REEEVALUATING POVERTY CONCENTRATION WITH SPATIAL ANALYSIS: DETROIT IN THE 1990S

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Abstract: Standard measures of poverty concentration based on census tracts may not accurately reflect neighborhood conditions because they offer a weak link to the underlying geography of a neighborhood. Changes in the spatial configuration of land use within a census tract can have the effect of increasing or decreasing the density of poverty. This study uses a dasymetric mapping technique in a raster GIS environment to intersect population data in a block group layer with land use categories from a land use layer. I produce poverty counts and rates at a much finer spatial resolution than a block group, with an explicit spatial relationship between population and surrounding neighborhood characteristics. I illustrate the technique for the City of Detroit by measuring poverty concentration change between 1990 and 2000. I find that poverty became more concentrated in space during the 1990s, counter to reports of diminishing poverty concentration that are based on the share of poor people in high-poverty tracts. [Key words: concentrated poverty, geographic information systems, spatial analysis, neighborhood effects, Detroit.]

INTRODUCTION

Concentrated poverty improved dramatically in the United States during the 1990s by most accounts (Jargowsky, 2003; Kingsley and Pettit, 2003). The standard measure of concentrated poverty is the share of poor people in an area who live in a census tract that exceeds some poverty rate threshold, typically 40% (Bishaw, 2005). For large-scale, cross-sectional studies nationwide, such census tract rates are effective estimates for making comparisons between cities or metropolitan regions. But the standard methods of measuring concentrated poverty may be misleading because they lack a meaningful spatial relationship to their immediate surroundings.

Neighborhood conditions influence poverty when they serve to isolate poor people from nonpoor people (Jencks and Mayer, 1990; Brooks-Gunn et al., 1997b), and isolation is partly determined by the spatial arrangement of neighborhood resources and opportunities; the density of supportive institutions, the mix of people and role models, and the proximity of jobs, schools, and services are a few examples. In other words, space matters in how we interpret poverty, and to rely heavily on a method that discounts space is to
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miss an opportunity for a more theoretically satisfying link to the urgent questions stemming from the concentration effects first proposed by Wilson (1987, 1996).

The main purpose of this paper is to explain a technique for estimating population distributions at a fine-grained spatial resolution, and to describe why such a technique has important implications for researchers who study poverty. I illustrate a method using geographic information systems (GIS) to calculate poverty rates that account for surrounding spatial change, using land use as a proxy for neighborhood conditions. Land-use change is important because the cities that show the most dramatic improvement in census tract poverty rates simultaneously faced substantial and potentially damaging shifts in land use. Housing abandonment, conversion from residential to nonresidential property, and gentrification are examples of land-use change with decisive effects on the density of poverty within a census tract. I illustrate the technique with a case study of concentrated poverty in the City of Detroit between 1990 and 2000. The new method proposed here produces several results that are different from those revealed by analysis of census tracts alone: maps show significantly different geographic patterns; the places where the number of people in poverty increased are concentrated in very small spaces; and a greater share of people in poverty lived at higher densities—poor people per given area—in 2000 than in 1990, a finding that runs counter to recent reports of diminishing concentration of poverty.

A second purpose is to illustrate how the technique can be applied to research questions on concentrated poverty, and in particular on evaluating spatial changes in the neighborhood characteristics that immediately surround people who live in poverty. Geographers and urban planners have recently developed highly detailed techniques for evaluating surrounding neighborhood conditions for the study of environmental justice (McMaster et al., 1997; Liu, 2001) and physical activity (Forsyth, 2005), and methods that produce data at a fine spatial resolution open up new approaches to poverty research.

CONCENTRATION EFFECTS AND SOCIAL ISOLATION

The sudden interest among social scientists in measuring the spatial concentration of poverty that emerged in the late 1980s relied on a conceptual framework formulated by William Julius Wilson (1987). He observed that severe economic deindustrialization pushed a growing share of inner-city Blacks out of the labor force at the same time that other members of the Black community joined the ranks of the middle class and left poverty-stricken neighborhoods. He coined the term concentration effects for an array of troubling social outcomes—such as chronic joblessness, high rates of crime, and out-of-wedlock childbirth—that result from large numbers of poor people living in close proximity to each other. Highly concentrated poverty brings disadvantage to some neighborhoods because, Wilson (1987, p. 60) argued, the social environment is characterized by extreme social isolation, a “lack of contact or of sustained interaction with individuals and institutions that represent mainstream society.” Poor Blacks, according to Wilson, lost contact with middle class Blacks who had previously served as role models of economic success and had maintained the local community institutions that provided connections to the larger mainstream society beyond the immediate neighborhood. Wilson hypothesized that people living in a community of highly concentrated poverty would face problems greater than others who are similarly situated but living in a
community with people of a more diverse range of social status. The conceptual framework thus provides a link between individuals and their local surroundings, with emphasis on social isolation as a community-level characteristic that derives from high rates of spatially concentrated poverty.

