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Evaluating a Community Based  
Homelessness Prevention Program: A  
Geographic Information System  
Approach

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# Evaluating a Community-Based Homelessness Prevention Program: A Geographic Information System Approach

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**ABSTRACT.** This article introduces and illustrates the application of Geographic Information System (GIS) technology to examine patterns of social services use in community-based interventions. By integrating management information system data from human service agencies and publicly accessible data from the U.S. Census within a spatially-referenced framework, the study illustrates that GIS analysis could help managers and planners of social services to assess the extent to which program implementation reflects adherence to a program concept and identify geographical areas with the greatest unmet service needs. The article demonstrates the application of GIS technology, based on an

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analysis of a citywide community-based homelessness prevention program in Philadelphia. [Article copies available for a fee from The Haworth Document Delivery Service: 1-800-342-9678. E-mail address: <getinfo@haworthpressinc.com> Website: <<http://www.HaworthPress.com>> © 2001 by The Haworth Press, Inc. All rights reserved.]

**KEYWORDS.** Community-based interventions, homelessness prevention, geographic information system, social service utilization

### **INTRODUCTION**

Geographic mapping in social work practice dates back to the late Nineteenth Century when settlement house workers at Hull-House developed a series of community maps as a means for assessing social and economic injustices in neighborhoods of Chicago (Davis & McCree, 1969; Holbrook, 1895; Tompkins & Southward, 1998). Social area analysis, introduced in the 1940s, integrated mapping with multivariate statistical methods and made possible the simultaneous analysis of multiple area characteristics (Shevky and Williams, 1949; Shevky and Bell, 1955).<sup>1</sup> Recent advancements in Geographic Information System (GIS) technology has made geographic mapping and spatial analysis methods even more accessible, resulting in their increased use in a variety of fields including urban planning, health care planning, and public and environmental health (Budic, 1994; Glass et al., 1995; Pine & Diaz, 2000; Richards, Croner, Rushton, Brown, & Fowler, 1999; Stallones, Nuckols, & Berry, 1992). However, applications of GIS technology in the social work literature have been limited, despite the emphasis on community-based interventions and geographically-targeted service delivery (Hoefler, Hoefler, & Tobias, 1994; Queralt & Witte, 1998a; Wier & Robertson, 1998). Additionally, prior studies employing GIS in the realm of social services have seldom applied the technology to program planning, development, and evaluation.

The purpose of this article is to introduce and illustrate the use of GIS technology to examine patterns of social services use in community-based interventions. Specifically, this paper focuses on the ways that GIS can be applied to monitor the implementation of a citywide community-based emergency assistance and case management program aimed at preventing homelessness. Prevention has been designated as one of the core components of the U.S. federal government's "Continuum of Care" policy to combat homelessness (Interagency Council on Homelessness, 1994). As a response to this policy imperative, community-based prevention centers were established in neigh-

borhoods in Philadelphia with the goal of diverting at-risk households from the public shelter system and connecting these households with community-based social services in order to stabilize their housing situation and income.

This article is structured as follows. We begin the paper by giving an overview of GIS and the ways that the technology has been applied to program planning, implementation, and evaluation. The overview is followed by a description of the Community-Based Homelessness Prevention Program (CHPP) in Philadelphia. The evaluation questions are then laid out and the data analytic procedures used to address the questions are discussed. Results of the analysis are described and concluding remarks are presented.

#### ***APPLICATIONS OF GEOGRAPHIC INFORMATION SYSTEM TO PROGRAM PLANNING AND EVALUATION***

The term “Geographic Information System” (GIS) refers to geographically oriented computer technology that combines hardware, software, and data to analyze and display spatial and non-spatial information in a manner that is accessible for users (Exter, 1992; Maguire, 1991). GIS may be considered a special case of management information systems (MIS) with the functions of capturing, storing, retrieving, manipulating, analyzing, and displaying data which are spatially referenced (Department of the Environment, 1987; Maguire, 1991). Three types of benefits of GIS applications have been identified in the academic and professional fields. They are: (1) integration of data from a variety of agencies and sources using a common reference system; (2) spatial display of data that is easy to understand; and (3) innovative analysis of data to inform and support decision-making (Petzold, 1994). Specifically, from the users’ point of view, GIS represents an important tool for managing and analyzing data about “where the features are” (geographic coordinate data) and “what they are like” (attribute data) (Cox, 1995).

In the past decade, GIS technology has increasingly been applied to inform program development and planning in the areas of health care, education, childcare, housing and homelessness. For example, Hirschfield, Brown, and Bundred (1995) used GIS to analyze the spatial distribution of community-based health services and the patients who use them in a community in Northwest England. The GIS database thus created was shown to be useful for assisting resource managers to plan and develop

community-based health services by identifying catchment areas for different services and by producing demographic, social and residential profiles for the patients who use them. In pursuit of a similar theme, Bullen, Moon, and Jones (1996) used GIS capacities to identify a nested hierarchy of localities for the management of primary health care in West Sussex, England. The derivation of localities was based on an array of spatial data including focal points of service provision, physical and psychological barriers to movement, administrative boundaries, and a large matrix of patient to general practitioner flows.

Based on tax assessor data, student records, and enrollment forecasts of a public school district in Southern California, Wilson (1994) demonstrated the application of GIS to determine the location of a new school and to draw school boundaries that would ensure reasonably balanced school enrollments based on ethnicity. Parsons, Chalkley, and Jones (1996), on the other hand, illustrated the way that GIS can be used to examine the effects of parental choice on geographically defined school catchment areas. The researchers pointed out that GIS is particularly useful for examining the "macro-structural" dimension of parental choice in terms of ease of access, home-school distance, and aggregate patterns of student flows, which has been neglected by researchers using traditional data collection methods such as standard questionnaires and interview surveys.

