

INTRAURBAN MIGRATION, NEIGHBORHOODS, AND CITY STRUCTURE¹

*Shipeng Sun*²

**School of Natural Resources & Environment
University of Michigan, Ann Arbor**

Steven M. Manson

**Department of Geography
University of Minnesota, Twin Cities**

Abstract: The neighborhood is the central analytical entry point into a wide range of research topics, but it is an open question as to what defines a neighborhood. Most quantitative neighborhood classification methods are based on the assumption that neighborhoods are composed of places with similar spatial and socioeconomic characteristics. While this assumption is both convenient and valuable in neighborhood classification, it tends to overlook critical features of lived experience, particularly human activities such as migration. This paper examines neighborhood classification through the lens of migration patterns in the Twin Cities Metropolitan Area of Minnesota. This study uses a parcel dataset to derive a near complete depiction of intraurban migration, which is then coupled to a new combination of methods informed by migration concepts to construct and analyze neighborhood structure. The results of this approach illustrate the value of combining data, method, and theory of human migration in neighborhood classification. [Key words: intraurban migration, neighborhood, urban segmentation, parcel data.]

INTRODUCTION

Segmentation is central to urban research. At their most generic, urban segments comprise a systematic regionalization of urban space based on factors such as social status, culture, public image, or perception. The most common term for an urban segment is the neighborhood, although there are others, such as place or community. The importance of segmentation is generally accepted, but there is little agreement on how to identify segments (Adams, 1973, 1977, 1991; Palm, 1978; Goodman, 1981; Gabriel, 1984; Bajic, 1985; Galster, 1996; Bourassa et al., 1999, 2003, 2007; Fletcher et al., 2000; Kearns and Parkinson, 2001; Watkins, 2001; Jones et al., 2004). Given this lack of agreement on what constitutes a neighborhood, a critical focus of urban research is delineating these segments and examining how their interaction with social forces, in particular those related to housing markets, influences salient characteristics of urban life ranging from traffic patterns

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²Correspondence concerning this article should be addressed to Shipeng Sun, School of Natural Resources & Environment, University of Michigan, Ann Arbor, Michigan 48109; phone: 734-764-2550; email: shipengs@umich.edu and Steven M. Manson, Department of Geography, University of Minnesota, 267 19th Avenue South, Minneapolis, Minnesota 55455; phone: 612-625-4577; fax: 612-624-1044; email: manson@umn.edu

and home prices to racial segregation and economic development (Brown and Chung, 2008).

There is a need for neighborhood classification schemes that focus on human dynamic *movement* to complement the bulk of existing schemes, which focus on human static *attributes* such as socioeconomic measures or political divisions. A renewed focus on movement is important primarily because the segmentation of urban space influences the strategies and behaviors of residents in search of new housing while this movement in turn defines segmentation (Clark, 1982; Jones, 2002; Bates, 2006). The large body of work on residential location choice, for instance, relies on urban segments across research domains ranging from housing policy development to research on racial segregation (Brown and Moore, 1970; Clark, 1982; Cronin, 1983; Anas and Duann, 1985; Ben-Akiva and Lerman, 1985; Clark, 1986b, 1991; Ben-Akiva et al., 1996; Kearns and Parkinson, 2001; Jones et al., 2004; Guo and Bhat, 2007).

We offer a new way to classify neighborhoods based on migration patterns. Section two reviews available neighborhood classification approaches and develops the theoretical foundation for this research. Section three describes data, including the development of intraurban migration from tax parcel data, and a methodology centered on a hybrid segmentation approach that combines self-containment analysis, minimum spanning trees, and network spatialization. Section four describes the advantages that these new data and methods confer on urban segmentation using the Twin Cities Metropolitan Area (TCMA) of Minnesota as a case study. The paper concludes with discussion and future research directions.