Early efforts to test Wilson’s conceptual framework operationalized concentrated poverty by identifying census tracts that surpassed some threshold share of the population living below the federally defined poverty level. Danziger and Gottschalk (1987), studying the period between the decennial censuses of 1970 and 1980, defined concentrated poverty as census tracts in which at least 40% of residents earned incomes below the federally defined poverty level, and confirmed Wilson’s hypothesis that the number of poor Blacks living in concentrated poverty increased in absolute numbers and as a share of all poor people. Jargowsky and Bane (1991) attempted to validate the 40% threshold by conducting field observations in several cities. And in a comprehensive study of neighborhood poverty nationwide, Jargowsky (1997) used census tracts and a 40% poverty rate cutoff to show that the number of high-poverty census tracts more than doubled nationwide from 1,177 in 1970 to 2,726 in 1990, and that the number of people living in them increased from 4 million to 8 million.

Wilson’s conceptual framework of concentration effects suggests that deconcentrating poor people will leave them better off. Yet in practice, recent public policy actions aimed at deconcentrating poverty have resulted in questionable benefits for poor people, both for those who leave high-poverty neighborhoods and for the neighborhoods they leave behind. Following the widely acknowledged failure of high-rise public housing developments and the landmark Gautreaux case that stemmed from that failure, current federal policy now seeks to deconcentrate poverty through a wide range of initiatives, including providing housing subsidies through mixed-income developments, building scattered-site public housing units, and sponsoring mobility programs that require tenants to relocate to neighborhoods with low rates of poverty (Goetz, 2003).

Although evidence suggests that many poor residents are largely better off after relocating away from high-poverty neighborhoods, some scholars have questioned the effects on poor residents in the long run (Popkin et al., 2000). For example, mobility programs must remain small in order to avoid political backlash from receiving communities (Goetz, 2003), and the small numbers make poor people in such communities politically vulnerable, with little chance of becoming full-fledged participants in the larger community. Many poor people discover that they miss the informal social support of their old neighborhoods—despite the troubling poverty—such as the ability to rely on friends and family for child care (Goetz, 2003). Some regret their move because they “experience discrimination from neighbors and others in the community, difficulty with transportation, loss of support and sense of community, and in some instances, still poor housing and neighborhood conditions” (Popkin et al., 2000, p. viii). That many poor people do not want to move from concentrated poverty is not surprising because, despite the range of painful difficulties such places impose on residents, these are the neighborhoods where people have learned to adapt to their conditions with creative institutions of their own making (Wacquant, 1997). Perhaps most troubling from the perspective of Wilson’s ideas is the finding that movers commonly keep to themselves and do not interact with their neighbors in their new communities (Popkin et al., 2000).
Aside from the effects on the people who move, efforts to deconcentrate poverty have been criticized for harming poor people who are left behind. First, dispersal policies tend to select the most advantaged of the poor for moving out of high-poverty neighborhoods, including those residents who are “more motivated, more functional, and have broader life experiences and abilities” (Goetz, 2003, p. 242). Second, some charge that deconcentrating the poor is an effort to dilute minority political strength by drawing down numbers of the Black community (Goetz, 2003). Third, initiatives such as HOPE VI to redevelop inner-city neighborhoods by achieving a wider mix of incomes have served to further isolate and alienate poor people in their own neighborhoods, and as rents rise many poor people are forced to flee their established social networks (Keating, 2000). And, finally, Venkatesh (2003) questions whether spatially concentrated poverty actually leads to the extreme social isolation that Wilson hypothesizes. Detailed ethnographic study of social interactions, according to Venkatesh, reveals a far more complex relationship between high-poverty neighborhoods and mainstream society, and that the geographic isolation of poor people may be less influential in their social isolation than are government actions such as improper policing practices and inequitable distribution of resources.

Despite these critiques of how Wilson’s conceptual framework is put into practice, social scientists need an accurate assessment of poverty concentration to continue the search for the causes and consequences of poverty. I demonstrate with this study how an explicit accounting of space can yield surprisingly different results than standard measures of poverty concentration.

THE ROLE OF SPACE IN THE ASSESSMENT OF POVERTY

Because census tract percentages have weak spatial dimensions, analysts who rely on them as the basis for measuring poverty concentration face two main problems. The first problem is well understood and stems from the fact that census tract poverty rates ignore the spatial organization of the tracts themselves. Known as the checkerboard problem, a measure of a city’s poverty concentration fails to account for whether census tracts are scattered throughout the city or clustered tightly together (White, 1983). Fortunately, many promising new approaches are emerging to address the spatial relationships among census tracts (Greene, 1991; Wong, 1993; Dawkins, 2004; Jargowsky and Kim, 2005).

The second problem deals not with the relationships among census tracts, but rather with the changes within a census tract, and is addressed with the method proposed here. One persuasive explanation for the improvement in poverty concentration during the 1990s is that residents experienced a growth in income due to the unusual national economic boom of the late 1990s that peaked around 2000 (Jargowsky, 2003). Another possible explanation for changes in poverty concentration is that the mix of people changed in high-poverty census tracts (Danziger and Gottschalk, 1987). If a disproportionate share of nonpoor people move in, or if poor people move out, a high-poverty tract will show a declining rate of poverty. Thus, census data can tell us that poverty concentration has changed, but they cannot tell us whether the reason for the change was higher incomes or selective migration.

