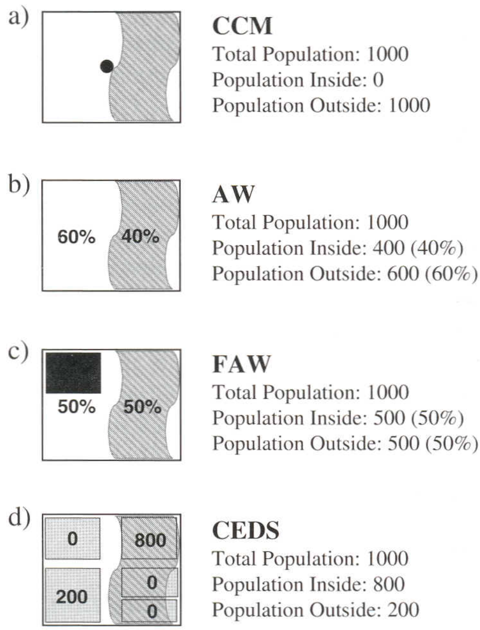

Fig. 5.2 Methodological differences and potential improvement of population estimation of the CEDS method (**d**), over the CCM – Centroid Containment method (**a**); AW – Areal Weighting (**b**); and FAW – Filtered Areal Weighting (**c**). Note that the *light grey* curved area represents a hazard area (e.g. floodplain) and the *black rectangle* in figure (**c**) represents an unpopulated area (e.g. park)

tract or block group polygons whose geometric centroids fall within the boundaries of interest, e.g., the floodplain (Fig. 5.2a).

Unfortunately, difficulties are encountered when trying to estimate population data within areas that do not coincide with the boundaries of census units. For instance, the boundaries of the floodplain are rarely, if ever, spatially coincident with the boundaries of census tracts, making it difficult to determine how many people are within the floodplain that intersects the census unit. This problem is commonly addressed by using areal weighting (AW), which is a spatial interpolation method that assumes a population is distributed homogeneously throughout a unit (Wu et al. 2005). This assumption also creates errors when trying to establish accurate counts for analyses that rely on a smaller, or different spatial unit of analysis than the original (Eicher and Brewer 2001; Holt et al. 2004).

With AW, if the boundaries of the phenomena of interest (e.g., floodplain) intersect a census unit a ratio based on areal proportions is applied to the population. If a quarter of an area is within the zone, one quarter of the population is assumed to be within the zone (Fig. 5.2b). Of course, in the real world, this assumption is a gross generalization and in hyper-heterogeneous urban areas like NYC can lead to incorrect estimation of the distribution of population in terms of both number and rate. Within census tracts and even block groups and blocks in NYC, there are very often enormous variations in land uses and population locations.

Areal weighting does not capture the nuances of complex urban areas. Filtered areal weighting (FAW) is an attempt to refine AW by using an ancillary data set to mask out uninhabited areas. The purpose is to redistribute the population only within inhabited areas, but its accuracy is still insufficient for performing environmental, health, or risk analyses in a city such as NYC (Fig. 5.2c).

Due to the inexact results of the previous three approaches, we needed an improved method to estimate population within impact zones. CEDS has provided superior results by disaggregating data to the tax lot level (Fig. 5.2d). One of the main benefits of using CEDS is that it can estimate population data within areas that do not coincide with the boundaries of census units, for instance, floodplain boundaries. Figure 5.3 illustrates the necessity for a finer-grained method such as CEDS in a hyper-heterogeneous setting. The figure shows a typical New York City block, illustrating that even within the relatively small geographic unit of a census block there is considerable variation in population density and land use types (Fig. 5.3).

5.2.1.2 CEDS Methodology

The Cadastral-based Expert Dasymetric system relies primarily upon two proxies for population distribution – residential area (RA), which is the amount of square feet designated for residential use in the tax lot, and number of residential units (RU), which is the number of individual dwellings in the tax-lot (LotInfo 2003). Both of these are proxies for the population in each tax lot, and are therefore inexact. The tax lot data do not reveal how many people live within each lot or within each residential unit on the lot, nor how many square feet of residential area exist for each person, therefore one must estimate the population by disaggregating from the census data using RA or RU as proxies.

CEDS-derived population estimates were calculated in a two-step process, with each step occurring at different scales. Step 1, which informs the expert system, disaggregates the census tract population (from the US Bureau of the Census) to the tax-lot level based on either the ratio of RA in the tax lot versus the RA in the entire census tract or the ratio of the number of RU in the tax-lot versus the RU of the tract. Tax-lots that contain a greater proportion of proxy units are assumed to have an equally greater proportion of the population. The estimated tax-lot level populations are then re-aggregated up to the census block group level and compared with the block group population data as reported by the US Census Bureau. The absolute difference between the CEDS-estimated population, for both RA and RU, is then assessed and summed over each block group in the tract. The ancillary dataset that functioned better (i.e., lower absolute difference) is then chosen to be used as the proxy data for the geographic sub-groups contained within that particular census tract during Step 2. Step 1 was repeated for each of NYC's census tracts. These data not only inform the expert system but also act as validation by comparing its performance with data disaggregated by different, more common, techniques such as filtered areal weighting, as shown in Fig. 5.4a and b. The figures, which compare scatterplots of CEDS and FAW NYC block group population estimates, reveal that CEDS produces a superior output.

Step 2 calculates the final CEDS-derived population. Each census block group, rather than census tract, is disaggregated to the tax-lot level using the higher functioning proxy unit (RA or RU), as determined in Step 1 by the expert system. The

