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## **Space and Change in the Measurement of Poverty Concentration: Detroit in the 1990s**

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## Space and Change in the Measurement of Poverty Concentration: Detroit in the 1990s

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### Abstract

Standard measures of poverty concentration may not accurately reflect neighborhood conditions because they offer a weak link to the underlying geography of a neighborhood. Changes in the spatial configuration within a census tract can have the effect of increasing or decreasing the density of poverty, and the cities that showed the most dramatic improvement in census tract rates simultaneously faced substantial and potentially damaging shifts in land use. This paper 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 (a) a substantially larger share of poor people in 2000 lived in places that exceeded the standard 40-percent threshold than is calculated by the aspatial census-tract approach; (b) poverty became more concentrated *in space* during the 1990s counter to the reports of diminishing poverty concentration that are based on the share of poor people in high-poverty tracts; and (c) poverty improved where neighboring land-use conditions also improved.

Keywords: concentrated poverty; geographic information systems; spatial analysis; neighborhood effects; Detroit

## **Introduction**

Concentrated poverty improved dramatically in the 1990s by most accounts (Jargowsky 2003; Kingsley and Pettit 2003). The standard measure of concentrated poverty is the share of poor people in a region who live in a census tract that exceeds some poverty rate threshold, typically 40 percent (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 surroundings.

Neighborhood conditions influence poverty when they serve to isolate poor people from nonpoor people (Brooks-Gunn, Duncan, and Aber 1997b; Jencks and Mayer 1990), 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 understand poverty, and to rely heavily on a method that discounts space is to 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 in geography, urban planning, and other social sciences 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 non-residential 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 than those that could be revealed by analysis of census tracts alone: maps show significantly different geographic patterns; poverty densities – poor people per given area – are strikingly high in places; and a substantially larger share of people in 2000 lived in places that exceed the 40-percent threshold than is calculated by the aspatial census-tract approach.

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 (Liu 2001; McMaster, Leitner, and Sheppard 1997) and physical activity (Forsyth and et al. 2005). The intention here is not to conduct a full analysis of neighborhood poverty, but rather to illustrate the kinds of questions that can be addressed regarding the influence of the built environment on poverty outcomes by using data at a fine spatial resolution. The findings suggests that while poverty conditions improved in the aggregate in Detroit, far more of the many who remain in poverty are experiencing deteriorating conditions than would be detected by standard formulations of poverty concentration.

## The Role of Space in the Assessment of Poverty

Because census tract percentages are weakly linked to space, 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 (Dawkins 2004; Greene 1991; Jargowsky and Kim 2005; Wong 1993).

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 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 moved in, or if poor people moved 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 sparse 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 density is likely to contribute to substantially different social circumstances under theories of neighborhood effects (Brooks-Gunn, Duncan, and Aber 1997a; Jencks and Mayer 1990).

Furthermore, gross density (based on total land area) is likely to have different consequences for social isolation than is net density (based on occupied land, a subset of total land). Two tracts may have equal populations but considerably different net densities. Imagine two tracts of equal area, both with a poverty rate of 40% made up of 2,000 poor people among 5,000. In one of the tracts, people are spread uniformly over 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 the neighborhood effects literature.

Why is density the more relevant measure for evaluating concentration effects? Highly concentrated poverty brings disadvantage to some neighborhoods because, Wilson (1987: 60) argues, 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." The idea that high levels of poverty concentration are related to harmful degrees of 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 1991:242). Contact and interaction are mediated by

space, where the intensity of people and institutions *in 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: 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, Morenoff, and Gannon-Rowley 2002: 443). Relying exclusively on census sociodemographic data can tell us about important dimensions of neighborhood poverty – such as women-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 – like 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 groups) 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 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. Indeed, the social scientists, urban planners, and community activists who carry out highly localized neighborhood analysis 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 is in effect 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,<sup>1</sup> 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: 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 have 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

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<sup>1</sup> Boundary 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.



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).

### ***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 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. The figure 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 we use 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.

[Figure 1 here]

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. We know

that people do not live in cemeteries or water, for example. If we can locate all uninhabited spaces like cemeteries and water, then we 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 that we assume that population is evenly distributed throughout a block group, so that the population density in Block Group 2 in the figure 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 does the ancillary data allow us to redistribute population *by area* of residential territory, but it also provides 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. If we can estimate the relative population densities among various housing types, then we can allocate 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, we 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 representations of population density that offer more precision than the underlying original data layer provides (Eicher and Brewer 2001; Langford and Unwin 1994). 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 example 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 over 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 subjectively-determined classes of population density, a step that he admitted was “based largely on guesswork” (Wright 1936: 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 region around Leicester in the United Kingdom, used 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 uniform across the region. Holloway, Schumacher, and Redmond (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 subjectively 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 U.S., 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 with 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 past dasymetric mapping efforts. Population is assigned to inhabited lands using subjectively determined percentages, and the population is assigned to ancillary classes without accounting for differences in area among the classes. For example, in the Eicher and Brewer (2001) study, 70% of a county's population is allocated to urban lands regardless of the share of the county's total area occupied by urban lands.