But there is yet another influence on poverty concentration, one that cannot be detected by census data alone. Changes in the spatial configuration within a census tract can have the effect of increasing or decreasing the net density of poverty. Density is more
theoretically relevant to Wilson’s (1987) concentration effects than is a census tract poverty rate. The poverty rate (the count of people per enumeration zone) serves as a proxy for density (the count of people per given area of land). But notice how a poverty rate is distinct from density. Consider two tracts with a poverty rate of 40%. One has four poor people out of a total of ten living in a large and sparsely settled tract; the other has 2,000 poor people among 5,000 in a small and crowded tract. Both have equal poverty rates but the second tract has a much higher poverty density. And a higher poverty density is likely to contribute to substantially different social isolation under theories of neighborhood effects (Jencks and Mayer, 1990; Brooks-Gunn et al., 1997a).

Furthermore, gross density (based on total land area) is likely to have different consequences for social isolation than does net density (based on occupied land, a subset of total land). Two tracts may have equal populations but considerably different net densities. Consider two tracts of equal area, both with a poverty rate of 40% made up of 2,000 poor people among a total of 5,000. In one of the tracts, people are spread uniformly across the entire tract. But in the second tract, an industrial wasteland occupies three-quarters of the tract’s area, leaving only a quarter of the space for housing. The second tract would have a net density four times higher than the first, with different social outcomes predicted by theories of concentration effects.

Why is density the more relevant measure for evaluating concentration effects? The idea that high levels of poverty concentration are related to harmful degrees of social isolation is reasonable to the extent that “a spatially concentrated or segregated group would be expected to have less contact with other groups than would one whose members were evenly distributed throughout a geographic area” (Greene, 1991, p. 242). Contact and interaction are mediated by space, where the intensity of people and institutions within a given geographic space—density—determine access to opportunity.

Most studies that examine the concentration effects of poverty are limited by their inability to properly capture complex spatial patterns and, furthermore, offer little theoretical link between space and social conditions. The most widely used data source—the decennial census—“does not provide measures of neighborhood characteristics that match the theoretical concepts” (Duncan and Aber, 1997, p. 65). A common approach is to assume that a census tract represents a neighborhood, and then to select the few relevant census variables that describe the kinds of people who live in the neighborhood: “the data sources traditionally relied upon by neighborhood researchers … typically provide information on the sociodemographic composition of statistical areas (e.g., poverty rate or racial makeup of census tracts) rather than the dynamic processes hypothesized to shape child and adolescent well-being” (Sampson et al., 2002, p. 443). Relying exclusively on census sociodemographic data can tell us about important dimensions of neighborhood poverty—such as female-headed households with children, unemployment rates, and the share of recipients of public assistance. But to capture the effects of other critical dimensions that influence poverty—such as crime, drugs, churches, community centers, and social ties stemming from daily activity patterns—we must turn to multiple data sources.

Enumeration zones (such as counties, census tracts, or block groupings) therefore constrain research on poverty and neighborhood effects in several ways: analysis is limited to the data attributes aggregated to the zone boundary; boundaries are approximations of neighborhoods, with some large and some small; and boundaries are not stable, making
assessments of change over time difficult. In addition to these problems, enumeration zones also present an important but overlooked obstacle to understanding poverty: our inability as analysts to accurately visualize the spatial patterns (Martin, 1996). This inability stems from problems inherent in commonly used choropleth mapping techniques. Choropleth mapping—using gradations of shading—is the most common means of displaying areal census data, providing an easy way to visualize how a socioeconomic attribute varies across geographic space. But choropleth maps have limited power for detailed analysis of social conditions at the scale of a neighborhood.

Researchers who perform highly localized neighborhood analysis therefore face several problems of misleading inaccuracies when using choropleth maps based on enumeration zones. First, the easy visualization comes at the price of much lost information: choropleth mapping achieves a smoothing out of data by suppressing the variation in an attribute through reclassifying values into just a few categories (Haining, 2003). The level of measurement, in effect, is reduced from ratio to ordinal. Second, the patterns of a choropleth map depend substantially on the analyst’s choice of both classification method and the number of data classes. Third, because census data are aggregated to enumeration zones that are for the most part arbitrarily drawn, choropleth maps “give the impression that population is distributed homogeneously throughout each areal unit, even when portions of the region are, in actuality, uninhabited” (Mennis, 2003, p. 31). Fourth, these arbitrary zones produce false and abrupt spatial discontinuities when presented in choropleth maps (Langford and Unwin, 1994). Thus, continuous data—such as population density—appear to exhibit distinct changes from one enumeration zone to the next. Finally, these arbitrary zones contribute to the dangers of the modifiable area unit problem (where results change depending on the size and configuration of the zones) and of the ecological fallacy, which stems from the aggregate nature of zonal data (Openshaw, 1984; Sheppard, 1995). It takes a careful analyst to avoid the mistake of drawing inferences about particular kinds of people from data aggregated to enumeration zones (Pickles, 1995), and the fallacy is especially risky with the case of Wilson’s theory of concentration effects because he claims that individual behaviors are influenced by aggregate neighborhood conditions.