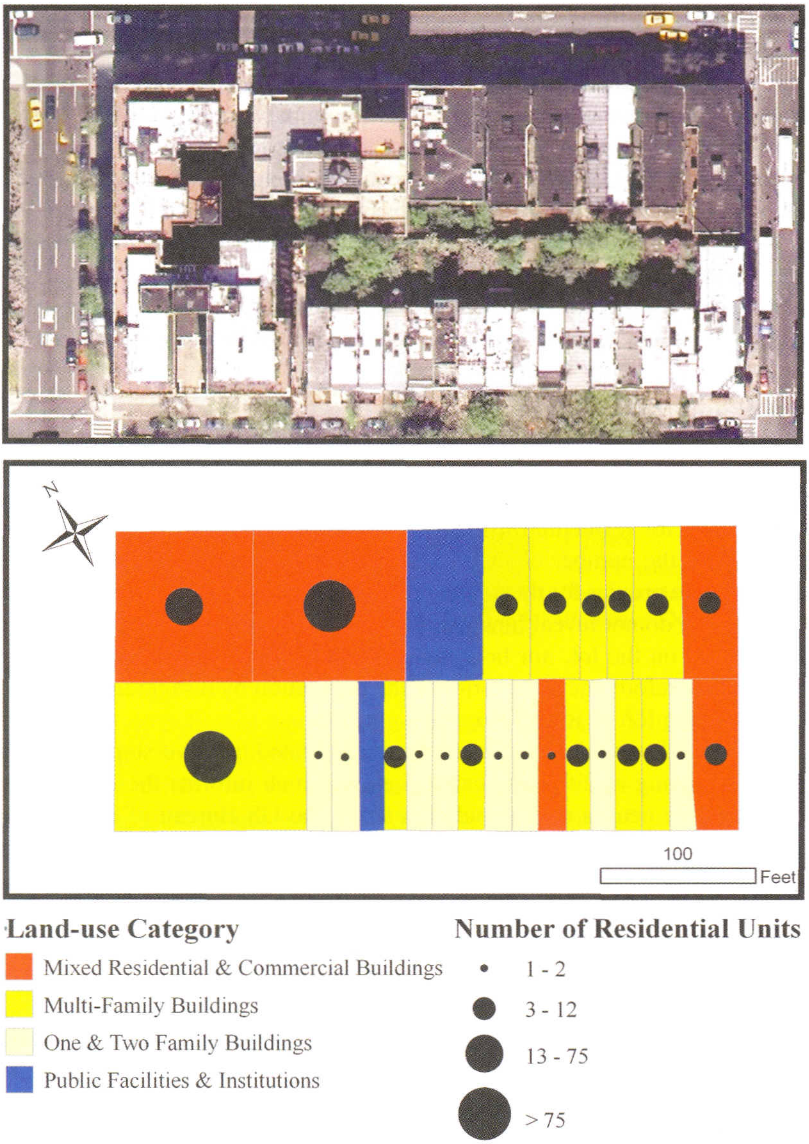

Fig. 5.3 Heterogeneity of a Manhattan city block. The orthophoto (*above*) and the cadastral map show the uneven distribution of land use categories and residential units at the tax-lot level even when examining only one city block. (There are, on average, more than 16 city blocks in a New York City census tract)
Source: NYCMap 2004; LotInfo 2003

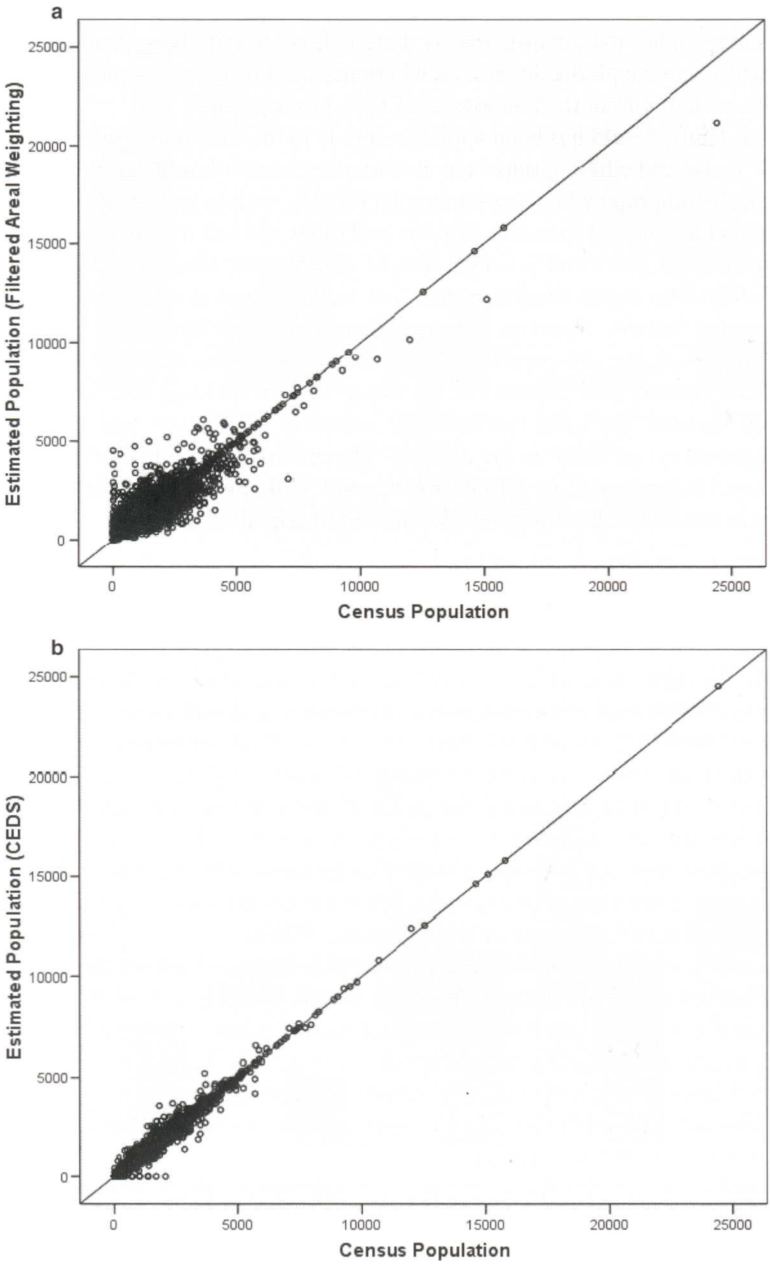

Fig. 5.4 Scatterplots of population estimations in New York City as compared to Census block group data using (**a**) Filtered Areal Weighting (FAW); and (**b**) CEDS

assumption is that when the source data is at a finer spatial resolution (census block groups are smaller than census tracts) there is less error in the system since CEDS is by nature a pycnophylactic process where mass is preserved (population numbers remain constant within the boundaries of each block group).

In this study, CEDS has been applied not only to the total population of NYC and specific racial and ethnic groups, but also to other census-based variables which are particularly important when assessing vulnerability, such as income (poverty status); educational attainment (persons 25 years and older without a high school diploma); age (persons 10 years and younger, and 65 and above); linguistic ability (persons 5 and older who speak English either 'not well' or 'not at all'); and disability (a self reported variable based on non-institutionalized individuals five years old and older). Although the sub-population estimations tend to be distributed similarly to the CEDS-derived total population, the expert system still functions independently for each variable. As such, the resulting estimates are distinct and vary in terms of redistribution ratios across the datasets. The census-based vulnerability variables have been disaggregated by CEDS, FAW, and CCM, and the resulting estimations of populations and sub-populations within the floodplain compared.

5.2.1.3 CEDS Results Versus Other Methods

In addition to total population numbers, ethnic and racial sub-populations were also spatially disaggregated to the property tax lot in this study to determine if there are any environmental justice impacts associated with flood risk in NYC (Fig. 5.4). Compared to the CEDS method, there are 37% (overall) fewer people estimated to be at risk from floods using the conventional areal weighting of census data and 72% fewer people at risk using the centroid containment selection method (Fig. 5.5). While minority populations city-wide do not disproportionately live within the floodplain, they are disproportionately undercounted by the traditional methods of population estimation. For example, in the floodplain, Non-Hispanic Blacks are undercounted at twice the rate of Non-Hispanic Whites.