NEIGHBORHOOD CLASSIFICATION

There is a broad array of approaches to segmentation (Reibel, 2011). Despite, or because of, the power and ubiquity of “the neighborhood” as a concept, its meaning and attendant derivation are often empirically underspecified (Galster, 2001). Almost all approaches use some form of base unit that serves as the building blocks from which urban segments are constructed. These units range in size, including individual parcels, blocks, block groups, census tracts, postal zones, and cities (Goddard, 1970; Getis and Ord, 1996; Bourassa et al., 1999; Boots, 2003). These units often have multivariate attributes attached to them that are in turn used in segmentation (Fusch and Ford, 1983; Adams, 1991). Most segmentation approaches focus on the *in situ* characteristics of base units, while fewer incorporate *relational* characteristics such as the movement of people among units (Durlauf, 1995, 2004; Galster, 2001; Kearns and Parkinson, 2001; Bolster et al., 2007). We can partition urban segmentation approaches into two groups, *in situ* and relational, defined in large part by the different forms of data on base units (Table 1). We examine these methods below and argue that a hybrid of *in situ* and relational approaches offers advantages in neighborhood delineation when the appropriate data and methodology are available to instantiate migration concepts.

Segmentation Approaches

Most segmentation approaches assume that a neighborhood is comprised of locations with similar characteristics (Reibel, 2011). The majority of segmentation schemes focus

TABLE 1. DATA USED FOR URBAN SEGMENTATION RESEARCH BY APPROACH

Approach	Data	Explanation	Usage	Examples
In situ	Housing prices	Estimated or sale prices of housing units (e.g., transactional price, price per square feet, or rental revenue).	Predominately used in hedonic housing price models.	Hoyt, 1939; Goodman, 1981; Goodman and Thibodeau, 1998, 2003; Clapp and Wang, 2006
	Composite characteristics	Structural, locational, and/or socioeconomic characteristics.	Serve as similarity indices and primarily used for cluster analysis.	Palm, 1978; Bourassa et al. 1999
	Style	Architectural style; distinctive structural features (e.g., classic chimney); durability.	Qualitative locational analysis	Fusch and Ford, 1983
	Historical context	Ethnicity, lifestyle, tastes, and/or status of the original residents. Growth patterns and development stages (e.g., infill vs. sprawl).	Historical analysis facilitated by inputs from local residents and experts on urban issues.	Adams, 1991; Gober and Burns 2002
	Public images	Perceived images of a neighborhood or an urban segment.	Adopted as neighborhood characteristics, by which similarity is judged. Or used as areal boundaries for different segments	Adams, 1991
	Individual memories	The memories and opinions of knowledgeable/experienced residents.		Hoyt, 1939
	Marketing practices	The segmentation used by housing sales representatives, appraisers, or realtors.		Palm, 1978; Bourassa et al. 2003
Relational	Transport linkages	Traffic patterns, such as taxi flow, among traffic zones.	Form an origin/destination matrix used for correlation analysis	Goddard, 1970
	Intraurban migration	Pattern of household migration and vacancy chains.		Adams 1973, 1977; Jones et al., 2004

on what may be termed *in situ* characteristics that describe the base unit attributes of the neighborhood, such as average house price or household income. Relational approaches instead focus on flows of people among base units, examining movements such as traffic, commuting, or migration.

Preexisting neighborhood schemes are very common, where segments are delineated on the basis of data collected for a reason such as taxation, population, transportation, education, urban planning, or postal service. While these zonations may actually map onto neighborhoods of interest, they are most often chosen because they are the existing reporting unit for readily available data that have been geographically aggregated to reduce computational burdens or protect privacy (Galster, 2001). Health data, for example, are often reported by zip code, while census data are grouped into tracts or block groups.

Perceptual neighborhoods are those identified by gathering data on how people perceive urban space and mentally apportion it into neighborhoods, commonly collected via survey or interview. There are three categories of perceptual data defined by the interviewee. First, the general public attaches a broad range of characteristics to places (e.g., safety, wealth, leisure), thereby forming urban segments through a shared vision that is often shaped by media (Glynn, 1986; Chaskin, 1997). Second, an insider view is developed by people who actually live in an urban segment or have substantial connections with that place; therefore, it is a local perspective that may not correspond to public views (McCann, 2002; Martin, 2003). Finally, there is an expert view developed by professionals, such as real estate agents, planners, and housing appraisers, who develop a sense of the urban segmentation through their work (Palm, 1978; Bourassa et al., 2003).