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 Illustration: 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 the City of Detroit in 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, Wolman, and Hill 2005). The most recent data on poverty show that Detroit was the most impoverished 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 rates are high today, some measures of poverty 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 any other metropolitan region, with a drop of 74 percent (Jargowsky 2003). A far larger share of Detroit's poor population lived in places of concentrated poverty in 1990 than in 2000: while 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). Even while census tract poverty rates improved, however, the city simultaneously lost over 6,000 acres of residential land to other uses, representing 15 percent

of residential space (Southeast Michigan Council of Governments (SEMCOG) 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 the City of Detroit, shown in the map of Figure 2. Note that two independent municipalities sit within the boundaries of Detroit. A more complete analysis would include these other municipalities, along with suburban jurisdictions that sit 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 illustrating the technique.

[Figure 2 here]

### ***Data***

For the original data boundary I use block groups in 1990 and 2000, with attribute data on poverty collected by the Census Bureau in 1989 and 1999. 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 and others (1976). The highest-level categories include, for example, Urban, Agricultural Lands, Forest, and Water. Within these broad categories are two levels of highly detailed sub-categories. At the second level within the Urban classification are such sub-categories as Residential, Commercial, and Industrial. These are further divided into a third level of detail, so that under Residential is 13 separate sub-categories, allowing for isolating areas based on population density. For example, we 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 sub-categories to define density classes for the purpose of redistributing population within a block group.

In addition to providing highly detailed information on residential land, the LULC data provide sufficient detail on nonresidential urban land to permit making an assessment of the conditions that surrounding housing areas in a neighborhood. We can isolate, for example, land that contains shopping centers, mixed business areas, and education, religious, and health facilities. Note, however, that a limitation of LULC data is that they do not provide a sense of scale of such places beyond the land area. We do not know whether a commercial area is big or small in terms of number of employees or square footage of building space; these would require different data sets which are typically difficult to obtain or expensive to purchase. LULC data only give us information on the size of land area and the kinds of activities that happen on that land. The strength of LULC data is in providing a consistent set of categories for assessing change over time, and at a fine level of spatial resolution.

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.

### ***Steps in the Method***

The goal is to calculate poverty rates for raster grid cells that are smaller than a block group. The poverty rate requires two populations, the number of people with incomes below the

poverty level and the number of people with incomes above the poverty level.<sup>2</sup> Both populations are assigned to grid cells and from them a poverty rate is calculated.

Each population is distributed to a grid cell according to a formula that accounts for two factors: (1) the relative share of *population density* among density classes in a block group, and (2) the relative share of *area* among density classes in a block group. A key step is defining the density classes, which is carried out through empirical sampling as proposed by Mennis (2003) as a way to avoid the pitfall of previous studies that relied on subjectively allocating population among various land uses. 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.

The goal in this step is to arrive at a formula for assigning population to any one density class within a block group. We know that population density is higher in multiple-family housing than in single-family housing, but we do not know how much higher. That is, if a block group contains more than one density class, we have no way of determining how to split up the block group population between the density classes. But if we can find typical population densities for the entire study area (City of Detroit), we can then assume that the mix of population densities

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<sup>2</sup> The sum of these two populations make up the universe of the “population for whom poverty status was determined,” which does not match precisely the total population due to the method of sampling used. For more information on poverty populations and the definition of poverty status, refer to census technical documentation (U.S. Bureau of the Census 2002b).



within any single block group occurs in the same proportion as the mix of densities throughout the study area. Fortunately, a substantial share of the block groups meet one of the following two conditions that do allow for finding population density: the block group is entirely covered by a single density class, or the block group contains within its boundaries only one density class. For each density class, then, a set of block groups is selected from throughout the study area that meet either of these two conditions. Then by using the total population and area of the density classes in this selection of block groups, we can calculate an aggregate population density. Table 1 shows the density classes, their associated land-use category, and in column (1) the aggregate population density derived by this sampling of block groups throughout the study area.

[Table 1 here]

Finally, 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:

$$d_c = \frac{p_c}{\sum_{c=1}^N p_c} \quad (1)$$

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,  $c = 1, 2, \dots, N$ .

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.