The utility of CEDS for estimating potentially impacted vulnerable populations is illustrated by the case study of Brighton Beach, Brooklyn, New York. Brighton Beach is a community on the peninsula of Coney Island, which is joined by an isthmus to the rest of the borough of Brooklyn (Fig. 5.6). The community is a fairly dense residential neighborhood with a large population of immigrants and residents of Russian and Ukrainian descent. A considerable portion of Brighton Beach is also within the FEMA 100-year floodplain.

Population within the floodplain was estimated using the centroid containment method, filtered areal weighting, and CEDS (Fig. 5.7). Of the just over 35,000 residents in Brighton Beach, CCM estimates 4661 (13.2%) are in the floodplain, FAW estimates 9487 (26.9%) are in the floodplain, while CEDS estimates 11,798 (33.5%) are in the floodplain.

The markedly different estimates for this neighborhood indicate that the centroid containment method yields the least satisfactory results, FAW is an improvement, and CEDS provides the most precise estimates for total population as well as for

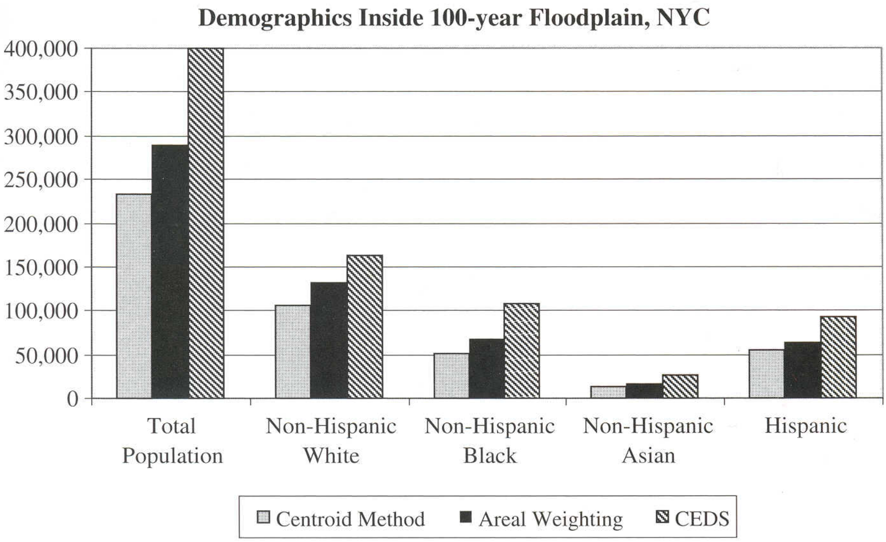

Fig. 5.5 Estimated populations and sub-populations within the 100-year floodplain in NYC comparing CEDS, FAW and CCM

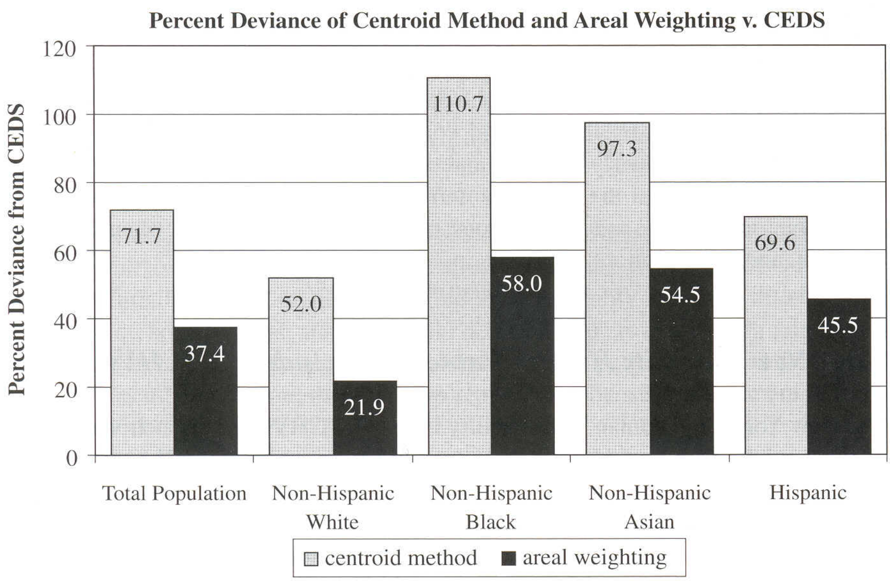

Fig. 5.6 Percent deviance of the Centroid Containment Method and AW vs. CEDS regarding undercounting of racial/ethnic groups

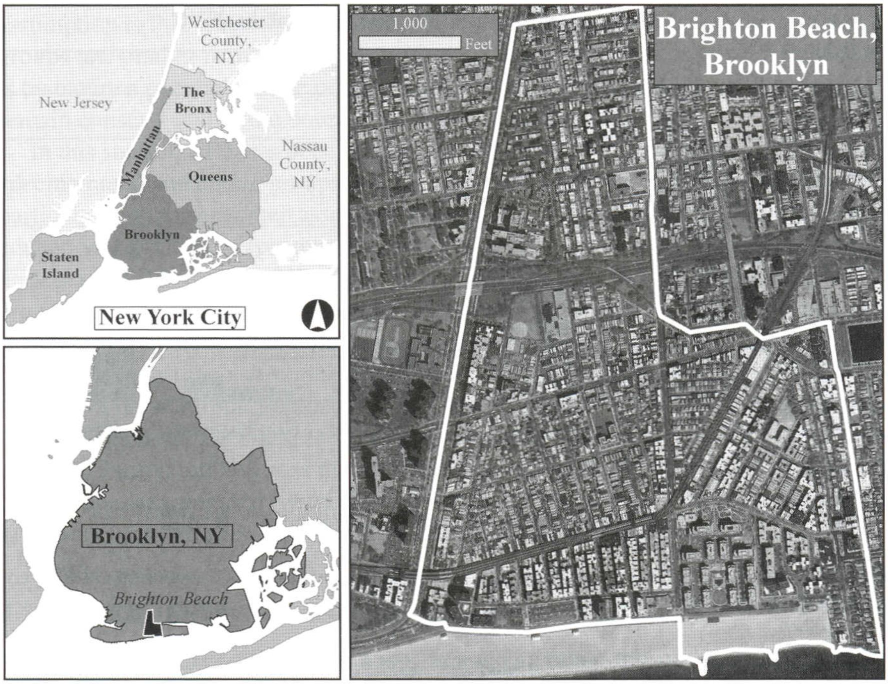

Fig. 5.7 Locator map of Brighton Beach community in Brooklyn, New York

all the sub-populations examined in the case study (Figs. 5.7, 5.8, and 5.9). Some populations estimated by the centroid containment method are undercounted by 200% or more (e.g., elderly 65 years and older; non-Hispanic black; and Hispanic) when compared against the estimates derived from CEDS. This undercounting of vulnerable populations can have serious ramifications for disaster planning, management, and mitigation.