In three recent articles, Queralto and Witte (1998a; 1998b; 1999) demonstrated how GIS technology could be used to describe the geographic distribution of childcare facilities, to examine the relationship between socioeconomic characteristics and neighborhood supply of licensed childcare, and to identify geographical areas with the greatest unmet need for childcare services. To highlight the utility of GIS for social work practice, the authors further illustrated how their geographically referenced data may help social services administrators locate areas with potential service-availability gaps, as well as areas that require client outreach.

Using prior address distribution of households admitted to public shelters in New York City and Philadelphia, Culhane, Lee, and Wachter (1997) conducted GIS analysis to identify communities with high risk of homelessness and to examine socio-economic and demographic characteristics that are associated with the risk. Three dense clusters of homeless origins were found in Philadelphia and three in New York City, accounting for, respectively, 67% and 61% of shelter admission. The researchers also found that the rate of shelter admission is strongly predicted by a number of demographic and socio-economic distress

factors including concentration of female-headed households with young children, poverty, persons of African-American descent, unemployment, housing abandonment, housing vacancy, housing overcrowding, and high rent-to-income ratio.

In summary, the foregoing studies attest to the potential use of GIS in various arenas of social planning and social services administration. In the following sections, we undertake a step-by-step approach to illustrate the GIS method to evaluate the implementation of a community-based homelessness prevention program.

**COMMUNITY-BASED HOMELESSNESS  
PREVENTION PROGRAM:  
PROGRAM THEORY AND DESIGN**

The concept of community-based prevention is predicated on the idea that emergency assistance and case management services should be available near where program participants live in order to facilitate service accessibility and participants' connection with other local health, education, and human service agencies to meet their service needs. The Community-Based Homelessness Prevention Program (CHPP) was initially launched as a pilot program in 1994 and expanded to its full capacity in 1997. The program was designed as one of the key components of City of Philadelphia's Homeless Assistance Continuum of Care system (Interagency Council on Homelessness, 1994), which comprises a typical array of housing and support services ranging from emergency shelters, transitional housing and permanent supportive housing. In the context of this array of services, the goal of homelessness prevention is to divert at-risk households from using public shelters by providing emergency cash assistance to address immediate housing crisis and by connecting at-risk households to community-based social services.

The concept of community-based prevention in Philadelphia has been informed by shelter utilization research conducted by Culhane and colleagues (Culhane et al., 1997). The three dense clusters of homeless origins, as noted in the previous section, are designated as the target areas for homelessness prevention. The idea of targeting services to high-risk areas is consistent with the "selected prevention" concept used by Gordon (1983, 1987).<sup>2</sup> In the design of CHPP, selected prevention is undertaken through locating community-based prevention sites in geographic areas that have a demonstrably high

rate of public shelter use according to prior address information of public shelter clients.

Six homelessness prevention centers were established in areas of Philadelphia where a high rate of shelter use has been reported among their residents. A seventh program site, located in the downtown area (Center City), was added because it is accessible by public transportation to residents throughout the City. The CHPP adopts a two-pronged approach to prevention by coupling emergency financial assistance with case management services. The rationale of this approach is to help at-risk households deal with their immediate needs, while at the same time addressing the complicated factors that have precipitated the crisis, thus reducing the risk of shelter use in the future.

Managers at the homelessness prevention program sites are expected to provide outreach to potential participants who live in the immediate area through a referral network of locality-based services agencies and through direct publicity. To obtain homelessness prevention services, potential participants must “prove” their eligibility by a complete documentation of their “near-homeless” status as indicated by their receipt of foreclosure notice, eviction notice, or utility shut-off notice. Services provided under the CHPP include a maximum grant of \$1,200 to be paid toward rent, mortgage, or utility; reimbursement of job search expenses; and six-month case management services.

### *EVALUATION QUESTIONS*

The primary goals of this paper are twofold: to examine the patterns of services use in relation to the concept of community-based homelessness prevention, and to identify ways to improve the targeting of prevention services to communities whose residents experience a high risk of homelessness. Two specific questions are formulated to achieve these goals.

1. What is the geographic distribution of CHPP participants in relation to the distribution of the risk of homelessness and the location of homelessness prevention sites?
2. In what ways can the location of CHPP sites be modified to facilitate a closer adherence to the concept of community-based homelessness prevention?

## **DATA AND METHODS**

### ***Description of Databases***

To address the evaluation questions, databases from the management information systems of CHPP and the city's centralized public shelter system (Office of Emergency and Shelter Services, acronym OESS) were obtained as part of the evaluation contract the senior author established with the city. For the purpose of this study, the CHPP database includes residential addresses of participants who received emergency assistance and case management services during the evaluation period from December 1, 1997 through November 30, 1998. The OESS database includes prior residential addresses of households that had sought shelter in the city's centralized public shelter system during the corresponding period. In addition to the two administrative databases, we extracted a number of demographic, housing, and socio-economic variables (to be described below) from the 1990 U.S. Census data file for Philadelphia (Summary Tape Files 1A and 3A).<sup>3</sup>

The CHPP database contains 1,943 unduplicated addresses of households that had received prevention services during the evaluation period. The addresses matched with the city's street file at a very acceptable rate (97%), resulting in the identification of 1,885 addresses.<sup>4</sup> Prior addresses from the OESS database, however, turned out to be more problematic. Of the 9,156 households that had sought public shelter between December 1, 1997 and November 30, 1998, only 62% (5,677) gave a prior residential address in Philadelphia. A total of 4,116 (78% of 5,677) of these addresses matched the list of addresses in Philadelphia and can be mapped in GIS.