In step 2, we calculate the area factor. If we were to allocate population to grid cells based on step 1 alone, we would be assuming that each density class occupies an equal share of a block group's area. That is, for five density classes, step 1 assumes that a block group is evenly partitioned into five equal spaces. Step 2 corrects for this by applying a weight based on the share of a block group's area occupied by a density class. The weighting factor is called the *area ratio*, a value calculated for each density class in each block group. It represents the *actual* share of the area occupied by a density class within a block group, relative to the *assumed* share of the area occupied by a density class within a block group under step 1 above. In other words, the area ratio is the actual area of density class within a block group divided by 1/5 of the block group area, expressed as:

$$a_{cb} = \frac{\left(\frac{n_{cb}}{n_b}\right)}{1/N} \quad (2)$$

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., area) in block group b;

N is the number of density classes considered in the region; for a set of N density classes,  $c = 1, 2, \dots, N$ .

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:

$$f_{cb} = \frac{d_c a_{cb}}{\sum_{c=1}^N d_c a_{cb}} \quad (3)$$

where:

$f_{cb}$  is the total fraction of density class c in block group b; all others as defined above.

In GIS, the total fraction is calculated in an attribute table, with a row for each block group and five separate fields for five density classes. In step 4, the task is to convert these tabular values to grid cells in a raster layer. By assuming that population density is uniform within any given density class, we divide the population assigned to a density class evenly among the grid cells that make up the density class within a block group, as follows:

$$pop_{cb} = \frac{f_{cb} pop_b}{n_{cb}} \quad (4)$$

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.

For each of two populations – the number of people above and below the poverty line – five raster grids are created, one for each density class, using a masking procedure to isolate cells within any given density class. The five layers are then combined into a single layer containing all five density classes. One layer consists of cells filled with the number of people above the poverty line. The second layer consists of cells filled with the number of people below the poverty line. Finally, from these two layers, the poverty rate is calculated in a third raster layer, completing the steps for one year of data.

### **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 showing 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. In contrast to the census tracts of Map A which give a false impression of continuity across space, the raster of Map B indicates a choppy, broken-up landscape. Map B suggests that the many places of high poverty that are surrounded by swaths of nonresidential space are effectively cut off from nearby neighbors, but that the degree of spatial isolation is not evenly distributed across the city.

[Figure 3 here]

By zooming into 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 shows substantial stretches of nonresidential space surrounding isolated pockets of high poverty. 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, parks, good jobs, a mix of businesses) than are others (busy roads, empty industrial sites, utility corridors). A census tract alone cannot address such a question, but the raster method proposed here provides a basis for assessing the spatial relationship between localized poverty and neighborhood surroundings.

[Figure 4 here]

### **Measurement of Change in Poverty Concentration**

The dasymetric mapping technique offers four important advantages over census tracts in assessing change in poverty through time. First, a raster grid allows for direct comparisons of space 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 of Figure 5 shows the absolute change in the number of people in poverty during the 1990s. Because the aggregate number of poor people in the city dropped considerably 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 color red, which appears 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 entire city, and that they are often surrounded by large sections where poverty diminished substantially. This combination of observations explains how poverty rates might drop at the resolution of census tracts, even while compact sub-areas within these census tracts experience dramatic rises in poverty.

A second advantage is in the ability to define concentration based on space, as a density rather than a poverty rate at an arbitrarily-sized census tract. Indeed, examining the data behind the map of Figure 5 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 find that the sum of the area of these zones – which are highly scattered throughout the entire 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.

Third, in addition to the advantages in visualizing the data and revealing pockets of concentrated poverty that go undetected by census tracts, the dasymetric mapping technique also produces a distribution among poverty threshold categories that differs from an analysis of census tracts alone. One of the problems with assessing poverty with poverty rate categories (such as 0-10%, 10-20% and so forth) is that the cutoffs are arbitrary: “there is little difference between a neighborhood with a 39.9 percent poverty rate and one with a 40.1 percent poverty rate” (Jargowsky 1997: 12). Indeed, Galster (2005) argues that marginal shifts across these

category thresholds are worrisome enough to question whether the shifts in poverty concentration during the 1990s were really as “stunning” (Jargowsky 2003) or “astonishing” (Kingsley and Pettit 2003) as reported, cautioning that to focus exclusively on those census tracts that dropped below the 40% threshold may be to miss the other census tracts that nevertheless worsened beyond a threshold where other damaging effects spill over to neighbors. If this as-yet-undetermined other threshold is indeed a better marker than the arbitrary 40% cutoff, then the dasymetric mapping technique may offer more refined measure of poverty distributions. For example, I find that in Detroit the share of people living in places with high percentages of poverty (over 40%) did not fall as significantly as reported by others using census tract analysis. Table 2 compares methods by contrasting the dasymetric technique to standard census tract poverty rates, using five categories of poverty rates. With data aggregated at census tracts, the share of poor people living in high-poverty tracts (40% and over) dropped by 37% during the decade. In contrast, the dasymetric mapping technique results in a less dramatic drop of 26%.