5.2.2 New York City Human Vulnerability Index (NYCHVI) Model

The New York City Human Vulnerability Index (NYCHVI) is a user-driven hazard-of-place model based on the Human Vulnerability Assessment (HVA), a qualitative risk analysis tool created by the Geospatial Research, Analysis, and Services Program (GRASP) at the Centers for Disease Control and Prevention (CDC). The HVA is an application composed of an ArcObjects® MXD project, as well as data layers crafted from US Census and ESRI® Data and Maps (ESRI®, Inc.).

Conventionally, in times of disaster, attention was focused on property loss rather than estimation of human casualties (Cutter et al. 2000). Disaster epidemiologists, however, are tasked with measuring and describing adverse health effects, and factors contributing to those effects, that result from natural and human disasters in

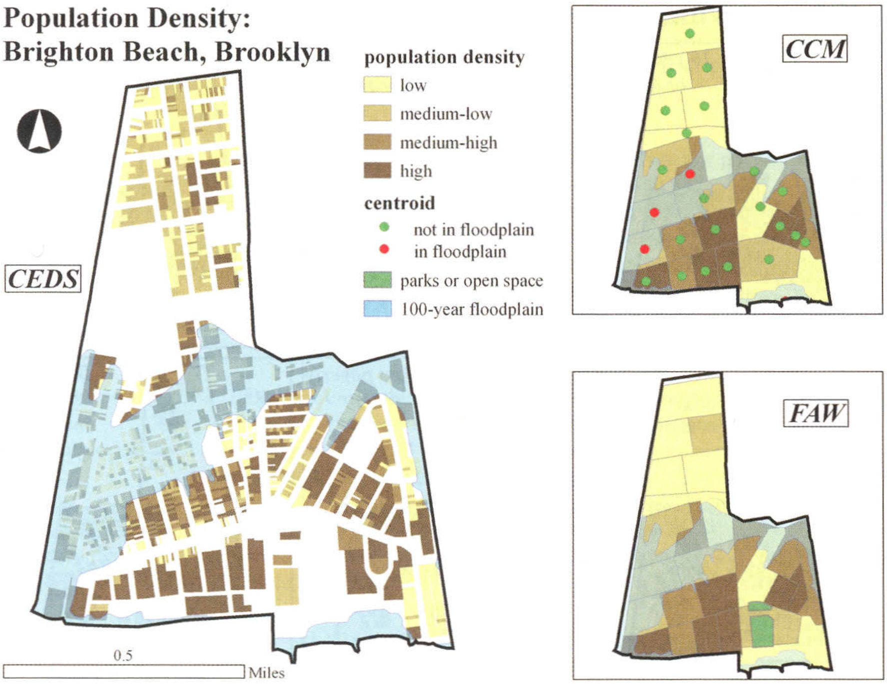

Fig. 5.8 Estimated total population densities in the case study area of Brighton Beach, Brooklyn, comparing CEDS, FAW and CCM. CEDS is aggregated to the tax lot, whereas FAW and CCM are at the census block group level. Population densities are shown in quartiles based on each dataset individually since the denominator (area) is not consistent across datasets (CEDS only accounts for the tax lot areas, whereas FAW and CCM utilize the entire census block group area)
Source: US Census 2000; LotInfo 2003; NYC Parks and Recreation Dept.; FEMA, Q3 2006

order to assess and meet the needs of disaster-affected populations. The HVA produces map-based reports "on-the-fly", allowing for the identification of populations potentially at risk of higher morbidity or mortality during a disaster. This model is intended to assist state and local decision-makers in targeting populations vulnerable to natural and man-made disasters. At this point in time, HVA is available only as a beta version, thus, its map reports may be subject to incompleteness or various inconsistencies.

5.2.2.1 Constructing the NYCHVI Model

In order to construct a locationally-relevant vulnerability index, it was necessary to modify and augment the national-level HVA by incorporating geographically specific datasets. The HVA model employs fifteen US Census variables at the census tract level. The model calculates the percentile rank of ninety or higher (PRC90) for each variable. If a variable is within the ninetieth percentile, it receives a PRC90 score of one. The overall vulnerability is determined by summing the

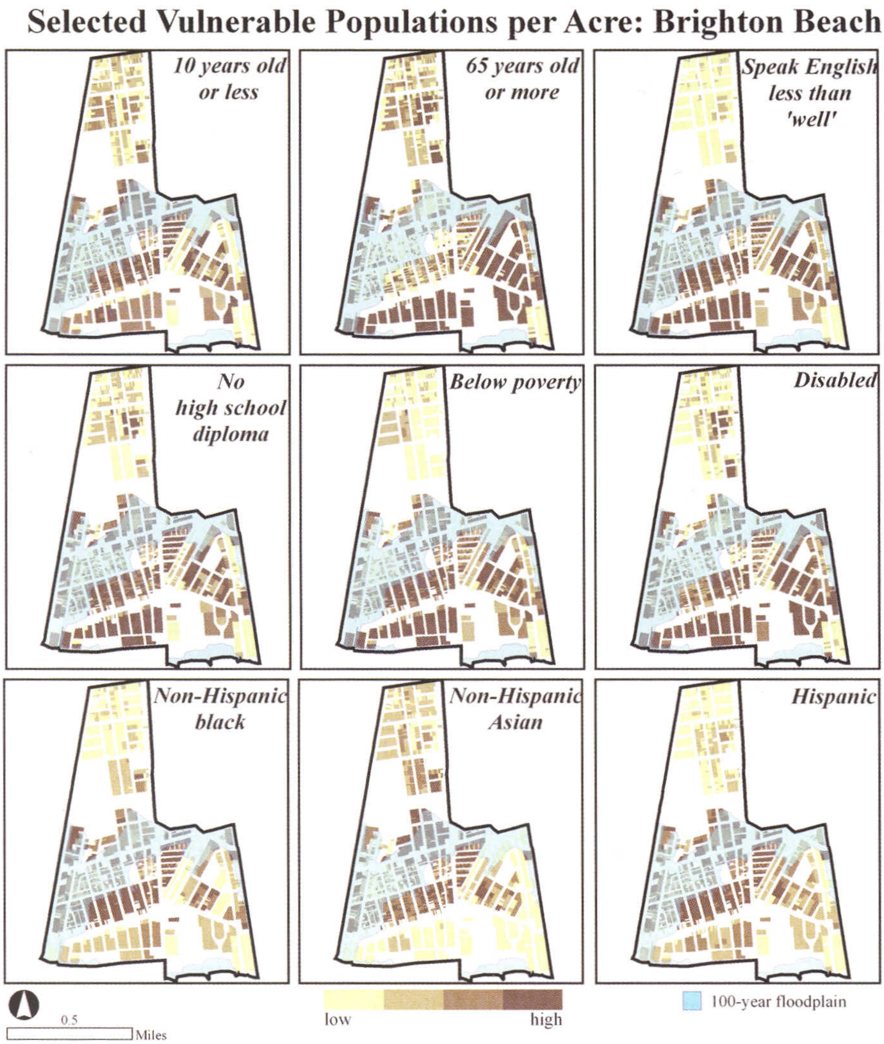

Fig. 5.9 Selected vulnerability variables – Persons per Acre. Each map represents a CEDS-derived variable at the tax lot level whose individual data range has been classified by quartiles
Source: US Census 2000; LotInfo 2003; NYC Parks and Recreation Dept.; FEMA, Q3 2006