The substantial amount of missing information on Philadelphia addresses prior to shelter use is not unanticipated considering the high residential instability experienced by a significant portion of the homeless population (Kuhn & Culhane, 1998) and given the fact that not all homeless persons were residents of the city in which shelter services are provided.<sup>5</sup> Nevertheless, the low yield rate of prior addresses should be considered a limitation of the study. At best, the prior addresses, through their aggregation, should be taken as a proxy for the areas in which households seeking public shelter have had some recent residence. In using the prior address data as a proxy, we make a strong assumption that missing prior addresses are distributed among various areas in the city in the same pattern as prior addresses that did match.

### ***Transforming Address Records into GIS and Integration of Data***

In this study, we undertook two steps to prepare, manage and display the GIS data. First, we “geo-coded” CHPP and OESS records using the street addresses of program participants in conjunction with the street file for Philadelphia. Geo-coding refers to the process of converting addresses to points on a map by assigning the “X” and “Y” coordinates (i.e., specific latitudes and longitudes). These records would appear as “dots” or “points” on the maps, specifying the locations of CHPP participants and prior residences of OESS clients. After geo-coding the records, we counted the number of CHPP and OESS addresses in each census tract by overlaying a map of census tracts in Philadelphia on a map containing the CHPP or OESS addresses. The aggregate address data at the census tract level were then merged with demographic, housing, and socio-economic data from the 1990 U.S. Census using a dBase file format. Using ArcView, a desktop software package for GIS analysis, each data element was then displayed as a layer in a map to facilitate analysis.

### ***Construction of Variables: Location Quotients and Social and Economic Distress Factor***

The units of analysis in this study are census tracts. There are 365 census tracts in Philadelphia, of which 29 are primarily non-residential tracts including parks, airports, and shipyards. We excluded the non-residential tracts from our analysis, resulting in a total of 336 tracts. Since the tracts vary widely in population density, percentages are computed for most of the variables included in the study.

*Location quotient*—To analyze the distribution of the CHPP participants and prior addresses of shelter users with thematic maps by census tract, we used location quotients (Culhane et al., 1997). The location quotient (LQ) is a ratio that compares the rate of a certain event or phenomenon for a unit area to the rate for a larger area that encompasses it (Bendavid-Val, 1983). In this study, census tracts represent unit areas and the city of Philadelphia represents the larger area. For example, if the overall city rate of prior addresses of OESS clients is .007 (i.e., 7 out of 1000 addresses in the city have a record in OESS), then a census tract with a rate of .014 (i.e., 14 out of 1000 addresses in the census tract have a record in OESS) would have an LQ of 2. Location quotients are a convenient way of standardizing data because census tracts vary in population size. Location quotients below one indicate that the census tract

rate is less than the city rate. Location quotients above one indicate how many times greater the census tract rate is from the city rate.

*Social and economic distress factor*—Given the limitation of the prior address variable discussed above, it was necessary to construct an alternative measure to capture the differential risk of homelessness among residents living in various census tracts in the city. Based on the work of Culhane et al. (1997), we identified five blocks of variables that have been shown to be associated with the risk of homelessness at the census tract level. These blocks of variables include: (1) race/ethnicity (blacks, Hispanics); (2) household structure (female-headed households with children age under 6, one-person households, households with subfamilies, overcrowded households); (3) community disinvestments (boarded up housing units, vacant housing units); (4) instability (recent move in 1989-90, rental housing); and (5) economic risk (households with public assistant income, households below 75% of poverty line, unemployment, rent-income ratio). All variables with the exception of the rent-income ratio are standardized as percentages.

Since the indicators of potential risks are highly correlated (correlation matrix available upon request), we used principal components analysis with varimax rotation to determine a smaller number of factors that can be used in the analysis (Coulton, Korbin, Su, & Chow, 1995; Kim & Mueller, 1978). Principal component analysis results, presented in Table 1, suggest that three factors adequately summarize the data and explain 78% of the variance. The first factor, which explains the largest proportion of variance (42.8%), is labeled social and economic distress (or distress factor). Eight of the 14 variables are loaded on this factor. Census tracts with a high score on this factor have high concentration of African Americans, female headed households with children age under 6, households with public assistance income, households with income below 75% of the poverty line, households with subfamilies, and unemployed persons. These tracts are also characterized by visible community disinvestments indicated by high rates of boarded-up and vacant housing units.

The second factor, which we label instability, includes percent of one-person households, percent of households that recently moved (one year before the 1990 Census), percent of rental units, and rent-income ratio. This factor explains 21.8% of the variance in the factor model. As Table 1 indicates, census tracts with a high score on this factor represent areas with a high concentration of one-person households and rental units and whose residents are residentially mobile. Although residents

TABLE 1. Means, Standard Deviations, Final Commonalities, Rotated Factor Loadings, and Percent Variance Explained for Factor Model of Risk of Homelessness

Variable	Mean	Standard Deviation	Final Commonalities	Factor 1	Factor 2	Factor 3
				Distress	Instability	Hispanic- Overcrowded
Proportion of Hispanics	0.055	0.127	0.790	0.019	0.016	<b>0.889</b>
Proportion of Blacks	0.390	0.395	0.758	<b>0.855</b>	-0.030	-0.166
Proportion of female headed households with children under 6	0.059	0.061	0.784	<b>0.715</b>	0.000	0.522
Proportion of one-person households	0.316	0.114	0.835	-0.158	<b>0.850</b>	-0.296
Proportion of households with public assistance income	0.149	0.130	0.875	<b>0.758</b>	0.031	0.547
Proportion of households with income 75% below poverty	0.152	0.127	0.870	<b>0.725</b>	0.290	0.511
Proportion of households recently moved (1989-90)	0.152	0.094	0.731	-0.181	<b>0.824</b>	0.141
Proportion of overcrowded households (over 2 persons per room)	0.004	0.008	0.731	0.173	0.140	<b>0.826</b>
Proportion of subfamilies	0.056	0.048	0.777	<b>0.813</b>	-0.274	0.200
Proportion of boarded-up housing units	0.024	0.038	0.719	<b>0.832</b>	0.166	0.015
Proportion of vacant housing units	0.109	0.073	0.721	<b>0.658</b>	0.535	-0.047
Proportion of persons unemployed	0.057	0.034	0.762	<b>0.834</b>	-0.022	0.256
Proportion of rented housing units	0.388	0.209	0.858	0.243	<b>0.886</b>	0.118
Rent income ratio	0.184	0.060	0.640	0.160	<b>0.714</b>	0.324

Note. N = 336.