[Table 2 here]

Finally, a fourth advantage in the assessment of poverty change is the ability to isolate territories within the city that experienced either worsening or improving conditions. We may want to know, for example, which locations experienced improvements in the poverty rate, and which places did not, so that we can test whether changes in neighborhood conditions contributed to changes in poverty. Table 3 presents a matrix of land area to show how places changed in their poverty rates during the 1990s. The rows represent poverty categories in 1990 and the 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 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 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. Each cell in the matrix represents a different kind of change, and the territories of these cells can easily be isolated for further focused analysis in a GIS.

[Table 3 here]

### **Analyzing Change in Surroundings**

The power of the dasymetric mapping approach goes considerably beyond improving upon measures of census tract poverty rates. The most significant strength of the method is in the range of spatial analysis that can be performed once a raster surface is estimated, allowing us to say something about the conditions in immediate surroundings. I illustrate how the method can be applied to a series of questions regarding the relationship between poverty populations and surrounding nonresidential land uses. The territory where people do not live is important for the conditions of distressed neighborhoods. The presence of schools, places of worship, and parks contribute to the vitality of a neighborhood, and this method allows us to assess how such places are changing.

Are changes in poverty related to changes in the nonresidential surroundings? I approach this question by using land use categories as proxies for neighborhood conditions, assuming that some kinds of land use development are more favorable to improvements in poverty than others. By “favorable,” I mean land use developments that are more likely to increase social interaction or improve access to meeting one’s daily needs. I classify all nonresidential land into three categories: Favorable (examples include parks, retail shopping, mixed business areas, and institutional establishments like community centers and schools), Unfavorable (for example,



utility infrastructure, extractive and barren lands), and Indeterminate (for example, industrial land). I use the category Indeterminate for development that does not clearly meet my definition of favorable. For example, industrial sites may be favorable if they provide local jobs, but if the site is vacant and dilapidated it may have the effect of discouraging social interaction.

To illustrate, I provide an example of preliminary analysis focused only on neighboring favorable land uses. In GIS, I create a raster layer to represent neighboring land use conditions, for both 1990 and 2000. Each cell is assigned a value representing the area of favorable lands within a half-mile-radius circular search area. Then, by comparing these two raster layers, and by linking them to other raster layers that describe poverty change, I construct Table 4 which provides a relationship between changes in surrounding land uses and changes in poverty status. For example, the cell at the intersection of row 1 and column 5 tells us that the places that changed from the lowest category of poverty rates (0-9.9%) to the category of highest poverty rates (40% and over), on average gained one acre of favorable land within a half-mile from home. The matrix suggests that poverty improved where neighboring conditions also improved. Many of the largest gains in favorable land uses occur below the matrix diagonal – the places where poverty rates improved. By contrast, nearly all of the places that lost favorable land uses occur above the matrix diagonal, where poverty worsened. A noteworthy finding from the matrix is that the places that remained in the highest poverty category (40% and over) during the decade show an average increase of ten acres of favorable land within a half mile. Furthermore, although not shown in the table I also find that the mix or variety of surrounding favorable land uses increased for these places as well. These results are consistent with gentrification occurring at the edges of high-poverty residences (Freeman 2004).

[Table 4 here]

The results should be read with caution due to several limitations in the analysis. First, any analysis of surrounding conditions is susceptible to misleading edge conditions. Because the spatial extent of the analysis is limited to the central city, and because two municipalities contained within the study area are excluded, a fuller analysis would require a broader spatial extent of study area. Second, a sensitivity analysis that uses a series of search radii in analyzing surroundings would strengthen the analysis, although I find that patterns hold for a radius of one mile as well as the half-mile evaluation reported above. Third, classifying nonresidential land uses into favorable and unfavorable is strictly subjective. Finally, land uses offer a convenient surrogate for the built environment but clearly cannot capture the complexity of neighboring conditions. However, 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 query relationships to poverty populations.

## **Conclusion**

We know that living conditions for people in poverty are made yet 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 with 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 like 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 one analytical scheme; and enables maps that provide more accurate visual portrayal of geographic patterns.

By illustrating the method with the case study of Detroit, we discover findings that would not be revealed by analysis of census tracts alone. First, neighborhood abandonment is so severe in some neighborhoods that islands of concentrated poverty are emerging, placing more distance between the neighborhoods and nonpoor people and institutions. Second, although poverty in the aggregate clearly improved in Detroit during the 1990s, the gains in *poverty concentration* may not be as dramatic 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 the relative shifts within a census tract, we run the risk of failing to see compact and isolated pockets of severe conditions of concentrated poverty. Finally, the results also offer preliminary evidence that poverty improved in those places where the surroundings experienced land use development of a kind that fosters social interaction. The technique outlined here offers the advantage of detecting patterns at highly detailed spatial resolution for the policy makers, urban planners, and community activists who work at the neighborhood scale to improve the lives of poor people.