Improving Poverty Study with Dasymetric Mapping

One approach to getting around these problems—the inaccuracies of choropleth mapping, representing concentration as a rate, and the absence of spatial relationships between people and their surroundings—is to detach the analysis from the arbitrarily drawn enumeration boundaries. Dasymetric mapping is a technique of areal interpolation that converts enumeration zones to smaller, more spatially relevant boundaries by adding supplementary information, thereby transforming data from one set of geographic boundaries to another (DeMers, 2005). The aim is to exploit the power of a GIS to integrate

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3Boundary locations have little spatial meaning relative to underlying social conditions. Census tracts are designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions. But in practice, the boundaries do not change in accordance to shifting conditions, and small tracts at the urban core capture space differently than large tracts at the suburban periphery.
dissimilar data sources by intersecting two or more data sets to produce a more precise estimate of a spatial distribution than would be possible with only one data set alone (Longley et al., 2005). Figure 1 illustrates how dasymetric mapping works, and shows two separate layers of data. The first is the original layer, shown as dark lines, consisting of a block group enumeration zone associated with attributes from the Census of Population and Housing, such as the number of persons below the federally defined poverty line. The second layer is the ancillary layer, data that can be used to infer spatial distributions within any single block group of the original layer. I use land use polygons in this study for the ancillary layer.

By using land use polygons, the ancillary layer serves two purposes for redistributing population within a block group. First, it identifies locations uninhabited by people. People do not live in cemeteries or water, for example. If I can locate all uninhabited spaces like cemeteries and water, then I can allocate population away from such areas. In Figure 1, the shaded areas are residential territory, and all population in a block group is allocated to these sub-areas within a block group. Population is never reallocated across a block group boundary, a constraint that preserves the original attribute data (Tobler, 1979). Note that the population density—on a people per area basis—would change substantially in Figure 1 after redistributing population with ancillary data. To calculate a population density for the original layer alone, in the absence of other information, would require assuming that population is evenly distributed throughout a block group, so that the population density in Block Group 2 in Figure 1 would be based on the full area of the block group. But after redistributing the population with ancillary data, the population density of Block Group 2 would be based on the area of polygon $c$, an area substantially smaller than the full block group.

Not only do the ancillary data allow for redistributing population by area of residential territory, but they also provide enough information to redistribute population within the residential territories themselves. The second main purpose served by the land use categories in the ancillary layer is to differentiate among residential areas by density classes—
categories based on degree of population density. For example, people living in multiple-
family housing in high-rise buildings occupy space at a higher density than people living
in single-family housing. Estimating the relative population densities among various
housing types allows for allocating population within residential areas accordingly. To
illustrate, Block Group 1 in Figure 1 contains two different density classes. Polygon a, the
darker-shaded residential area, represents a higher population density (e.g., high-rise
multiple-family housing) than polygon b (e.g., single-family housing). Because polygon
a is at a higher population density than polygon b, and because a and b occupy an equal
share of block group area, I can assign more of the block group population to
a than to b. One of the main tasks in the steps that follow is to determine how much more of the block
group population should be assigned to a than to b.

This method of dasymetric mapping has been shown to produce accurate representa-
tions of population density that offer more precision than the underlying original data
layer provides (Langford and Unwin, 1994; Eicher and Brewer, 2001). The method is
conceptually straightforward, but somewhat cumbersome to carry out in a GIS, which
perhaps explains why it is not widely used in social science scholarship.

In an early demonstration of the technique, Wright (1936) cautioned against the use of
choropleth maps for studying socioeconomic data, and offered the method of dasymetric
mapping as a more accurate depiction of the variation in population across space. In a
study of Cape Cod in Massachusetts, he redistributed township population in two steps.
He first identified uninhabited lands using topographic maps from the U.S. Geological
Survey and his own knowledge of the area. He next divided the inhabited lands into sub-
jectively determined classes of population density, a step that he admitted was “based
largely on guesswork” (Wright, 1936, p. 104).

Later studies followed Wright’s example by first isolating inhabited lands and then
estimating population densities. Langford and Unwin (1994), using census data in the
area around Leicester in the British Midlands, employed detailed remote sensing images
in a raster data structure as ancillary data, and they collapsed all land cover categories into
either “occupied” or “unoccupied” classes. Their approach does not differentiate between
population densities within the occupied class, assuming that housing types are uniformly
spread across the region. Holloway et al. (1999), estimating 1990 population density
around Missoula, Montana, used multiple ancillary layers in identifying uninhabited
lands, including land ownership, topography, and land cover. Like Wright, they subjec-
tively assigned predetermined population densities to land cover categories, allocating
80% to urban areas, 10% to open lands, and 5% to each of agricultural and wooded lands.
Eicher and Brewer (2001), in a study that evaluates several dasymetric techniques using
county-level population data for a region of 159 counties in the eastern United States,
similarly assigned predetermined percentages to three land use classes within a county:
70% of county’s population was assigned to urban lands, 20% to agricultural/woodland,
and 10% to forested lands. They pointed out that a major weakness in their three-class
approach is that they did not account for the area of each land use class in a county.