Percent variance explained: 77.5%

in “residentially unstable” tracts pay a high portion of their income on rent, they are not necessarily impoverished.

The third factor is labeled Hispanic-overcrowded and explains 12.9% of the variance. As shown in Table 1, this factor represents the degree of concentration of Hispanic and overcrowded households. Moreover, further analysis (results not shown, but to be provided upon request) indicates that census tracts that are high on the Hispanic-overcrowded factor (a factor score of 2 or above) have a concentration of poverty and public assistance households that is comparable to census

tracts that are high on social and economic distress factor (also measured as having a factor score of 2 or above). Census tracts that are high on the Hispanic-overcrowded factor, however, do not show significant signs of community disinvestments (i.e., with high concentration of boarded-up and vacant housing units), as is the case among census tracts that are high on the distress factor. As the next section explains, we used scores on the social and economic distress factor to identify geographic areas with residents facing a high risk of homelessness.

## **RESULTS**

### ***The Geographical Distribution of CHPP Participants in Relation to the Concept of Community-Based Homelessness Prevention***

*The geographic distribution of CHPP participants*—Figure 1 shows a census tract map of the distribution of CHPP clients, standardized using location quotients. The locations of the seven homelessness prevention sites were geo-coded on the map. Clearly, there is a cluster of relatively high utilization ( $LQ > 3.01$ ) among census tracts surrounding program site 1 in the neighborhood known as Point Breeze (labeled in Figure 1). As the descriptive statistics on the Point Breeze CHPP service cluster in Table 2 shows, 289 participants, or 15% of all CHPP participants ( $N = 1,885$ ), came from the 11 census tracts comprising this service cluster. The Point Breeze CHPP service cluster makes up of 3.5% of the city's total households and 5.7% of the city's poverty households with income below 75% of the poverty line.

Another cluster of concentrated homelessness prevention service use is located around program site 5 in the North Philadelphia area (labeled in Figure 1). As the descriptive statistics on the North Philadelphia CHPP service cluster in Table 2 shows, the 19 census tracts, varying in CHPP utilization rate from 1.2 to 4.5 LQ, together account for 16.2% of all households participating in the CHPP (305 out of a total of 1,885 participants). The North Philadelphia CHPP service cluster makes up of 6.2% of the City's total households but 13.1% of the City's poverty households.

Comparing the "CHPP LQ" column of the two service clusters (Table 2) shows that residents of the Point Breeze service cluster were more likely to receive homelessness prevention services than residents of the North Philadelphia service cluster. All census tracts comprising the Point Breeze service cluster have a CHPP LQ of 3.33 and over, com-

FIGURE 1. Census Tract Map of the Distribution of CHPP Participants



pared to only 4 out of the 19 census tracts comprising the North Philadelphia service cluster. Despite this difference, it is unlikely that program site 1 is inappropriately targeting its services to Point Breeze residents or that the residents are over-utilizing homelessness prevention services since stringent eligibility criteria were imposed on program participation at all sites. While our analysis identifies this pattern of service utilization, it does not explain it. Addressing the question of why a certain distribution pattern exists requires the employment of other data collection procedures including interviews with program staff and survey of potential program participants.

TABLE 2. Descriptive Statistics of the CHPP Service Clusters and Listing of Census Tracts by CHPP Service Use, Prior Address, and Distress Factor

Point Breeze CHPP Service Cluster				North Philadelphia CHPP Service Cluster			
Total number of households: 20,977				Total number of households: 37,629			
Total number of poverty households: 4,896				Total number of poverty households: 11,149			
Percent of City's household: 3.5%				Percent of City's household: 6.2%			
Percent of City's poverty households: 5.7%				Percent of City's poverty households: 13.1%			
Tract ID	CHPP LQ	Prior address LQ	Distress Factor	Tract ID	CHPP LQ	Prior address LQ	Distress Factor
0019	8.38	<b>4.86</b>	1.74	0200	4.51	<b>4.15</b>	1.20
0021	6.08	1.76	1.41	0148	3.93	<b>4.53</b>	<b>2.45</b>
0031	5.44	2.62	1.31	0203	3.71	2.55	1.74
0020	5.28	2.26	1.26	0137	3.33	<b>3.03</b>	1.70
0022	4.80	2.51	1.11	0169	3.29	2.74	1.59
0032	4.19	2.12	1.07	0172	3.23	2.05	1.12
0033	3.97	1.82	0.44	0140	3.23	<b>5.01</b>	1.90
0037	3.90	1.03	0.01	0201	3.17	<b>3.08</b>	1.14
0014	3.87	2.58	0.54	0173	2.88	2.18	1.48
0013	3.58	2.24	0.94	0151	2.66	2.67	1.78
0030	3.33	1.42	0.36	0202	2.37	2.32	1.23
				0167	2.30	<b>3.50</b>	1.58
				0149	1.86	2.96	1.88
				0168	1.70	2.62	1.77
				0153	1.70	<b>4.67</b>	<b>2.21</b>
				0152	1.34	<b>3.11</b>	<b>3.48</b>
				0139	1.22	<b>4.79</b>	1.87
				0138	1.18	<b>3.02</b>	<b>2.26</b>
				0147	1.15	<b>4.62</b>	<b>3.69</b>
Total number of CHPP participants: 289				Total number of CHPP participants: 305			
Total number of census tracts: 11				Total number of census tracts: 19			

**Note.** Total number of households in the City: 603,069; total number of poverty households: 85,330. Poverty households are defined as households with income below 75% of the poverty line. Highlighted are tracts with a prior address LQ of more than 3 or a distress factor score of more than 2.