PRC90 for all variables, which are not standardized and are weighted equally. The HVA overall vulnerability score can range from zero (very low vulnerability) to fifteen (extremely vulnerable). In addition, these fifteen variables can be organized into four indicator groups that measure the source of social vulnerability: *Socio-Economic* (income, poverty, employment, and education); *Household Structure and Disability* (age, dependency, disability, and single-parenting); *Race and Ethnicity* (minority status and non-English speaking); and *Housing and Transportation* (urban/rural housing, crowding, and transportation) (Table 5.1). These indicator

Table 5.1 HVA Variables (adapted from CDC 2008)

Variable	Data source*	Additional description
Group A. Socio-economic status		
1. Percent individuals below poverty	2000 US Census, Summary File 3, Population for Whom Poverty Status is Determined, Table P88. Ratio of Income in 1999 to Poverty Level	Individuals below poverty = "Under 0.50" + "0.50 to 0.74" + "0.75 to 0.99". Percent of persons below federally-defined poverty line, a threshold that varies by the size and age composition of the household. Denominator is total population where poverty status is checked.
2. Percent civilian unemployed	2000 US Census, Summary File 3, Population 16 years and Over, Table P43. Sex by Employment Status	Based on total population 16+. Civilian persons unemployed divided by total civilian population. Unemployed persons actively seeking work.
3. Per Capita Income in 1999	2000 US Census, Summary File 3, Total Population, Table P82. Per Capita Income in 1999	The mean income computed for every person in the census tract.
4. Percent persons with no high school diploma	2000 US Census, Summary File 3, Population 25 Years and Over, Table P37. Sex by Educational Attainment	Percent of persons 25 years of age and older, with less than a 12th grade education (including individuals with 12 grades but no diploma).
Group B. Household structure and disability		
5. Percent persons 65 years of age or older	2000 US Census, Summary File 3, Total Population, Table P8. Sex by Age	Percent persons 65 years of age or older.
6. Percent persons 17 years of age or younger	2000 US Census, Summary File 3, Total Population, Table P8. Sex by Age	Percent persons 17 years of age or younger.
7. Percent persons more than 5 years old with a disability	2000 US Census, Summary File 3, Civilian non Institutionalized Population 5 Years and Over, Table P42. Sex by Age by Disability Status by Employment Status	Percent civilian population not in an institution that are 5 years of age and older with a disability.
8. Percent male or fe-male householder, no spouse present, with children under 18	2000 US Census, Summary File 3, Households, Table P10. Household Size by Household Type by Presence of Own Children Under 18 Years	Other Family: Male Householder, no wife present, with own children under 18 years + Other Family: Female Householder, no husband present, with own children under 18 years.

Table 5.1 (continued)

Variable	Data source*	Additional description
Group C. Minority status and language		
9. Percent Minority	2000 US Census, Summary File 3, Total Population, Table P6. Race and Table P7. Hispanic or Latino by Race	Total of the following: "Black or African American alone" + "American Indian and Alaska Native alone" + "Asian alone" + "Native Hawaiian and Other Pacific Islander alone" + "Some Other race alone" + "Two or more races" + "Hispanic or Latino – White alone".
10. Percent persons 5 years of age or older who speak English less than "well"	2000 US Census, Summary File 3, Population 5 Years and Over, Table P19. Age by Language Spoken at Home by Ability to Speak English	For all age groups and all languages – the total of persons who speak English "not well" or "not at all".
Group D. Housing and transportation		
11. Percent multi-unit structure	2000 US Census, Summary File 3, Housing Units, Table H30. Units in Structure	Percent housing units with 10 or more units in structure
12. Crowding	2000 US Census, Summary File 3, Housing Units, Table H30. Units in Structure	At household level, more people than rooms. Percent total occupied housing units (i.e., households) with >1 person per room
13. No vehicle available	2000 US Census, Summary File 3, Occupied Housing Units, Table H44. Tenure by Vehicles Available	Percent households with no vehicle available.
14. Percent of persons in group quarters	2000 US Census, Summary File 3, Total Population, Table P9. Household Type by Relationship	Percent of persons who are in institutionalized group quarters (e.g., correctional institutions, nursing homes) and non-institutionalized group quarters (e.g., college dormitories, military quarters).
15. Percent mobile homes	2000 US Census, Summary File 3, Housing Units, Table H30. Units in Structure	Percent housing units which are mobile homes

*Beginning in 1790, the United States Census Bureau has conducted a decennial count of everyone living in the United States and its territories. In-depth population and housing data collected on a sample basis from the Census 2000 long form survey in addition to topics from the short form 100-percent data (age, race, sex, and vacancy status) are presented in Summary File 3. This includes population totals for ancestry groups as well as selected characteristics for a limited number of race and Hispanic or Latino categories. For more information on the United States Census, please refer to http://www.census.gov/.

groups are based on eleven factors devised by Cutter et al. (2003) to distinguish US counties according to level of social vulnerability in relation to environmental hazards. The HVA presents this information in a dynamic letter-sized cartographic report that includes six maps: one for each indicator group, an overall index and a reference map. The HVA model is national in scope and generates user-driven reports by county (e.g., Kings) or region (e.g., New York, NY – Northeastern New Jersey). This coarse scale may not provide adequate detail for local jurisdictions (CDC/ATSDR 2008). In addition, the HVA contains variables that are geared toward suburban or rural areas (number of mobile homes, for instance) and is therefore inappropriate for an urban hazard-of-place model.

The HVA variables are selected to serve as a broad overview and are considered a guide for potential indicators of vulnerability. A good vulnerability index emphasizes hazards that could potentially impact a community, indicates possible locations of hazard-related damage, and identifies those community elements that should be addressed to lessen exposure. NYCHVI (Table 5.2) is intended to enhance the HVA for New York City, not only by using locationally-specific data, but also by

Table 5.2 NYCHVI variables

Variable	Data source*	Additional description
Group A. Socio-economic status		
1. Percent individuals below poverty	Same as HVA (Table 5.1).	Same as HVA.
2. Percent civilian unemployed	Same as HVA.	Same as HVA.
3. Per Capita Income in 1999	Same as HVA.	Same as HVA.
4. Percent persons with no high school diploma	Same as HVA.	Same as HVA.
Group B. Household structure and disability		
5. Percent persons 65 years of age or older	Same as HVA.	Same as HVA.
6. Percent persons 10 years of age or younger	2000 US Census, Summary File 3, Total Population, Table P8. Sex by Age	Percent persons 10 years of age or younger
7. Percent persons more than 5 years old with a disability	Same as HVA.	Same as HVA.
8. Percent male or female house-holder, no spouse present, with children under 18	Same as HVA.	Same as HVA.
Group C. Minority status and language		
9. Percent Minority	Same as HVA.	Same as HVA.