These studies reveal two major problems with previous dasymetric mapping efforts.
Population is assigned to inhabited lands using subjectively determined percentages, and
population is assigned to ancillary classes without accounting for differences in area
among the classes. For instance, in the Eicher and Brewer (2001) study, 70% of a
county’s population is allocated to urban land regardless of the actual share of the county’s total area occupied by urban land.

Mennis (2003) developed a technique that addresses both shortcomings. To improve on the subjectively defined percentages, he empirically sampled population density to arrive at percentage assignments that are rooted in observed measures. Then, to address differences in area among ancillary classes, he used a weighting technique based on areal interpolation to modify the percentages assigned to ancillary classes.

CASE STUDY: APPLYING DASYMETRIC MAPPING TO POVERTY IN DETROIT

To demonstrate the technique of dasymetric mapping, I use Mennis’s (2003) approach, but apply it to poverty populations in Detroit for both 1990 and 2000. My goal is to intersect population data in a block group layer with land use categories from a land use layer, and by converting from polygon boundaries to raster cells, to produce poverty counts and rates at a much finer spatial resolution than a block group. The result will be a new data set that offers an explicit spatial relationship between population and highly localized surrounding land uses that is directly comparable over time. The new data set can then be used to answer a series of questions about the change in poverty concentration between 1990 and 2000 that could not be addressed with census tract or block group data alone.

Detroit has been one of the nation’s most troubled central cities for decades, with severe rates of crime, unemployment, neighborhood abandonment, and poverty (Furdell et al., 2005). It was the most impoverished large city in the nation in 2003, with more than one in three residents living below the federal poverty line (U.S. Bureau of the Census, 2005, Table R1701). Even though poverty remains troublesome in Detroit, measures of poverty concentration based on census tract rates showed substantial improvement during the 1990s. For example, Detroit’s decline in the number of people living in high-poverty neighborhoods in the 1990s was higher than in any other metropolitan region, with a drop of 74% (Jargowsky, 2003). And a far larger share of Detroit’s poor population lived in places of concentrated poverty in 1990 than in 2000: whereas 36% of the city’s poor people lived in “extreme-poverty tracts” (where 40% or more of residents are below the poverty line) in 1990, just 10% of poor people lived in such tracts by 2000 (Kingsley and Pettit, 2003). Jargowsky and Yang (2006, p. 67) evaluated improvements in social conditions nationwide during the 1990s based on four common indicators—male unemployment, high school dropouts, female-headed households with children, and households on public assistance—and concluded that “the changes experienced by inner-city neighborhoods are nothing short of profound.” They used the well-known criteria for defining “underclass neighborhoods” devised by Ricketts and Sawhill (1988), and then compared the count of census tracts between 1990 and 2000 that simultaneously met the criteria. Detroit was among the metropolitan areas showing the greatest improvement in the reduction of “underclass neighborhoods,” and the authors tentatively suggested that the improvement in social problems may result from reductions in poverty concentration.

All of these studies reporting improvements in poverty concentration were based on poverty rates of census tracts. But even while census tract poverty rates improved in Detroit, however, the city simultaneously lost over 6,000 acres of residential land to other uses, representing 15% of the total residential space (Southeast Michigan Council of
Governments, 2004). What is the effect of such dramatic land use change on the geographic concentration of poverty?

For the study area, I restrict my analysis to the municipal boundaries of Detroit, mapped in Figure 2. Note that two independent municipalities—Highland Park and Hamtramck—lie within the boundaries of Detroit. A more complete analysis would include these other municipalities, along with suburban jurisdictions that lie beyond the municipal boundary, to detect patterns in poverty throughout the region. Because the data processing is extensive, however, I chose to focus exclusively on the central city for the purpose of demonstrating the technique.

Data

For the original data boundary I use block groups in 1990 and 2000. Block groups are the smallest geographic unit at which census data are provided from the long-form questionnaire. For the ancillary layer, I use Land Use/Land Cover data (LULC) provided by the Southeast Michigan Council of Governments. The LULC data were derived from aerial photography, gathered in 1990 and 2000, and consist of polygons of land classified by types of urban development, following a standard hierarchical system proposed by Anderson et al. (1976). The highest level categories include, for example, Urban, Agricultural Lands, Forest, and Water. Within these broad categories are two levels of
highly detailed subcategories. At the second level within the Urban classification are such subcategories as Residential, Commercial, and Industrial. These are further divided into a third level of detail, so that under Residential constitutes 13 separate subcategories, allowing for isolating areas based on population density. For example, I can distinguish between multiple-family housing in high rises from multiple-family low-rise development from single-family housing. The dasymetric mapping technique uses these residential subcategories to define density classes for the purpose of redistributing population within a block group.