*The geographic distribution of CHPP participants in relation to the distribution of the risk of homelessness—*Prior addresses of households that have sought emergency shelter services were aggregated by census tracts in order to compare the geographic distribution of the risk of homelessness to that of CHPP participants. Comparison between Figures 1 and 2 shows that while all 11 census tracts comprising the Point Breeze service cluster have a CHPP participation rate that is more than 3 times the city rate, only one of the 11 tracts in the cluster has an LQ of more than 3 on prior addresses (comparing the “CHPP LQ” and “Prior

Address LQ” columns of Table 2). By way of contrast, 11 out of 19 census tracts in the North Philadelphia service cluster have a very high rate of homelessness, as indicated by a prior address LQ of greater than 3.

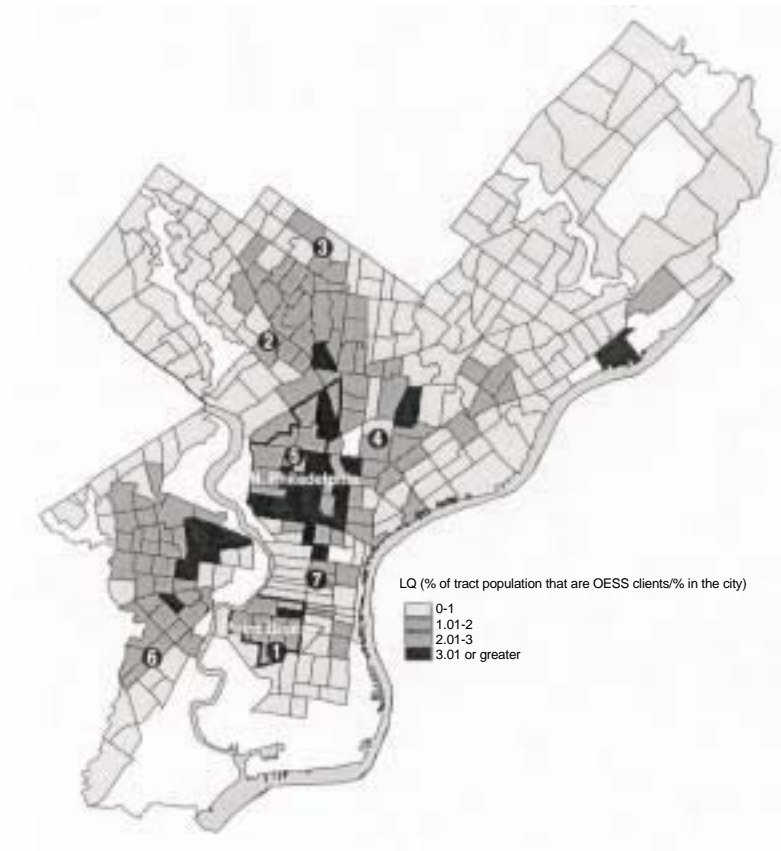
Figure 3 further shows that none of 11 tracts in the Point Breeze service cluster falls into the category with the highest concentration of social and economic distress (refer to the “Distress Factor” column of Table 2), defined as having 2 standard deviations above the mean distress factor score (standardized to be 0). In contrast, five out of the 19 tracts in the North Philadelphia service cluster have a distress factor score that is more than 2 standard deviations above the mean, and all 19 tracts have a factor score at least 1 standard deviation above the mean.

The maps displayed (Figures 1-3) give an impression of the spatial relationship between the level of CHPP service use and the distribution of risk of homelessness among census tracts in the city. The Pearson correlation coefficients in Table 3 show that the rate of CHPP participation is moderately correlated with both the rate of shelter use (as indicated by prior addresses) and the extent of social and economic distress in a census tract. The correlation between the risk of homelessness as measured by the rate of shelter use within a census tract and social and economic distress is very high, indicating a dependable relationship between the two variables.<sup>6</sup>

*Distance traveled by CHPP participants at different sites*—Table 4 examines the geographic distribution of CHPP participants in relation to the location of homelessness prevention sites by calculating the distance that CHPP participants had to travel to obtain homelessness prevention services. Recall that the program site 7 was chosen because of its central location and was not designed to be a community-based service site. From the data displayed in Table 4, it is clear that great disparity exists in relation to the distance traveled by participants receiving services at the 7 prevention sites. As expected, participants at program site 7 (the Center City site) traveled the longest distance by far, with 74% of the site’s participants traveling more than 3 miles to receive prevention services. In contrast, participants receiving services at program site 1 tend to make the shortest journey to the prevention center. Only 12% of its participants traveled more than 3 miles to the prevention center.