Grouped neighborhoods stem from methodologies that group similar base units together. These methods can be categorized into non-spatial and spatial clustering methods (Guo, 2008; Logan et al., 2011; Mikelbank, 2011; Reibel, 2011; Reibel and Regelson, 2011). Non-spatial clustering methods utilize aspatial characteristics to group similar base units, such as aggregating census tracts according to average household income and ethnic composition, or using statistical models to determine how attributes can explain differences among base units (Goodman, 1981; Goodman and Thibodeau, 1998; Vicino et al., 2011). Spatial methods go one step further by trying to satisfy a given spatial requirement. Distance penalty methods, for example, are less likely to group otherwise similar units as geographic distance among them increases, while spatial-constraint methods consider spatial topology such as contiguity or adjacency among base units in a group. The actual computational implementation of aspatial and spatial grouping methods is quite varied, ranging from statistical and visual methods to geocomputational techniques like artificial neural networks, self-organizing maps, and evolutionary algorithms (Martin, 1998; Kauko et al., 2002; Bação et al., 2005).

Focal neighborhoods are defined by a process of centering a regular geometric region (e.g., a circle, rectangle, or polygon) on base units as a function of Euclidean or transportation network distances (Guo and Bhat, 2007). While this specification can improve the fitness of some quantitative models, it can ignore the broader spatial context of an urban area in that these arbitrary neighborhoods may not map onto “real” neighborhoods. Of course, the same critique can be leveled against preexisting neighborhoods and perceptual neighborhoods developed by differing constituencies, highlighting the fact that there are many competing methods for creating plausible neighborhoods (Clapp and Wang, 2006; Weiss et al., 2007).

Relational neighborhoods differ from other approaches because they focus on the connections among base units more than their inherent characteristics. Relational neighborhoods are created on the assumption that locations that have more or stronger connections with other locations can be used to delineate urban segments. Transportation data, for example, can be used to delineate urban segments via pairings of home and work units; a large number of residents who live in one place and travel to the same work location may indicate that these locations are the nuclei of urban segments. Researchers have used a variety of relationships among segments, including taxi flows and migration patterns extracted from phone books and surveys (Goddard, 1970; Adams 1973, 1977; Jones, 2002).

Intraurban Migration as a Basis for Segmentation

Intraurban migration offers particular utility in defining relational neighborhoods. Intraurban migration is defined as movement within an area such that commuting to the same employment is still possible (Quigley and Weinberg 1977; Clark 1986a). The chief “push” factor for household relocation is dissatisfaction with current dwelling caused by changes in employment or the life course. The main “pull” factor for seeking a new dwelling resides in the quality and price of housing as defined by characteristics such as structure, accessibility, neighborhood characteristics, and public services (Clark, 1986a). Because intraurban migration and neighborhoods exert mutual influences upon each other, data on migration is an important ingredient in defining relational neighborhoods.

Neighborhoods are critical to intraurban migration because they offer a shortcut in an important decision-making process. Assessing even a handful of possible homes is expensive in terms of time and other resources, and this assessment and the broader decision to move to a new residence is made even more difficult by the fact that housing is the biggest investment for many households (Adams, 1984). To alleviate the burden of housing search and make the process more efficient, people generally target specific neighborhoods according to their housing knowledge and perception of urban space. In terms of perceiving neighborhoods, households develop limited mental maps or images of the city. People rely on public media, real estate agents, and social networks to construct their perceptions of neighborhoods (Palm, 1985; Krysan, 2008). The strongest sense of urban space is still local, however, and defined by the household’s activity space, or the area where its members conduct most of their day-to-day activities (Adams, 1969; Newsome et al., 1998; Lin and Long, 2008). Given that this activity space is often centered on the home, households develop spatially bounded mental maps defined by directional bias and distance decay, in that they generally know more about closer places than those further away (Adams, 1969; Clark, 1986a; Cervero and Wu, 1997; Clark et al., 2003; Vandersmissen et al., 2003).

Material concerns amplify the effects of distance decay on the perception of neighborhoods, particularly in the form of short-distance dominance, or where all other things being equal, people prefer to move shorter distances than long ones (Haynes and Fotheringham, 1984). Intraurban migrants usually make partial housing adjustments, or tend to make incremental adjustments in size or type of housing instead of moving into drastically different abodes. These incremental shifts make it more likely that households move to nearby neighborhoods because these areas have housing stocks similar to the current one. Households also tend to choose new residences nearby because short moves reduce fit-in costs such as learning new commuting routes or joining new recreational facilities, and more broadly, nearer moves tend to reflect the fact that residential choice is conditioned and constrained in part by the choices available (Roseman, 1971; Adams et al., 1973).