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## Appendix

Table 1. Population Density Fraction, by Density Class, City of Detroit, 2000

<b>Density Class</b>	<b>Land Use Category</b>	<b>(1) Population Density (people per acre)</b>	<b>(2) Population Density Fraction, d</b>
1	Single family housing	84	0.100
2	75% or more vacant	21	0.025
3	Up to 75% vacant	42	0.050
4	Multi-family, low-rise	180	0.214
5	Multi-family, high-rise	514	0.610
	Total	843	1.000

Source: U. S. Bureau of the Census (1993; 2002a); Southeast Michigan Council of Governments.

Table 2. Comparing Methods: Population Distribution by Poverty Categories, City of Detroit, 1990-2000

Poverty Category (%)	Method 1: Census Tracts			Method 2: Dasymetric Mapping		
	Share of Poverty Population		Change In Share 1990- 2000	Share of Poverty Population		Change In Share 1990- 2000
	1990	2000		1990	2000	
1 0-9.9	1.57	2.36	0.79	2.21	2.33	0.12
2 10-19.9	8.16	13.32	5.16	7.61	15.42	7.81
3 20-29.9	14.74	28.56	13.83	13.23	25.72	12.49
4 30-39.9	21.00	38.29	17.28	22.11	27.95	5.84
5 40 and over	54.53	17.47	(37.06)	54.84	28.57	(26.27)
Total	100.00	100.00	0.00	100.00	100.00	0.00

Source: U. S. Bureau of the Census (1993; 2002a); Southeast Michigan Council of Governments.



Table 3. Land Area (in Acres) by Change in Poverty Category, City of Detroit, 1990-2000

Poverty Category (%)		1	2	3	4	5	6	Total
0-9.9	1	3,634	3,069	841	174	55	235	8,007
10-19.9	2	1,812	3,887	2,300	633	232	340	9,204
20-29.9	3	610	3,568	2,459	1,014	494	429	8,574
30-39.9	4	284	1,588	3,220	2,608	1,539	802	10,042
40 and over	5	24	1,011	3,729	5,562	5,060	1,821	17,208
Nonresidential	6	367	1,261	1,022	890	1,165	31,154	35,858
								88,894

Note: Rows are poverty categories for 1990, columns are poverty categories for 2000. Shaded cells represent territories where poverty rates increased between 1990 and 2000. Source: U. S. Bureau of the Census (1993; 2002a); Southeast Michigan Council of Governments.

Table 4. Change in "Favorable" Land Use Area Within Half Mile Radius, by Poverty Category, City of Detroit, 1990-2000

Poverty Category (%)		1	2	3	4	5	6
0-9.9	1	6	7	(4)	(3)	1	5
10-19.9	2	7	8	4	5	(7)	(3)
20-29.9	3	8	7	1	(2)	13	1
30-39.9	4	4	1	9	1	(2)	(1)
40 and over	5	35	13	3	(2)	10	12
Nonresidential	6	13	54	13	15	24	(4)

Note: Rows are poverty categories for 1990, columns are poverty categories for 2000. Shaded cells represent territories where poverty rates increased between 1990 and 2000. Source: U. S. Bureau of the Census (1993; 2002a); Southeast Michigan Council of Governments.