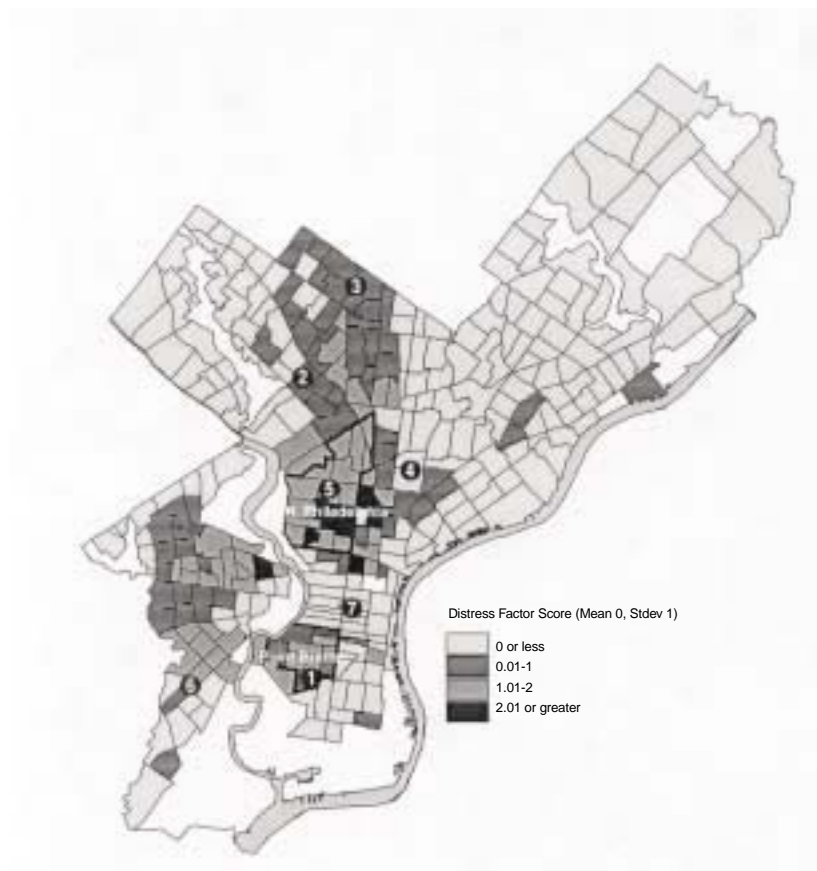
The location of program site 3 and the distance its participants had to travel to receive services at the site warrants some consideration. Given its location at the border of the city, program participants could be expected to travel a greater distance to receive services there. However, program site 6 is also located at the edge of the city (refer to Fig-

FIGURE 2. Census Tract Map of the Distribution of Prior Addresses (OESS)



ure 4), but participants do not travel as far to receive services at that site. Apparently, the difference between program sites 3 and 6 is that the latter is the only prevention center that provides services to a relatively expansive area west of the Schuylkill River (labeled in the map), covering neighborhoods in the West Philadelphia and Southwest Philadelphia areas. Indeed, Figure 4 shows that nearly all participants (97%) at program site 6 came from census tracts west of the Schuylkill River.

FIGURE 3. Census Tract Map of Social and Economic Distress



***Towards a Closer Adherence to the Concept of Community-Based Homelessness Prevention: How Can GIS Analysis Inform the Relocation of Program Sites?***

GIS analysis can help social service administrators to address two related questions regarding program modification and development: (1) Where should a new program site be located (or which existing site should be closed or relocated) to facilitate a closer adherence to the community-based prevention model? (2) Which areas with a demon-

TABLE 3. Means, Standard Deviations, and Zero Order Correlations Among CHPP Service Use, Prior Addresses, Distress Factor, Instability Factor, and Hispanic-Overcrowded Factor <sup>#</sup>

	1	2	3	4	5
1. Location quotient of CHPP service use					
2. Location quotient of shelter use	0.594**				
3. Social and economic distress factor	0.584**	0.801**			
4. Instability factor	0.059	0.177**	0		
5. Hispanic-overcrowded factor	0.030	0.119*	0	0	
Mean	1.011	1.124	0.000	0.000	0.000
Standard deviation	1.207	1.250	1.000	1.000	1.000
N = 336					

**Note.**

<sup>#</sup> The correlation between the three factors are set at 0 for Varimax rotation.

\*\* Correlation is significant at the 0.01 level (2-tailed).

\* Correlation is significant at the 0.05 level (2-tailed).

stably high risk of homelessness need to be targeted due to low levels of utilization of prevention services among their residents?

To address the first question, we examined the distributions of prior addresses of shelter clients and social and economic distress in relation to the location of program sites. For illustrative purposes, we set the criteria for high level of homelessness prevention service needs as census tracts that have a prior address LQ of more than 2 and a distress factor score of more than 1. Figure 5 shows five clusters of census tracts that fall into the category of high levels of service needs. Table 5 shows, for each cluster, the number of census tracts and households, the mean CHPP LQ, the mean prior address LQ, the mean factor score, and the prevention program sites located in the vicinity of the cluster.

The results indicate that there is a need to locate a homelessness prevention site in the West Philadelphia area (i.e., the area west of the Schuylkill River and north of Market Street). Although this area has almost twice as many households as the Point Breeze area, there is no prevention service site located in its vicinity. It is not surprising that the West Philadelphia area has the lowest mean LQ on prevention services use, despite the fact that it ranks second on both prior addresses of shelter clients, as well as social and economic distress. A second finding concerns the probable misplacement of program site 3. This particular program site is not situated in close proximity to any of the five clusters of high service needs. Given the fact that only 2 program sites (sites 4

TABLE 4. Distance Traveled by Participants by Program Site

Program site	Within 1 mile	Within 2 miles	Within 3 miles
1	56%	86%	88%
2	13%	28%	58%
3	14%	30%	44%
4	17%	38%	57%
5	48%	76%	85%
6	23%	45%	77%
7	3%	14%	26%