In sum, both the real and perceived features of neighborhoods have a significant impact on the housing search process, and can therefore be potentially revealed by the processes and patterns of migration. The perception and material reality of neighborhoods exert a number of mutually supporting pressures on households that encourage them to spatially bound their search for new homes. As examined next, this conceptual view on the search process provides the underpinnings for classifying neighborhoods by using the actual intraurban migration patterns of households.

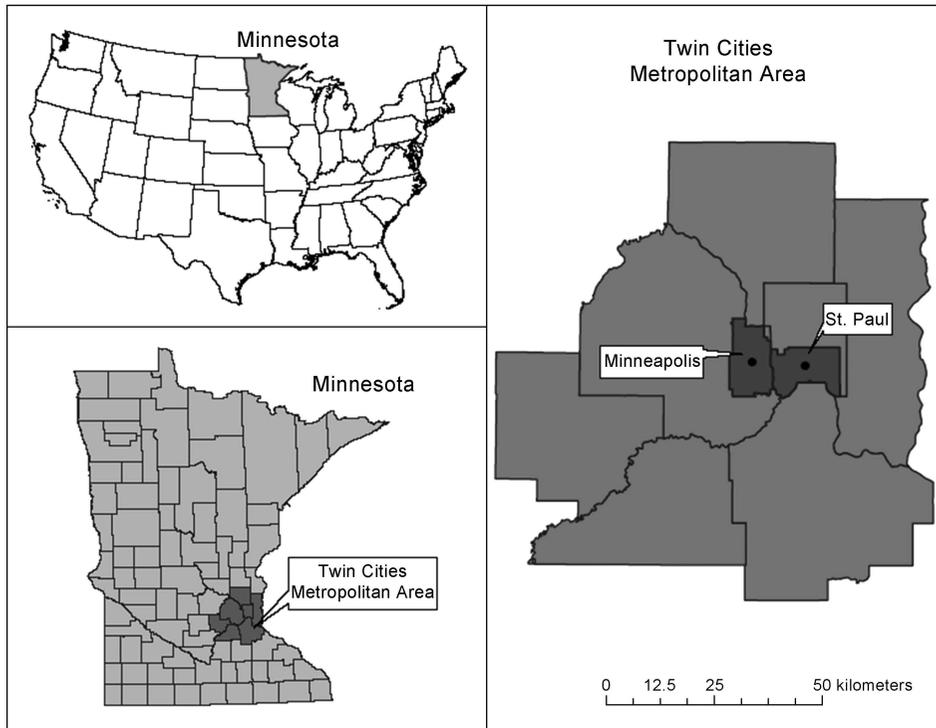


Fig. 1. Twin Cities Metropolitan Area.

DATA AND METHODOLOGY

Intraurban migration provides the conceptual underpinnings for the data and methods for a new approach to neighborhood segmentation. We developed this study for the Twin Cities Metropolitan Area of Minnesota, United States. This 7,700 km² region is home to 2.8 million people and is comprised of seven counties: Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, and Washington (Fig. 1). We used two kinds of data, preexisting regionalizations and information on actual household migration. We coupled these data to a hybrid segmentation methodology that combines aspects of grouping approaches with relational ones, via a blend of self-containment, minimum spanning trees, and network spatialization. This hybrid approach provides a multiscale urban segmentation based on intraurban migration flows that, as explored below, offers several advantages in understanding the formation and structure of urban segments.

Data

Most data used in neighborhood classification are collected at multiple scales, over various spatial units, and by different agencies. We used two different kinds of data. First, we assessed nine different preexisting regionalizations, such as zip codes and census tracts,

and chose a single kind—realtor zones—to act as base units. Second, we measured actual migration patterns of households among these units as derived from parcel data, or data that describe the spatial location of individual plots of land and their owners.