The LULC data consist of vector polygons. I converted the LULC data to a raster grid with a 250-foot resolution, a cell size small enough to capture the smallest block group. All subsequent raster grids created in the analysis conform to this 250-foot resolution.

Finally, for the numbers of people living in poverty, I use data collected by the Census Bureau for the decennial censuses of 1990 and 2000 (which are based on incomes from 1989 and 1999). The Census Bureau uses the federal government’s official poverty definition, which was originally developed in 1964 (U.S. Bureau of the Census, 2002b). Many scholars and public officials have raised questions about the accuracy of this official measure of poverty (Citro and Michael, 1995). Because the official measure fails to adapt to rapidly changing social conditions, the results of any study that makes comparisons over time (such as the one presented here) should be interpreted cautiously.4

Steps in the Method

The goal is to allocate block group poverty populations to raster grid cells within the block group. The population is distributed to a grid cell according to a formula that accounts for two factors: the relative share of population density among density classes in a block group; and the relative share of area among density classes in a block group. I illustrate the technique in four steps: (1) calculating the density factor, (2) calculating the area factor, (3) combining the results from the first two steps to calculate grid cell populations in a table, and (4) constructing raster grids from the table results.

Step 1 begins by defining the density classes from land use categories, with the aim of differentiating among housing types. I define five density classes that correspond to five land use categories, in order of increasing density: single-family housing where 75% or more of housing units are vacant; single-family housing where up to 75% of units are vacant; single-family housing; low-rise multiple-family housing; and high-rise multiple-family housing. Defining the density classes is carried out through empirical sampling, as proposed by Mennis (2003), as a way to avoid the pitfall of previous studies that relied on

4The official measure of poverty is an important social indicator that affects public policies, government programs, and the public’s perception of the problem. But it is widely considered flawed by the social scientists who nonetheless use it regularly in their work. The current measure has remained largely unchanged over decades and may no longer provide an accurate picture of material deprivation in the United States today because of several weaknesses: it does not distinguish between the differing needs of workers and nonworkers; it does not account for differences among population groups; it fails to account for price differences among regions across the nation; and, most important for this study, it fails to adjust to far-reaching changes in the economy and in public policies so that comparisons over time are highly questionable (Citro and Michael, 1995).
subjectively allocating population among various land uses. I assume that the relative share of population densities within any single block group occurs in the same relative share of densities throughout the study area (City of Detroit). Table 1 shows the density classes, their associated land use category, and in column 1 the aggregate population density.

The population density fraction is the share of a block group’s population that will be allocated to a particular density class within the block group. It consists of a relative proportion of the aggregate population densities and is calculated according to the following formula:

\[
d_c = \frac{p_c}{\sum_{c=1}^{N} p_c}
\]

where: \(d_c\) is the density fraction for density class \(c\); \(p_c\) is the population density (people/square mile) for density class \(c\); for a set of \(N\) density classes, \(c = 1, 2, \ldots, N\).

The results are listed in column 2 of Table 1 for the year 2000. Note that the density fraction for a particular density class is calculated for the entire study area—in this case, for the City of Detroit. So the density fraction for a particular density class is applied to every block group in the city.

Step 2 calculates the area factor by applying a weight based on the share of a block group’s area occupied by a density class, expressed as:

\[
a_{cb} = \frac{\left(\frac{n_{cb}}{n_b}\right)}{1/N}
\]

where \(a_{cb}\) is the area ratio of density class \(c\) in block group \(b\); \(n_{cb}\) is the number of grid cells (i.e., area) of density class \(c\) in block group \(b\); \(n_b\) is the number of grid cells (i.e.,

<table>
<thead>
<tr>
<th>Density class</th>
<th>Land use category</th>
<th>Population density (people per acre)</th>
<th>Density fraction (d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Single-family housing</td>
<td>84</td>
<td>0.100</td>
</tr>
<tr>
<td>2</td>
<td>75% or more vacant</td>
<td>21</td>
<td>0.025</td>
</tr>
<tr>
<td>3</td>
<td>Up to 75% vacant</td>
<td>42</td>
<td>0.050</td>
</tr>
<tr>
<td>4</td>
<td>Multifamily, low-rise</td>
<td>180</td>
<td>0.214</td>
</tr>
<tr>
<td>5</td>
<td>Multifamily, high-rise</td>
<td>514</td>
<td>0.610</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>843</td>
<td>1.000</td>
</tr>
</tbody>
</table>

area) in block group \( b \); \( N \) is the number of density classes considered in the region; for a set of \( N \) density classes, \( c = 1, 2, \ldots, N \).

Step 3 combines the results from above into a single expression, the total fraction, which jointly accounts for the contribution of both the relative density and area of a density class within a block group. The total fraction is expressed as:

\[
f_{cb} = \frac{d_c a_{cb}}{\sum_{c=1}^{N} d_c a_{cb}}
\]

where: \( f_{cb} \) is the total fraction of density class \( c \) in block group \( b \); all others as defined above.