Table 5.2 (continued)

Variable	Data source*	Additional description
10. Percent persons 5 years of age or older who speak English less than "well"	Same as HVA.	Same as HVA.
Group D. Housing and transportation		
11. Percent multi-unit structure	Same as HVA.	Same as HVA.
12. Crowding	Same as HVA.	Same as HVA.
13. No vehicle available	Same as HVA.	Same as HVA.
14. Percent of persons in group quarters	Same as HVA.	Same as HVA.
Group E. Public health		
15. AIDS	New York State Department of Health SPARCS – 2006 Persons, ICD-9: 042–044	Percent of population that underwent an AIDS-related hospitalization
16. Asthma	New York State Department of Health SPARCS – 2006 Persons, ICD-9: 493	Percent of population that underwent an asthma-related hospitalization
17. Cancer	New York State Department of Health SPARCS – 2006 Persons, ICD-9: 140–208	Percent of population that underwent a cancer-related hospitalization
18. Diabetes	New York State Department of Health SPARCS – 2006 Persons, ICD-9: 250	Percent of population that underwent a diabetes-related hospitalization
19. Heart Condition	New York State Department of Health SPARCS – 2006 Persons, ICD-9: 390–429	Percent of population that underwent a heart condition-related hospitalization

*Established in 1979, the Statewide Planning and Research Cooperative System (SPARCS), a comprehensive data reporting system, is the result of cooperation between the health care industry and government. While SPARCS was initially created to gather information on hospital discharges, it currently collects patient level data on patient characteristics, diagnoses and treatments, services, and charges for every hospital discharge, ambulatory surgery patient, and emergency department admission in New York State. The World Health Organization's International Classification of Diseases Ninth Revision (ICD-9) is designed to facilitate international comparability in the collection, processing, classification, and presentation of mortality and morbidity statistics. In SPARCS, all hospital discharges are assigned an ICD-9 code based on the disease or condition associated with the hospitalization. For more information on the SPARCS dataset, please refer to http://www.health.state.ny.us/statistics/sparcs/.

expanding the model to take additional factors such as biophysical information into account – the HVA currently does not include a biophysical vulnerability component. Thorough vulnerability indices provide analysis of all critical public and private facilities and infrastructure (CDC/ATSDR 2008). For example, "special needs" facilities (i.e., health care facilities, schools, day care centers, and senior centers) are at higher risk because their occupants are dependent on others for their well being (Cutter et al. 2000). Proximity to "lifeline" resources including key infrastructure (e.g., public transit) and emergency response facilities (e.g., fire houses) may provide valuable information for mitigation planning. Capability of structures and lifeline systems to withstand past disasters is yet another consideration (Noji 1992). A comprehensive vulnerability index must also contain spatial information regarding areas prone to natural hazards (e.g., floodplain) (Cutter et al. 2000; Fedeski and Gwilliam 2007). Thus, important elements that (ideally) should be included in a hazard vulnerability index model include hazard-specific layers such as floodplain, hazardous waste facilities, building data, special needs facilities (e.g., hospitals, schools, eldercare centers), infrastructure (e.g., bridges, transportation, utilities), and public health data (e.g., hospitalization records regarding medically vulnerable individuals) other than the limited disability fields of the 2000 Census Survey (Table 5.3).

Elements should be symbolized employing a standard set of symbols developed for Emergency Management and First Responder agencies at the National, State, Local and Incident level that provide immediate and general understanding of the event (Homeland Security Working Group 2005).

The NYCHVI examines areas (ranging from borough to tax lot) within New York City's boundaries. This index can aid disaster preparation, management, mitigation, and recovery by identifying the locations of specific sub-populations that are at increased risk in a natural disaster.

5.2.2.2 NYCHVI Methods and Results

NYCHVI's (Table 5.2) variables for *Socio-economic Status* (Group A), and *Minority Status and Language* (Group C) are identical to those of HVA (Table 5.1). NYCHVI's *Household Structure and Disability* (Group B) category differs from that of HVA by the replacement of the original variable "Percent persons 17 years of age or younger" with "Percent persons 10 years of age or younger." Epidemiological literature suggests that younger children are more vulnerable to hazards than teenage adolescents and adults (Noji 1997). For the *Housing and Transportation* (Group D), the metric "Percent mobile homes" was removed because very few (~0.07%) of New Yorkers reside in mobile homes. NYCHVI's main departure from HVA is found with the addition of a new group of variables examining public health indicators (Group E). These data originated from New York State's Department of Health, Statewide Planning and Research Cooperative System (SPARCS), which estimates vulnerability based on pre-existing medical conditions (i.e., heart condition, AIDS, asthma, diabetes, and cancer).

Table 5.3 NYCHVI natural hazard and spatial layers

Spatial sector	Layer file	Source
Infrastructure	Subways	New York City Transit (NYCT)
	NYC streets (Linear Integrated Ordered Network – LION streets)	City of New York Department of City Planning (DCP)
	Property tax lot data – (Planning Primary Land Use Tax Lot Output – PLUTO)	City of New York Department of City Planning (DCP)
	Buildings footprints	New York City Department of Information Technology and Telecommunications (DoITT)
Biophysical	100-floodplain	Federal Emergency Management Agency (FEMA)
Lifeline	Police stations	City of New York Police Department (NYPD)
	Fire houses	New York City Fire Department (FDNY)
Special needs	Senior centers	New York City Department for the Aging (DFTA)
	Senior facilities	New York City Department for the Aging (DFTA)
	Charter schools	New York City Department of Education (DOE)
	Day care centers	City of New York Department of City Planning (DCP)
	Institutional housing	City of New York Department of City Planning (DCP)
	Hospitals	New York City Office of Emergency Management (OEM)
	Special education	New York City Department of Education (DOE)
	Regional schools	New York City Department of Education (DOE)

These pre-existing medical conditions are also used to create the New York City Department of Health and Mental Hygiene's Community Health Profiles, annual reports that address the health status and vulnerability of NYC neighborhoods (NYC-DOHMH 2006).