We gathered data on nine regionalization systems for potential use as base units in our segmentation process. Regionalization systems can act as segmentations, as described above, where preexisting data aggregations act as a proxy for an urban segmentation scheme. Census tracts, for example, are often used as “neighborhoods” because they are the reporting unit for important socioeconomic data such as average income or ethnicity. The nine systems that we examined are: (1) *counties* (7 total) which serve as a useful basis for understanding policy effects on housing; (2) *high-level realtor zones* are 10 divisions that describe large swaths of the region that the National Association of Realtors deems coherent housing areas; (3) the 11 *traffic sectors* used for regional transportation planning and funding; (4) expert judgment of urban planners yields 16 discrete *perceptual neighborhoods*; (5) there are 54 *school districts* that are de facto neighborhoods for many home buyers interested in housing; (6) *ZIP codes* (149) are often used in research because personal information is often aggregated to these areas, such as in reporting health statistics; (7) there are 198 *low-level realtor zones* that nest within the high-level realtor zones; (8) 674 *census tracts* which, like zip codes, are often taken as proxies for neighborhoods in research because that is how census data are reported; and (9) 1001 *traffic analysis zones* (TAZ) that are often used in land use, transportation, and employment research. We acquired boundary files for counties, census tracts, zip code areas, traffic analysis zones, and school districts from MetroGIS (www.datafinder.org), a regional government data agency. We digitized realtor zones from published maps, and developed zones from expert judgment derived from local planners and researchers.

In addition to developing data for these preexisting zonations, we developed parcel data to give us measures of intraurban migration. The regional planning authority, the Metropolitan Council, collects these data primarily to generate property tax forms for county government. These data are valuable for intraurban migration and urban segmentation research because they represent a nearly complete list of homeownership for a specific area from which we can reconstruct migration. The parcel dataset contains homeownership for all parcels in the seven-county metropolitan area, which makes it possible to determine where owners move. We used data for 2005 and 2006 that includes the seven TCMA counties.

Developing migration data from parcels requires comparing the owners of a parcel across years, detecting valid owner changes, and matching the owner in previous and next year for moving in and moving out. We implemented several algorithms in a C# program to develop these data. First, we used an intelligent name comparison routine to detect changes of owner names in the parcel data records (after Levenshtein, 1966). If the percentage of matched parts or letters was beyond a set criterion, the two names were defined as the same. For instance, George Washington and G. Washington would be judged as the same person. We then removed non-individual owners like government agencies, educational institutions, and property developers. In order to weed out absentee-owners and to differentiate renters from owners, we only kept parcel records with the same mailing and property addresses. To further exclude homeowners who are in residential transition, own multiple properties, or engage in speculation, we removed people with more than two properties in one tax year. Once the data were cleaned, the program matched owner

names across years to construct migration origin and destination pairs. For example, if a homeowner named John Anderson owns one parcel A in 2005 and owns one parcel B in 2006, then John Anderson is thought as moving from A to B. The parcel dataset for 2006 has 1,043,949 valid records that have both unique parcel ID and owner name, of which 904,201 are owned by 813,056 individual homeowners. Among these homeowners, 757,224 have only one property in the Twin Cities. For the 2005–2006 period, we identified 55,112 housing turnovers; however, most of them were first-time homebuyers or out-migrants who left the Twin Cities area. In the end, about 4,800 valid origin-destination pairs were identified and each of them describes the migration of a homeowner from one property to another entirely within the metropolitan area (Sun, 2009). This number is low relative to possible moves but also offers the least likelihood of false positives.

Segmentation

Data in hand, the first step to neighborhood classification is *self-containment analysis*, which allows us to select a regionalization system that provides the base units for subsequent neighborhood classification. We assessed the nine different systems described above with respect to self-containment, or the extent to which they maximize within-unit migration and minimize between-unit migration (after White 1983, 1986; Jones et al. 2004). This approach relies on the fact that one of the most significant features of intraurban migration is the dominance of inner-migration, or where the origin and destination are the same. If the inner-migration percentage is high for some particular zonation system (i.e., people are inclined to stay within that subdivision), it implies that these units are more coherent and homogeneous as a neighborhood (Jones, 2002). This approach is analogous to the grouping approach to segmentation described above in that it assumes neighborhoods have a degree of internal homogeneity.

The primary challenge in assessing self-containment is that within-unit migration percentages decrease with the average size of zones. If the goal were to simply maximize this percentage, the best choice would be a single zone spanning the entire study region because it would boast complete within-unit migration. Instead, we must assess each regionalization to account for the effect of subdivision size and actual migration behavior. Longstanding research finds there is a mathematical relationship between the average within-unit migration percentage and the size of zones that accounts for the fact that people tend to move shorter distances than longer ones if given a choice, which can be expressed as a negative exponential distribution (Clark, 1986a; Clark et al., 2003). Suppose the area of a metropolitan area is S and the move distances follow a standard negative exponential distribution $f(x) = \lambda \cdot e^{-\lambda \cdot x}$ and $F(x) = \int_{x=0}^d f(x) \cdot dx = 1 - e^{-\lambda \cdot d}$, where x is move

distance. The parameter λ is estimated as 0.16 using maximum likelihood estimation with move distance in miles. If the number of zones is N , then the average area of each zone is S/N and the average move distances within these divisions are $r = \sqrt{\frac{S/N}{\pi}}$, assuming each

zone is circular. From these assumptions, the theoretical within-unit migration rate is

$$\rho = 1 - e^{-\lambda \cdot r} = 1 - e^{-\lambda \sqrt{\frac{S}{\pi \cdot N}}} \quad (1)$$