Step 4 converts the total fraction from the previous step to grid cells in a raster layer, as follows:

\[
pop_{cb} = \frac{f_{cb} \cdot pop_b}{n_{cb}}
\]

where: \( pop_{cb} \) is the estimated population in a grid cell of density class \( c \) in block group \( b \) (population can be any count variable, such as the number of people below the poverty line, or the number of people above the poverty line); \( pop_b \) is the population of block group \( b \); \( f_{cb} \) and \( n_{cb} \) are defined above.

The final result is a raster layer consisting of cells filled with the number of people below the poverty line, with one layer for each of two years.

**VISUALLY COMPARING MAPPING METHODS:**
**CENSUS TRACTS VS. DASYMETRIC MAPPING**

Figure 3 compares two maps of the poverty rate, with one showing a choropleth map of data aggregated to census tracts, and the other displaying a continuous raster surface derived from the dasymetric mapping technique. The most striking difference between the maps is the amount of nonresidential land revealed by the raster version. Map A, which shows census tracts, gives a false impression of continuity across space. By contrast, the raster of Map B indicates a choppy, broken-up landscape. Map B reveals that the many places of high poverty are surrounded by swaths of nonresidential space and effectively cut off from nearby neighbors, and furthermore that the degree of spatial isolation is not evenly distributed across the city.

By zooming in on a small part of the city, Figure 4 illustrates the degree of detail provided by the dasymetric mapping method. It compares the same data at three spatial resolutions: a single census tract (panel A); the three block groups that make up the census tract (panel B); and the raster grid cells derived from dasymetric mapping (panel C). The white space of panel C represents nonresidential development which misleadingly appears to be absent from the census tracts of panel A. Notice that the raster of panel C

show substantial stretches of nonresidenti al space surrounding isolated pockets of high poverty.

**MEASURING CHANGE IN POVERTY CONCENTRATION**

The dasymetric mapping technique offers four important advantages over census tracts in assessing change in poverty. The first is the ability to define concentration based on space, as a density rather than a poverty rate at an arbitrarily sized census tract. Table 2 compares the residential density of people below the poverty line in 1990 and 2000, and confirms what the visual inspection suggests: a greater share of people in poverty lived at higher densities in 2000 than in 1990. For example, 20% of poor people lived at a density greater than 20 poor people per acre in 2000, compared to just 5% of poor people in 1990. Furthermore, the places where poverty increased contained a much larger share of the city’s poor people in 2000 than they did in 1990. For example, by isolating the zones where the number of poor people increased by at least 100%, I found that the sum of the area of these zones—which are highly scattered throughout the city—constitute about 10% of the city’s residential land (based on 2000). These zones contained just 5% of the city’s poor population in 1990, but contained 22% of the city’s poor population by 2000. This finding that poor people are living in closer proximity to other poor people in 2000 compared to 1990 is surprising in light of the nationwide studies that reported dramatic improvements in poverty concentration (Jargowsky, 2003; Kingsley and Pettit, 2003).

A second advantage is that a raster grid allows for direct comparisons of territory over time, so that the data can be visualized with maps that compare the same locations from one period to the next. Because census tract boundaries change from one decennial census to the next, such maps are difficult to construct using census tracts alone. To illustrate, the map in Figure 5 shows the absolute change in the number of people living in poverty during the 1990s. Because the aggregate number of the poorest of people in the city dropped considerably by official estimates during the 1990s—from 328,500 in 1989 to 243,000 in 1999—it is not surprising that the vast majority of the city’s territory in the map shows a decline in the number of people in poverty. But Figure 5 also makes clear that change in poverty was not at all uniform in space. Indeed, the places where the
number of people in poverty increased are concentrated in very small spaces. The spatial concentration of worsening poverty is represented in Figure 5 by the dark-shaded areas, with the places that experienced the highest increase in poverty appearing so small on the map as to be difficult to detect. With close inspection, the map helps us see that poverty increased in very small pockets, that these pockets are scattered throughout the city, and that they are often surrounded by large areas where poverty diminished substantially.

A third advantage in the assessment of poverty change is the ability to isolate territories within the city that experienced either worsening or improving conditions. Table 3 provides a matrix of poverty population densities to show how places changed in their poverty rates during the 1990s. The rows represent poverty categories in 1990 and the
Table 4. Change in Land Area (in Acres) by Poverty Category, City of Detroit, 1990–2000