As with HVA, NYCHVI overall vulnerability is determined by summing the PRC90 for all variables featured in Table 5.2 (which are not standardized and are weighted equally), with an overall vulnerability score that can range from zero (very low vulnerability) to nineteen (extremely vulnerable). While HVA calculates the PRC90 on a national level, NYCHVI determines PRC90 on a city level. In other words, HVA compares a census tract to all other census tracts within the United States while NYCHVI compares a census tract to all other census tracts within

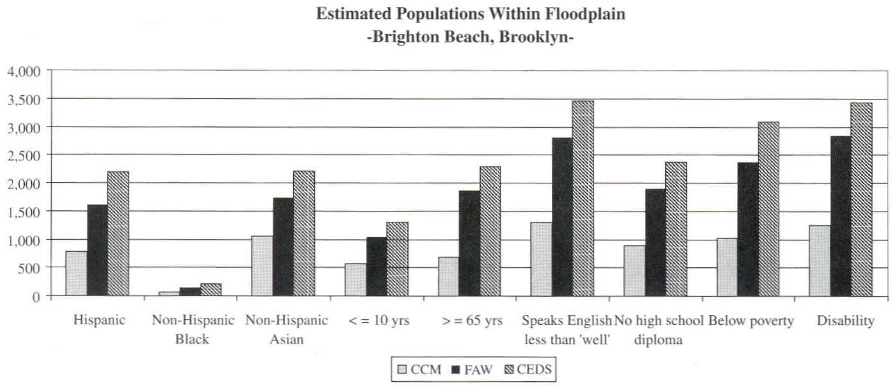

Fig. 5.10 Estimated total and sub-populations within the 100-year floodplain in the case study area of Brighton Beach, Brooklyn, comparing CEDS, FAW and CCM

New York City. A user-driven NYCHVI report for the Brooklyn neighborhood of Brighton Beach is shown in Fig. 5.10.

The "Special Needs" dataset (Table 5.3) was created to account for the facilities where particularly vulnerable populations gather, including hospitals, day care facilities, schools, institutions and senior housing. "Lifeline" and "Infrastructure" datasets incorporate data regarding transportation, residential (tax) lots, building footprints and emergency responder location (e.g., fire, police). Finally, a biophysical vulnerability component (FEMA's 100-year floodplain) was added. Where feasible, overlays were symbolized using the Homeland Security Emergency Management Symbol set. Figures 5.11 and 5.12 depict user-driven NYCHVI letter size (11″ X 8.5″) reports featuring a finely detailed map for the Brighton Beach area of Brooklyn (Please note, these reports are for illustrative purposes and have been reduced to fit the pages of this book). These figures depict neighborhood level maps of the same extent and are meant to be viewed as a set. Figure 5.11 plots the hazard vulnerability variables while Fig. 5.12 is a block level detail of Fig. 5.11 showing important features such as building level data as well as the floodplain.

5.3 Discussion

CEDS and NYCHVI can work in tandem, yet independently, as illustrated in Figs. 5.7, 5.8, 5.9, 5.10, 5.11, 5.12, and 5.13. As an example, we introduce the case study area of Brighton Beach, Brooklyn. NYCHVI can be used to quickly and efficiently disseminate crucial information to decision-makers and field personnel via an easily understood and interpreted dynamic user-driven and interactive cartographic product. For instance, the NYCHVI tool can be utilized to site critical care facilities (e.g., temporary housing, triage units, morgues) as well as expedite flexible

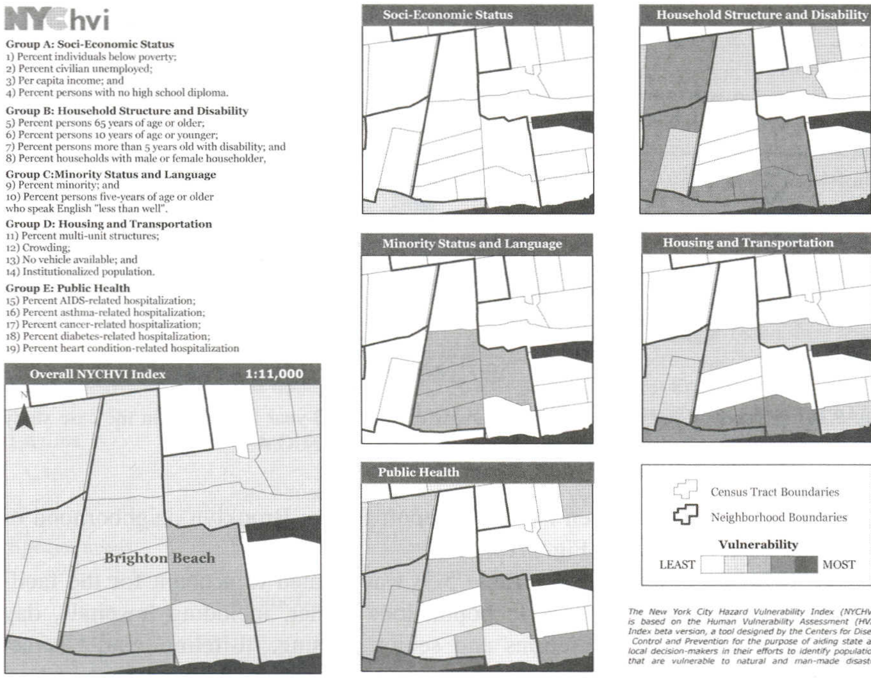

Fig. 5.11 NYCHVI print-out depicting five indicator groups and resulting overall index for the neighborhood of Brighton Beach, Brooklyn, NY at a scale of 1:40,000
Source: Tables 5.1, 5.2 and 5.3

planning for evacuation routes as information about the areal extent and magnitude of the disaster becomes available. For pre-disaster planning and mitigation, the NYCHVI model can be used to identify communities most vulnerable to flood hazards based on various socio-demographic factors. This ability enables more effective educational outreach, including the ability to create and distribute linguistically- and culturally-appropriate bulletins and publications. NYCHVI can also be employed to target specific at-risk communities for pre- and post-disaster resource allocation, based on socio-economic need and the particular health concerns of their residents.

Figure 5.11, for example, illustrates the potentially devastating effects of a flood on both special needs facilities and transportation systems. Several schools, childcare and eldercare institutions are either within the floodplain or are cut off from the main landmass by the floodplain's extent. The same situation holds true for the subway lines servicing the neighborhood as well as for a network of major and minor roadways. Figure 5.12 displays a specific grade school and neighboring residential buildings that are at risk of from the flood hazard.