## Figures

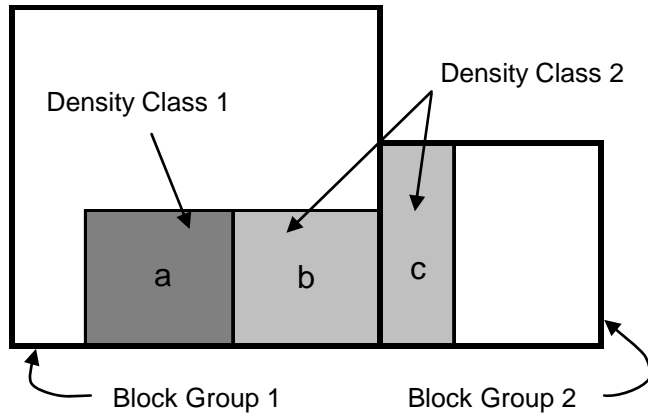


Figure 1. Schematic Illustration of Dasymetric Mapping Method

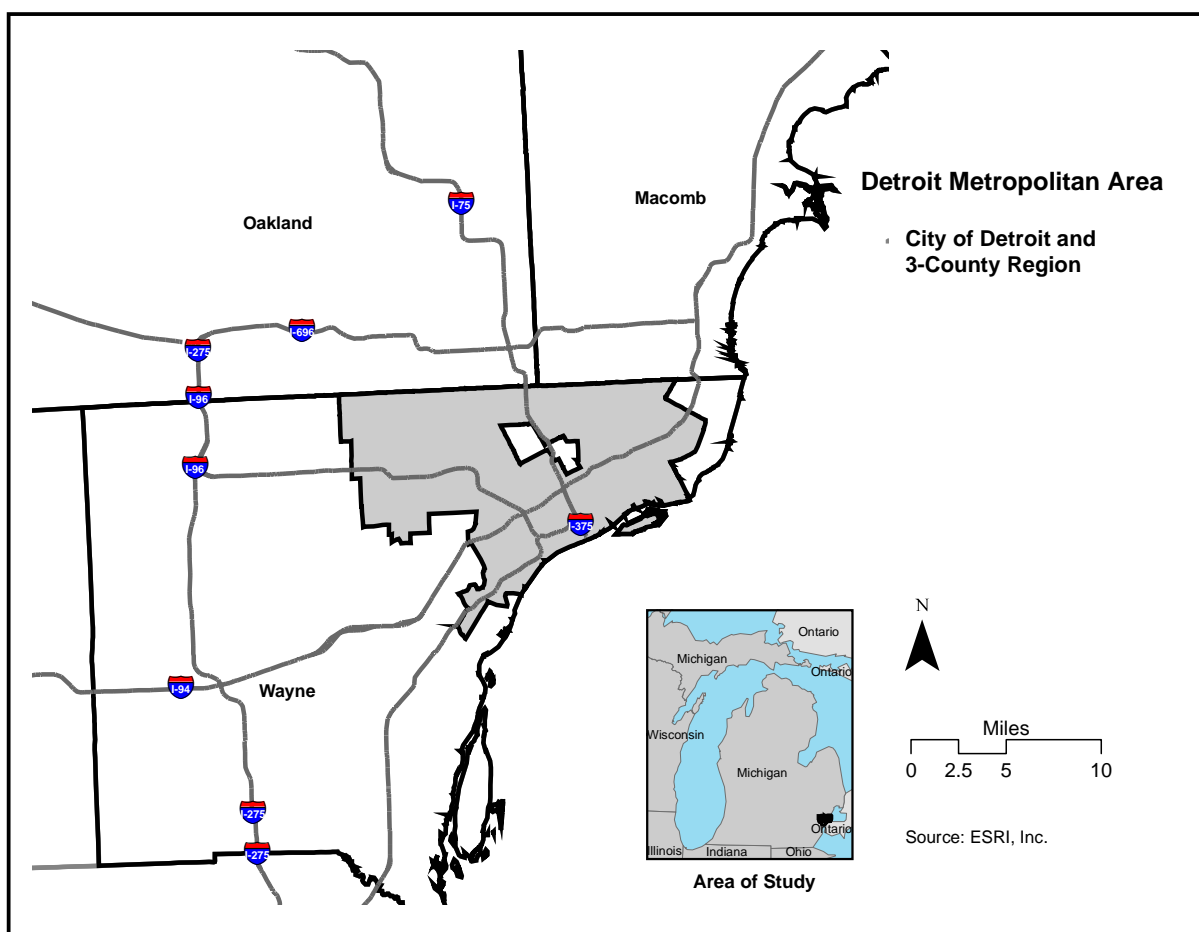


Figure 2. Overview of the City of