<table>
<thead>
<tr>
<th>Poverty category (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–9.9</td>
<td>3,634</td>
<td>3,069</td>
<td>841</td>
<td>174</td>
<td>55</td>
<td>235</td>
<td>8,007</td>
</tr>
<tr>
<td>10–19.9</td>
<td>1,812</td>
<td>3,887</td>
<td>2,300</td>
<td>633</td>
<td>232</td>
<td>340</td>
<td>9,204</td>
</tr>
<tr>
<td>20–29.9</td>
<td>610</td>
<td>3,568</td>
<td>2,459</td>
<td>1,014</td>
<td>494</td>
<td>429</td>
<td>8,574</td>
</tr>
<tr>
<td>30–39.9</td>
<td>284</td>
<td>1,588</td>
<td>3,220</td>
<td>2,608</td>
<td>1,539</td>
<td>802</td>
<td>10,042</td>
</tr>
<tr>
<td>40 and over</td>
<td>24</td>
<td>1,011</td>
<td>3,729</td>
<td>5,562</td>
<td>5,060</td>
<td>1,821</td>
<td>17,208</td>
</tr>
<tr>
<td>Nonresidential</td>
<td>367</td>
<td>1,261</td>
<td>1,022</td>
<td>890</td>
<td>1,165</td>
<td>31,154</td>
<td>35,858</td>
</tr>
</tbody>
</table>

Rows are poverty categories for 1990, columns are poverty categories for 2000. Italicized cells represent territories where poverty rates increased between 1990 and 2000.


Columns represent corresponding poverty categories in 2000. For an example of reading the table, the cell at the intersection of row 1 and column 5 tells us that the poverty population density increased by 4.5 people per acre in the places that experienced a worsening rate of poverty, from the category of the lowest poverty rate (0–9.9%) in 1990 to the category of the highest poverty rate (40% and over) in 2000. The matrix diagonal represents territory where the poverty category did not change during the decade. Cells above the diagonal are the places where poverty rates worsened during the decade, and cells below the diagonal are places where poverty rates improved.

Table 4 illustrates another example of comparing territories over time, as a matrix of the change in land area by poverty rate categories. For instance, the cell at the intersection of row 1 and column 5 tells us that 55 acres of land converted from the category of the lowest poverty rate (0–9.9%) in 1990 to the category of the highest poverty rate (40% and over) in 2000. The table indicates that the places where poverty rates worsened during the decade were confined to relatively small portions of the city’s territory. Each cell in such matrices represents a different kind of change, and the territories of these cells can easily be isolated for further focused analysis in a GIS.

Finally, the fourth and most significant strength of the dasymetric mapping method is in the range of spatial analysis that can be performed once a raster surface is estimated, allowing for the assessment of conditions in adjacent areas. Unlike census tracts alone, this method explicitly accounts for nonresidential space. And the territory in which people do not live is important for the conditions of distressed neighborhoods. The presence of schools, parks, and places of worship contribute to the vitality of a neighborhood, and this method allows for assessing how such places are changing. Recall that the map in Figure 4 revealed isolated pockets of high poverty surrounded by substantial stretches of nonresidential space. Do large expanses of nonresidential space contribute to the isolation that people in poverty experience? Some kinds of nonresidential space are more likely to strengthen social interaction and promote access to opportunity (community
centers, good jobs, a mix of businesses) than others (busy roads, empty industrial sites, utility corridors), and the raster method proposed here provides a basis for assessing the spatial relationship between localized poverty and neighborhood surroundings. Moreover, because the method allows for direct comparisons over time, it makes it possible to compare change in poverty to change in surroundings. To illustrate how such an analysis might proceed, by defining land use developments that are more likely to increase social interaction or improve access to meeting one’s daily needs, future research could investigate whether poverty improved where neighboring conditions also improved. A major advantage of this technique is that multiple other layers of data—such as the location of jobs, community centers, or places of worship—could readily be added within the same analytical framework to interrogate relationships to poverty populations.

CONCLUSION

We know that living conditions for people in poverty are made even more difficult when immediate neighbors are also struggling with poverty. And a growing body of literature suggests that localized neighborhood conditions have an independent effect on a person’s poverty status. Yet analysts rarely evaluate changes in poverty using measures that account for spatial change. This study develops a straightforward technique for estimating the spatial distribution of poverty. It offers a number of advantages with an analytical framework that detaches poverty analysis from zones such as census tracts or block groups: it provides an explicit spatial link to surrounding conditions; allows for calculating poverty rates at uniform and comparable spatial units; permits conducting analysis of change with consistent spatial units over time; provides the ability to assemble dissimilar data sets into a single analytical scheme; and enables the making of maps that provide more accurate visual portrayal of geographic patterns.

By illustrating the method with the case study of Detroit, I discovered findings that would not be revealed through analysis of census tracts alone. First, neighborhood abandonment is so severe in some neighborhoods that islands of concentrated poverty are emerging, placing greater distance between poor neighborhoods and nonpoor people and institutions. Second, although poverty in the aggregate improved in Detroit during the 1990s, the gains in poverty concentration may not be as striking as found in previous studies. The finding that poverty is becoming more concentrated in space runs counter to the widely reported findings that are based on census tract poverty rates. Small pockets of substantial increases in poverty that are surrounded by diminishing poverty can result in a drop in the poverty rate at the resolution of a census tract. But without examining relative shifts within a census tract, we run the risk of failing to see compact and isolated pockets of severe conditions of concentrated poverty. The methodology outlined here offers the advantage of detecting patterns at highly detailed spatial resolution for the policymakers, urban planners, and community activists who operate at the neighborhood scale to improve the lives of poor people.

REFERENCES