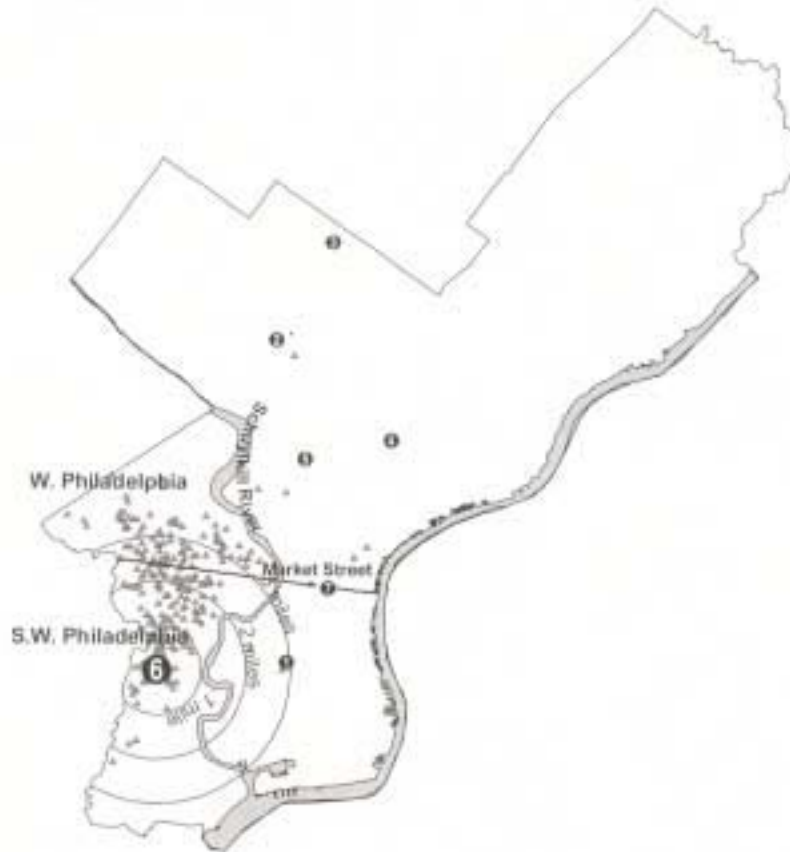
and 5) are located near or within the North Philadelphia cluster, and that the cluster contains 54% (42,450 out of 78,080 households) of all households in areas with high levels of service need, it is reasonable to recommend the relocation of program site 3 to the North Philadelphia area.<sup>7</sup>

Another way to look at improving program targeting is to identify census tracts that have high levels of service needs but low levels of service utilization. Figure 5 and Table 6 identify five such tracts, which have a prior address LQ of more than 3, a distress factor score of more than 1.5, and a CHPP LQ of less than 1. Two of these tracts are located in West Philadelphia and 3 in North Philadelphia. Together, there were 5,388 households living in these census tracts. Although 129 households seeking emergency shelter services had registered their prior addresses in one of the five tracts, only 5 households in these tracts received CHPP services during the study period.

### ***SUMMARY AND CONCLUSION***

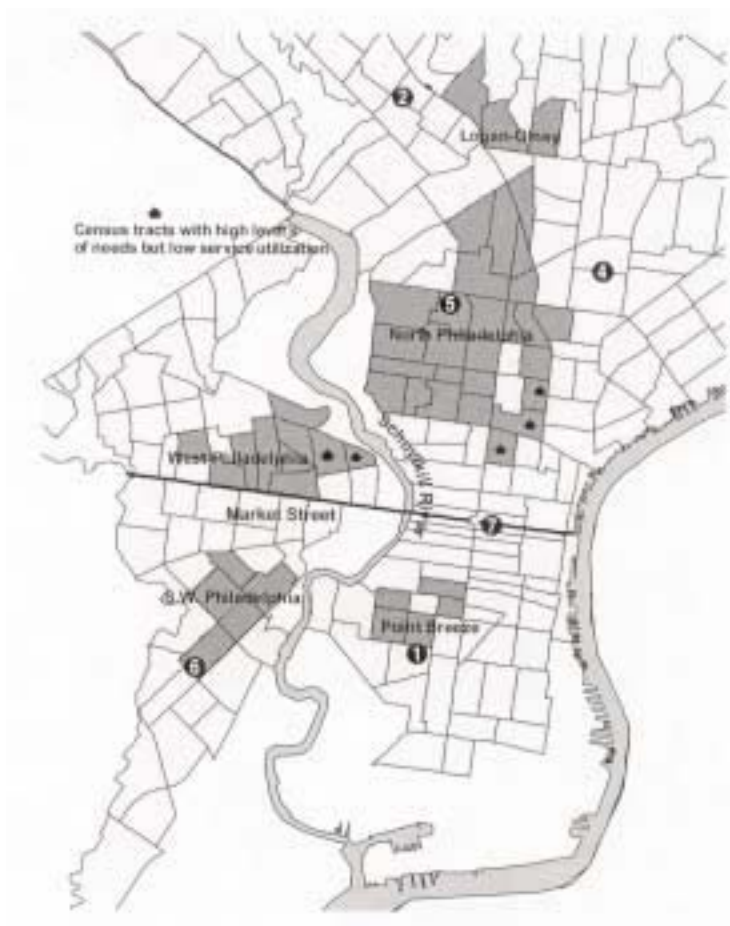
The study reported in this paper has shown that management information system data from human service agencies and publicly accessible data such as those from the U.S. Census can be effectively used in conjunction with Geographic Information Analysis analysis. By integrating a large amount of data within one geographically-referenced framework, social service administrators could monitor the patterns of social service utilization, assess the extent to which different program sites adhere to the community-based program model, determine social services site location, and identify geographical areas with the greatest unmet service needs.

FIGURE 4. Distance Traveled by Participants of Program Site 6



The advantage of the GIS method lies in its ability to produce analyses and display geographically referenced information that are easy to understand and that have potential implications for program planning and program development. The cost of investing in the GIS hardware and software environment notwithstanding, the procurement of data for GIS analysis could be quite manageable and practicable. Increasingly, human service agencies are collecting data on a day-to-day basis about their consumers using their management information system. Moreover, collaboration between agencies providing services to the same client system within a locality such as Philadelphia offers an opportunity

FIGURE 5. Geographical Areas with High Levels of Service Needs



to address program planning and development questions that could help planners and social service managers to improve the service system to meet the multifaceted needs of its clientele. As illustrated in this paper, integrating available MIS data from two components of the Continuum of Care system in Philadelphia provides invaluable information on what communities need to be targeted with homelessness prevention services and on where an additional program site should be located to better ad-