CEDS provides more precise estimates of populations and sub-populations that could be directly affected by flooding, enabling efficient pre-disaster evacuation planning and allocation of post-disaster emergency resources. Used in tandem with

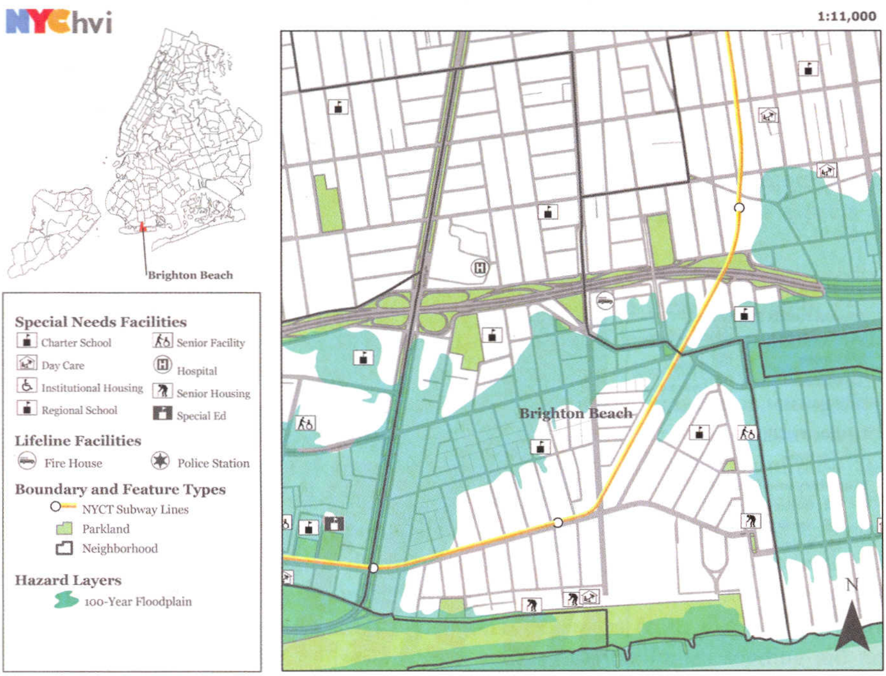

Fig. 5.12 NYCHVI user-driven report featuring overlay of lifeline and special needs facilities affected by a FEMA 100-year floodplain for the neighborhood of Brighton Beach, Brooklyn, NY at a scale of 1:10,000
Source: See Tables 5.1, 5.2 and 5.3

NYCHVI, the information is even more compelling. For instance, by examining the easternmost census tract in Brighton Beach (Fig. 5.10), NYCHVI reveals a comparatively high level of vulnerability mainly due to public health concerns, linguistically ability, and preponderance of specific age cohorts. Simultaneously, CEDS (Fig. 5.8) reinforces this impression by providing the absolute numbers and concentrations of vulnerable populations in categories such as disabled, elderly, children, limited English-speaking ability, lower-income, and racial/ethnic minorities.

5.4 Conclusion

The purpose of this chapter is to demonstrate the utility of two new complementary geomatic techniques: CEDS and NYCHVI. Using cadastral-based dasymetric disaggregation of census data, as well as the creation of vulnerability indices, more accurate and nuanced information is made available for emergency response and disaster planning.

Fig. 5.13 NYCHVI user-driven report showing life line, special needs and residential buildings affected by FEMA 100-year floodplain for the neighborhood of Brighton Beach, Brooklyn, NY at a scale of 1:1900
Sources: Tables 5.1, 5.2 and 5.3

Both CEDS and NYCHVI enhance understanding of the geographic extent and magnitude of vulnerability to the flood hazard in New York City, providing significantly improved vulnerability estimates over previous methods. Through the addition of important elements, the manipulation of existing variables, and the incorporation of particularized spatial data layers and supplementary indicator data, the resulting NYCHVI is an overall vulnerability index based on potentially exposed population and population density, salient population indicators, and social and biophysical vulnerability. The disaggregation of census data with the CEDS technique results in a more precise way to delineate the boundaries containing populations potentially impacted by hazards.

The CEDS and NYCHVI methods are complementary but not duplicative, and each has specific purposes. CEDS provides general and sub-population density information revealing those who are especially vulnerable to hazards. NYCHVI examines relative quantities (e.g., rates, percentages) of vulnerable populations' potential exposure to flood risk in order to assist with resource allocation and plans for the provision of emergency services. Together, CEDS and NYCHVI provide a more comprehensive and accurate estimate than would be obtained using either method individually because they are taking into account different factors at different spatial scales.

While there is a benefit to examining vulnerability at different scales, inherent difficulties arise if one wishes to devise a single standard metric for a combined vulnerability index. NYCHVI works with census tract level data (e.g., health data), which is unlikely to be available at a finer resolution. CEDS performs at the tax lot level. While it might be possible to integrate CEDS and NYCHVI into a single index in the future, it currently seems more useful to retain them as separate indices since they are measuring different aspects of vulnerability.

There are substantial policy implications if CEDS and NYCHVI are used to estimate and identify populations at risk. These tools can more accurately determine the number of people at risk, as well as provide a more realistic indication of their socio-demographic characteristics. This knowledge can support planning efforts for emergency management, preparation, prevention, mitigation, and recovery planning, as well as encourage planning and response activities be crafted to address the specific needs of the populations involved. Culturally- and linguistically-appropriate materials can be developed to improve disaster preparation by better informing potentially affected communities, and also to better serve specific populations in a disaster's aftermath. Having precise knowledge of a at-risk populations' general health conditions (e.g., disabilities, mobility issues) that might complicate preparation or response activities (e.g., evacuation) could be critical in the event of a disaster. Such access also facilitates sending aid targeted to areas most in need of immediate help, for instance, areas with a high proportion of the elderly, disabled, or young. Since it has been shown that traditional methods of estimation significantly undercount populations of non-Hispanic Blacks, Hispanics, and those 65-years old or older that are located in NYC's flood hazard zones, these and similar populations will also benefit from these new models.

CEDS and NYCHVA can serve as a model to help other municipalities develop customized methods to estimate vulnerability to hazards, tailored to the specific conditions and characteristics of their locales. While this study focused on the flood threat, the models can estimate vulnerability and exposure to other types of hazards such as earthquakes, extreme weather events, and technological disasters (e.g., chemical spills, nuclear/toxic releases). By improving on past methods, CEDS and NYCHVA provide a robust visualization of biophysical and social vulnerability with more precise quantification of potential exposure.

Acknowledgments This research was partially supported by the National Oceanic and Atmospheric Administration's Cooperative Remote Sensing Science and Technology Center (NOAA-CREST) under NOAA grant number NA17AE162. The National Institute of Environmental Health Sciences of the National Institutes of Health also provided critical support for this project under NIEHS grant number 2 R25 ES01185-05. The statements contained within this paper are not the opinions of the funding agencies or the US government, but reflect the authors' opinions. This research was also supported by a Faculty Research Award from the Professional Staff Congress of the City University of New York (PSC-CUNY), Awards # 69372-0038, "Perfecting the Denominator: Developing a Cadastral-based Expert Dasymetric System in New York City."

List of Acronyms

ATSDR	Agency for Toxic Substances and Disease Registry
AW	Areal weighting
CCM	Centroid Containment Method
CDC	Centers for Disease Control and Prevention (US)
CEDS	Cadastral-based Dasymetric Expert System
FAW	Filtered Areal Weighting
FEMA	Federal Emergency Management Agency
GIS	Geographic Information System
GISc	Geographic Information Science
GPS	Global Positioning Systems
GRASP	Geospatial Research, Analysis, and Services Program
HAZUS	Hazards US
HVA	Human Vulnerability Assessment
NYC	New York City
NYCHVI	New York City Hazards Vulnerability Index
RA	Residential Area
RU	Residential Units
SPARCS	Statewide Planning and Research Cooperative System (New York State Department of Health)

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