Detroit and 3-County Region, 2000

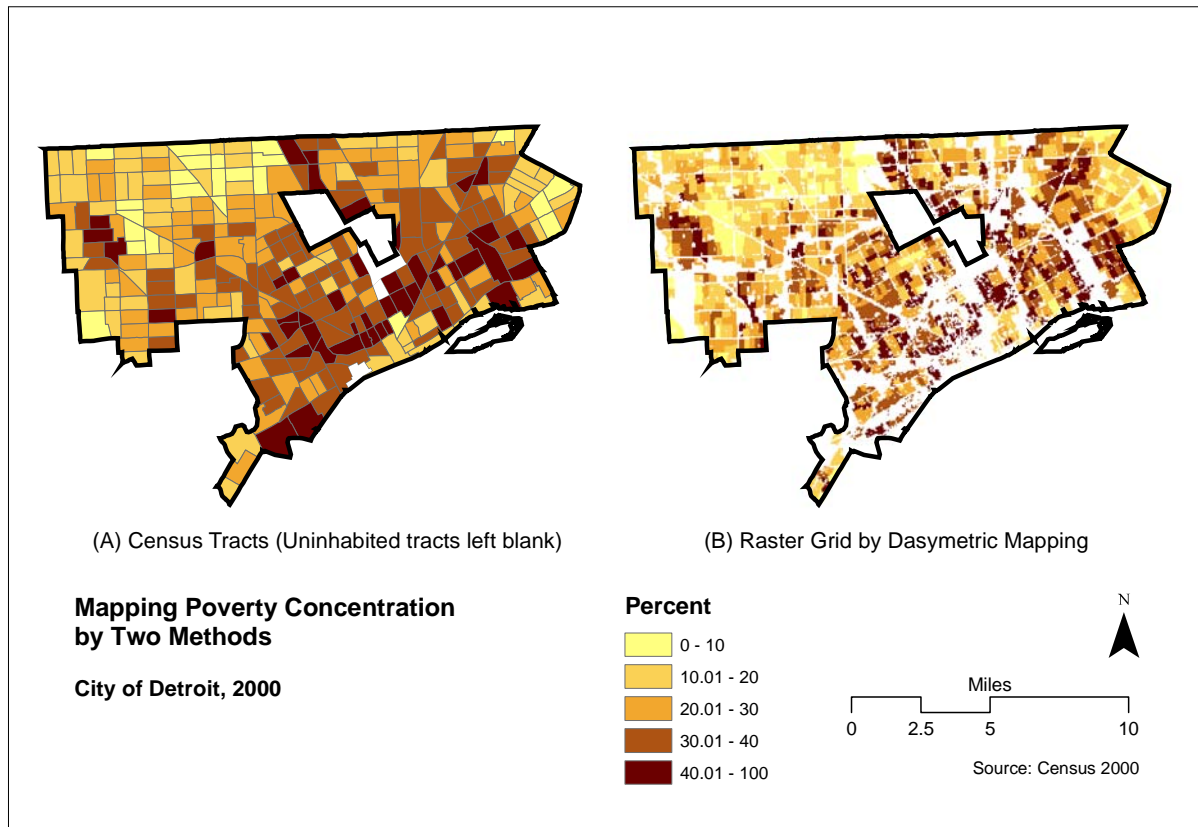


Figure 3. Comparing Poverty Concentration Patterns by (A) Census Tracts and (B) Raster Grid, City of Detroit, 2000