The total within-migration rates adjusted by the size of the metropolitan area is

$$\sum \rho = N \cdot \left(\frac{1 - e^{-\lambda \sqrt{\frac{S}{\pi \cdot N}}}}{1 - e^{-\lambda \sqrt{\frac{S}{\pi}}}} \right) \quad (2)$$

When calculating the total or average within-unit migration rate for a region, the distribution of base unit sizes also has an impact and must be taken into account. Unlike a uniform distribution, the negative exponential distribution has an uneven spatial pattern, in which larger regions have fewer samples when adjusted by area due to the effect of distance decay. To calculate the theoretical value of the total within-unit migration rate in the case of varied regions, the sizes of base units are determined by a series of random numbers ε_i , $1, 2, \dots, N$ instead of the average size and they are also scaled to ensure the total area of all units remains the same, as follows:

$$\rho_i = 1 - e^{-\lambda \cdot r_i}, r_i = \frac{\varepsilon_i \cdot S}{\sqrt{\pi \sum \varepsilon_i}} \text{ and } \sum \rho = \sum_{i=1}^N \left(\frac{1 - e^{-\lambda \sqrt{\frac{\varepsilon_i \cdot S}{\pi \cdot \sum \varepsilon_i}}}}{1 - e^{-\lambda \sqrt{\frac{S}{\pi}}}} \right) \quad (3)$$

The mathematical relationship between the number of zones and the expected within-unit migration rate allows us to analyze how migration rates of real-world regionalization systems fare against the theoretical distribution given by Equations 2 and 3. Real-world regionalizations that exhibit higher than expected migration rates are more self-contained than those that have lower rates. For the purposes of our study, instead of serving as a standalone segmentation method, this approach allows us to choose the best system of zones that can act as the base units for the remainder of the urban segmentation process.

The second step in segmentation is constructing a *minimum spanning tree* (MST) from the base units selected by the self-containment analysis. An MST is a special network structure that connects all nodes with a minimum total distance (Graham and Hell, 1985; West, 2001). For urban segmentation, MSTs treat base units as nodes in a network where each unit is connected to immediately neighboring units, thus preserving information about the contiguity of base units. An MST minimizes the length of a path connecting all base units while ensuring that every unit is linked to a similar unit. The MST is partitioned into a hierarchy of branches via one of a number of approaches, including removing branches with maximum dissimilarity (Tu et al. 2005), removing links that most contribute to overall heterogeneity (Assunção et al., 2006; Guo, 2008); or building out from “hot spots” of similar base units (Mu and Wang, 2008).

The key advantage of MSTs is that they can identify hierarchies of base units. Self-containment analysis alone does a good job of identifying neighborhoods based on migration, but it does not accommodate the fact that base units often form nested hierarchies where collections of individual units effectively act as a single neighborhood at larger scales. When using the commonly employed census tract as a base unit, for example,

rural regions on the outskirts of a city may handily map onto a single-tract neighborhood because population densities are lower and tracts are accordingly larger. In the middle of the city, however, high population densities can mean that a single census tract may only encompass a couple of blocks that do not constitute their own neighborhood, but instead belong to a larger neighborhood. Particularly promising in identifying hierarchies are minimum spanning trees with spatial constraints, a form of grouping segmentation as described above (Tu et al. 2005; Assunção et al., 2006; Guo, 2008). We apply this approach to the base units developed from the self-containment analysis, where similarity of units is defined by maximum migration flows and constrained by adjacency.