TABLE 5. Geographical Areas with High Level of Service Needs as Indicated by A Prior Address LQ Greater than 2 and Distress Factor Score Greater than 1

Geographical Areas	No. of Tracts	No. of Households	CHPP LQ (mean)	Prior address LQ (mean)	Distress Factor (mean)	Program Site
Logan-Olney	3	5,865	2.51	2.67	1.32	2
North Philadelphia	26	42,450	2.14	3.44	2.00	4, 5
Point Breeze	5	7,206	5.62	2.87	1.30	1
West Philadelphia	10	13,641	1.50	3.23	1.55	No site
Southwest Philadelphia	5	8,918	1.67	2.67	1.40	6
Not in Areas of Needs	N.A.	N.A.	N.A.	N.A.	N.A.	3, 7

**Note.**  
 Total number of tracts with high service needs: 49; total number of households: 78,080.

TABLE 6. Descriptive Statistics of Census Tracts with High Level of Homelessness Prevention Needs but Low Level of CHPP Service Utilization

Area	Tract ID	No. of Households	Distress Factor	Prior Address LQ	No. of Prior Addresses	CHPP LQ	No. of CHPP Participants
North Philadelphia	0145	638	1.73	3.21	14	0.00	0
North Philadelphia	0141	1,090	1.57	3.50	26	0.00	0
North Philadelphia	0132	1,209	3.41	2.42	20	0.54	2
West Philadelphia	0108	1,514	2.10	4.54	47	0.42	2
West Philadelphia	0109	937	1.70	3.44	22	0.35	1

**Note.**  
 Total number of households: 5,388 (North Philadelphia: 2,937; West Philadelphia: 2,451).

dress the unmet needs of households that have an indicated risk of homelessness.

Having enumerated the utility of GIS technology to inform social service planning, it should be cautioned that the analyses derived from application of the technology do not yield definitive answers. As Noble and Smith (1994) contended, population needs indications may not necessarily reflect actual needs for service provision. Areas that are identified to have a great need for homelessness prevention services but have exhibited low levels of service use may have other service programs (besides the prevention sites) available in the community that offer similar supports for residents to deal with their housing problems. Residents from these areas may prefer to use resources from their informal support networks than formal social services to manage their precarious

housing situation (Baker, 1994). While these “extraneous” factors could as well explain the gap between service needs and utilization, GIS technology does have the capability of giving “*a priori* indications of unmet need which provide an informed starting point for further investigation on the ground by community workers and development workers” (Noble & Smith, 1994, 374).

Thus, GIS technology constitutes a helpful tool for guiding managers of social services to pose additional questions for understanding the implementation process of community-based interventions. In the example presented in this paper, an obvious question to ask is what accounts for the variability in being “community-based” among the different prevention program sites. While our results suggest that the locality of the program site could have affected the geographic distribution of program participants, other factors might have come into play in explaining the disparity in service use patterns among program sites. Is the difference among program sites a function of the amount of effort the respective sites have devoted to community outreach? Or is the difference attributable to the type of organization (such as multi-service agency versus housing advocacy group) operating the prevention program? Another question concerns the presumably beneficial effect of receiving services at a site close to participants’ homes. Do participants actually benefit from receiving services at a site close to home? More specifically, are participants who receive services in their own community more knowledgeable about other social services in the community, and as a result more likely to use them appropriately and creatively in the event of future housing crisis? Geographic Information System technology, used in conjunction with other methods of program evaluation including key informant interviews, participant observation, and community survey, could shed lights on the ways to improve the implementation of a social service program.

## NOTES

1. Piasecki and Kamis-Gould (1981, 5) define social area analysis as “a set of integrated procedures designed to identify characteristics and attributes which meaningfully differentiate geographically defined population subgroups.” Through factor analysis, social area analysis collapses area characteristics into theoretically meaningful typologies. See also Smith (1979).

2. “Selected prevention” is one of the three levels of prevention, according to a schema of preventive medicine used by Gordon (1983, 1987). The three levels of prevention—universal, selected, and indicated prevention—were adapted from the public

health distinctions of primary, secondary, and tertiary prevention introduced by the Commission on Chronic Illness (1957). Universal prevention refers to interventions available to the general public regardless of an identified risk of the target problem. Selected prevention refers to interventions targeted to individuals at risk due to their membership in some groups. Indicated prevention differs from universal and selective prevention by targeting interventions to individuals, who, upon screening or examination, are found to manifest characteristics that place the individuals at high risk of the target problem.

3. The use of the 1990 Census data has potential limitations given that this analysis was conducted nearly ten years after the Census data were collected. Estimates that are based on changes since 1990, made by the U.S. Census Bureau and other private vendors, offer alternative data to the 1990 Census data. Estimated census data, however, have limitations of their own because they rely largely on existing census data to determine trends. Indeed, it can be argued that these projected estimates would become less reliable as they attempt to obtain estimates over a longer span of time from the original Census data collection. In light of these limitations, the Census Bureau's plans for using local administrative data to estimate changes may provide more accurate estimates in the future.

4. A street file uses a series of line segments to represent each range of house numbers for all streets in Philadelphia.

5. Although Philadelphia's public shelter system has a residency requirement of 6 weeks or more, non-residents are sheltered as part of the mandatory shelter provision policy in effect on extremely cold or hot days. Some non-residents may be admitted in violation of the residency policy. Moreover, persons who enter the shelter system after 5 p.m. or who stay at the shelter for only one night do not report a prior address (Culhane et al., 1997).

6. This is in sharp contrast with the small relationships found between the rate of shelter use and instability factor and between the rate of shelter use and the Hispanic-overcrowded factor.

7. North Philadelphia refers to the central part of Philadelphia north of Market Street. While program site 3 is located at northern part of Philadelphia in the vicinity of Ogontz and Oak Lane neighborhoods, it is not considered part of North Philadelphia.

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