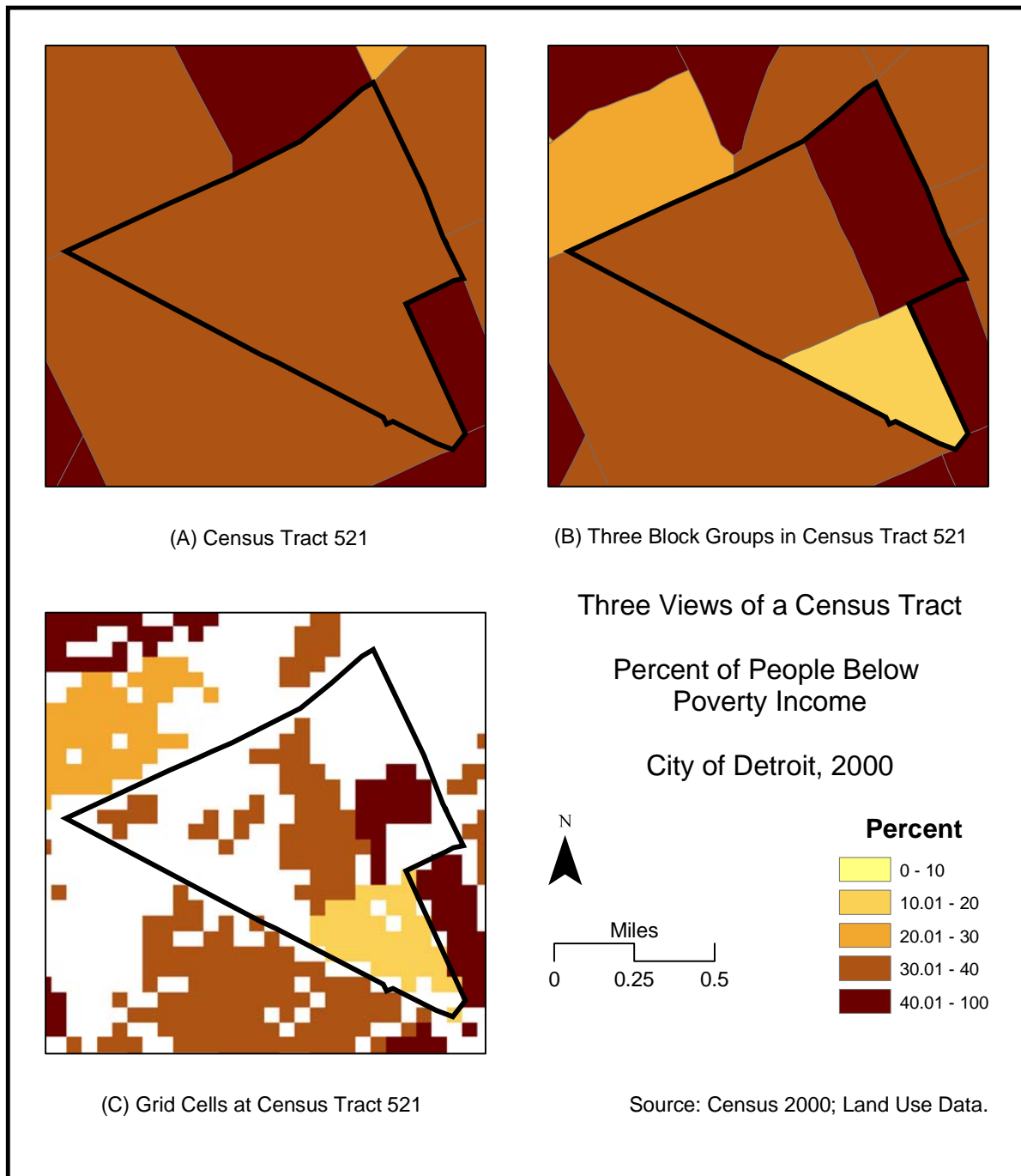


Figure 4. Comparing Poverty Concentration in Three Views: (A) Census Tract, (B) Block Groups, (C) Raster Grid, City of Detroit, 2000

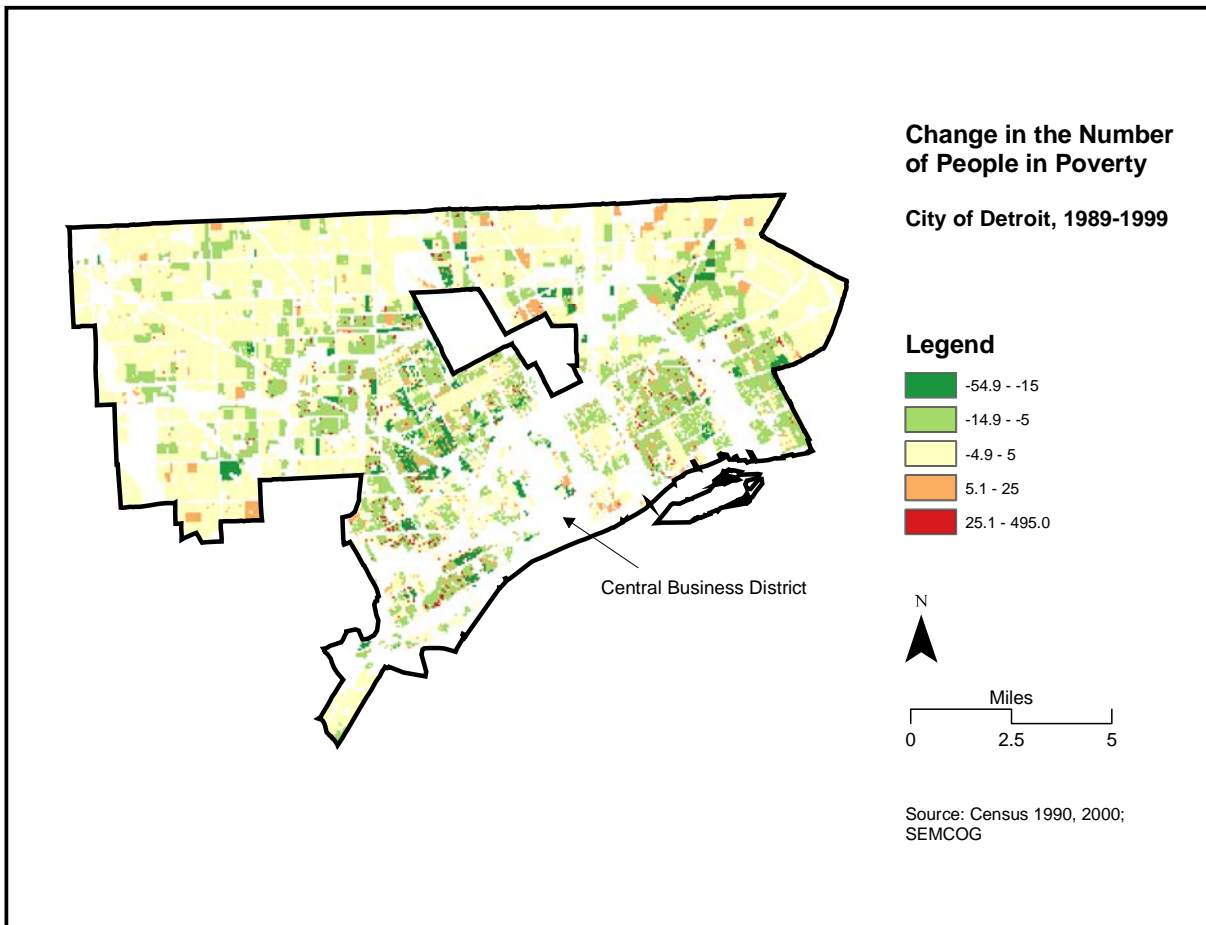


Figure 5. Change in the Number of People in Poverty, City of Detroit, 1989-1999