The third step in segmentation is *network spatialization*, which is used as a companion to MST. While MSTs can analyze migration flows among base units, they utilize just one link—the most significant—between zones to define branches. By ignoring other links that are only slightly less important, MST misses useful information. Imagine a situation where a given unit has a good deal of eastward migration to a single adjacent unit and a greater amount of westward migration that happens to be split between two adjacent units. All other things being equal, the MST will designate the eastward migration as being more significant despite the fact that there is greater adjacent westward migration that is masked by an accident of geography. We can regain this information via network spatialization, which uses the sum of all migration flows among base units to effectively reposition them according to their migration flows. We used the Fruchterman-Reingold method for network spatialization, which is part of a larger class of graph-drawing approaches that treats the data involved as if they were measuring forces in a physical system (Fruchterman and Reingold, 1991). In essence, the method simulates a system of springs that join base units, where the strength of the spring is proportional to the migration flow between units. Larger flows between units serves to draw them closer together than they would otherwise be according to single migration flows, and the effect of opposing flows is balanced. We used this approach because it is a well-understood and effective way of apportioning flows among units in graph format (Borgatti et al., 2009).

In sum, we used several complementary segmentation methods to develop a hybrid solution that meets a number of needs. Self-containment analysis indicated which preexisting regionalization should be used as a basis for analysis. MSTs and network spatialization are then used with these base units to develop hierarchical clusters of zones to designate an urban segmentation. MST gives the optimal spatially constrained representation of urban segmentation as a function of migration, whereas network spatialization accounts for the complexity of migration flows among base units. These three methods in concert provide a multiscale urban segmentation based on intraurban migration flows.

MIGRATION-BASED NEIGHBORHOOD CLASSIFICATION IN THE TWIN CITIES

We classified TCMA neighborhoods based on existing regionalizations and migration information from parcel data. We used the hybrid urban segmentation method drawing on self-containment analysis, MST, and network spatialization. We find this combination of data and method, drawing as it does on several conceptual models of intraurban migration, offers a powerful way to understand urban segmentation.

Step one, self-containment analysis, uses inner-migration rates to analyze nine different systems of subdivisions (Table 2). We compared the inner-migration rates of each of the

TABLE 2. INNER-MIGRATION RATE IN THE TCMA, 2002–2007

Regionalization	Divisions	06–07	05–06	04–05	03–04	02–03	Average
County	7	0.74	0.72	0.66	0.77	0.78	0.73
Realtors high-level	10	0.61	0.61	0.62	0.60	0.61	0.61
Traffic sector	11	0.56	0.56	0.52	0.56	0.59	0.56
Experts	16	0.46	0.45	0.45	0.44	0.50	0.46
School district	54	0.42	0.46	0.36	0.42	0.48	0.43
ZIP code	149	0.29	0.32	0.24	0.26	0.34	0.29
Realtors low-level	198	0.29	0.31	0.26	0.26	0.34	0.29
Census tracts	674	0.15	0.15	0.12	0.13	0.17	0.14
Traffic analysis zone	1001	0.13	0.15	0.11	0.12	0.16	0.13

nine preexisting regionalizations against both theoretically predicted values as given by Equations 2 and 3. The low-level realtor zones and TAZs have higher values than expected (Fig. 2) which indicate that these zonations are more self-contained than others and are therefore more likely to be seen as neighborhoods in terms of migration patterns.

The “neighborhood” character of low-level realty zones and TAZs is reasonable. Housing submarkets adopted by realtors are based on city or township boundaries, except in Minneapolis and St. Paul, where smaller scale zones are defined. These regions both define housing search and migration behavior, as when home buyers search online listings by realty zone, and are defined by this behavior, as when realtors draw boundaries in order to reflect migration patterns. TAZs map onto neighborhoods because they are determined by variables (e.g., household income, number of vehicles, family size) that are highly correlated with the socioeconomic status of the households residing in the zones and are therefore internally coherent in the way sought by in situ grouping approaches to segmentation. We chose realtor zones as the base unit for neighborhood aggregation and classification because they perform well in the self-containment analysis and because traffic analysis zones are not large enough on average to host a sufficient number of migrations during the study period for the next steps of the analysis.

In step two of the analysis, we created an MST of migration flows among the base units selected in step one, real estate zones. This MST identifies three salient features. The first is the existence of “hot spots” in the regional housing market, defined as base units that serve as the roots of many branches, meaning that they attract a disproportionate number of homeowners from neighboring cities (e.g., Minnetonka, Plymouth, Brooklyn Park, Woodbury, Lakeville, Eden Prairie, and Cotton Grove). These hotspots form the skeleton of the third-tier suburbs, attract new homebuyers, and also define the migration destination for the local sectional housing submarket identified in Adams and VanDrasek (1993).

Secondly, despite the fact that Minneapolis and St. Paul have similar economic characteristics in housing and population and excellent transportation linkages, a relatively small number of homeowners move between these two core cities. This phenomenon is consistent with the “sibling rivalry” effect between neighboring big cities and service centers, where people develop a neutral to antagonistic view toward adjoining cities in comparison to their home city (Nordstrand, 1973; Adams and VanDrasek 1993; City-Data, 2010).

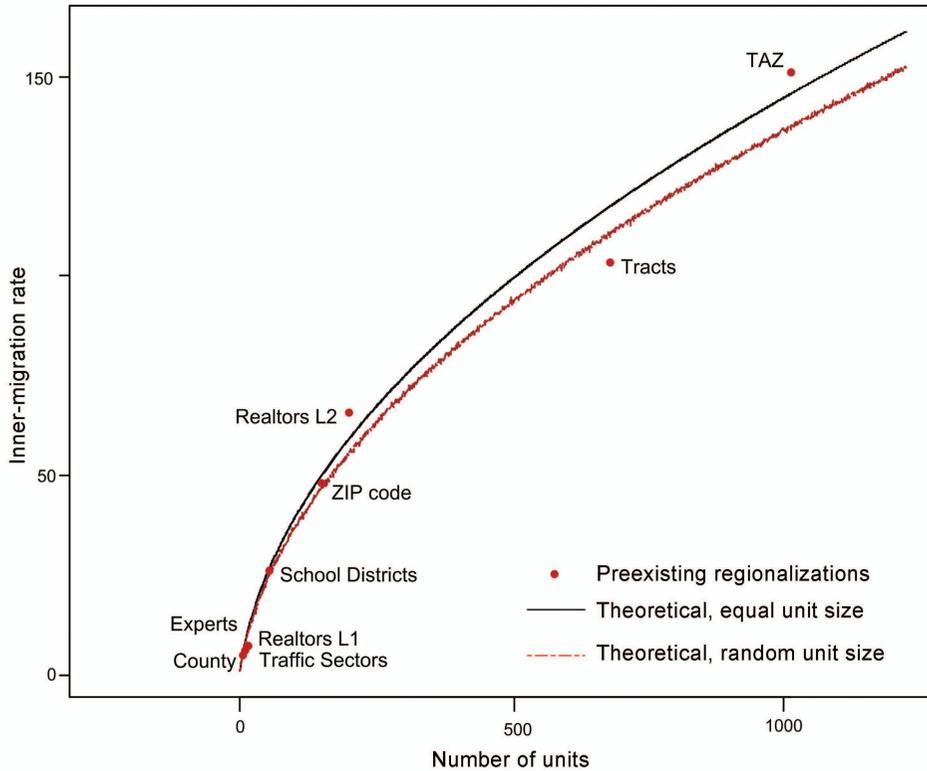


Fig. 2. Inner-migration rates. An inner-migration rate that is higher than the theoretical (calculated using Eq. 2) and simulated values (using Eq. 3) implies that people are more likely to move within that subdivision and identify it as the same neighborhood.

Third, we see a sectoral structure within the central cities, in that migration is less likely between sectors, even when they adjoin, than migration outward from the segment. Minneapolis is divided into three parts from a migration perspective, namely Northeast, North/Northwest, and South (more details below) and St. Paul is similarly divided into four sectors from downtown toward the northwest, northeast, west/southwest, and southeast (Fig. 3). This finding reconfirms the conceptual understanding of sectoral bias in intraurban migration, where movement is more likely along an axis defined between home and the central city, and by suburbanization, as households socially move upwards and spatially move outwards through a filtering process primarily along neighborhood sectors (Hoyt, 1939, 1970; Adams, 1991; Adams and VanDrasek, 1993; Mikelbank, 2011).

Step three is network spatialization. To demonstrate how this approach can be used with migration data to develop urban segments, we can compare networks based on geographic distance and migration flows. A network diagram of actual geographic distances (Fig. 4A) has links between base units with lengths corresponding to their actual Euclidian distance from one another. In contrast, a network diagram of migration flows, where the length of each link is proportional to the reciprocal of gross migration between base units, draws units that have greater inter-unit migration flow closer to each other while simultaneously

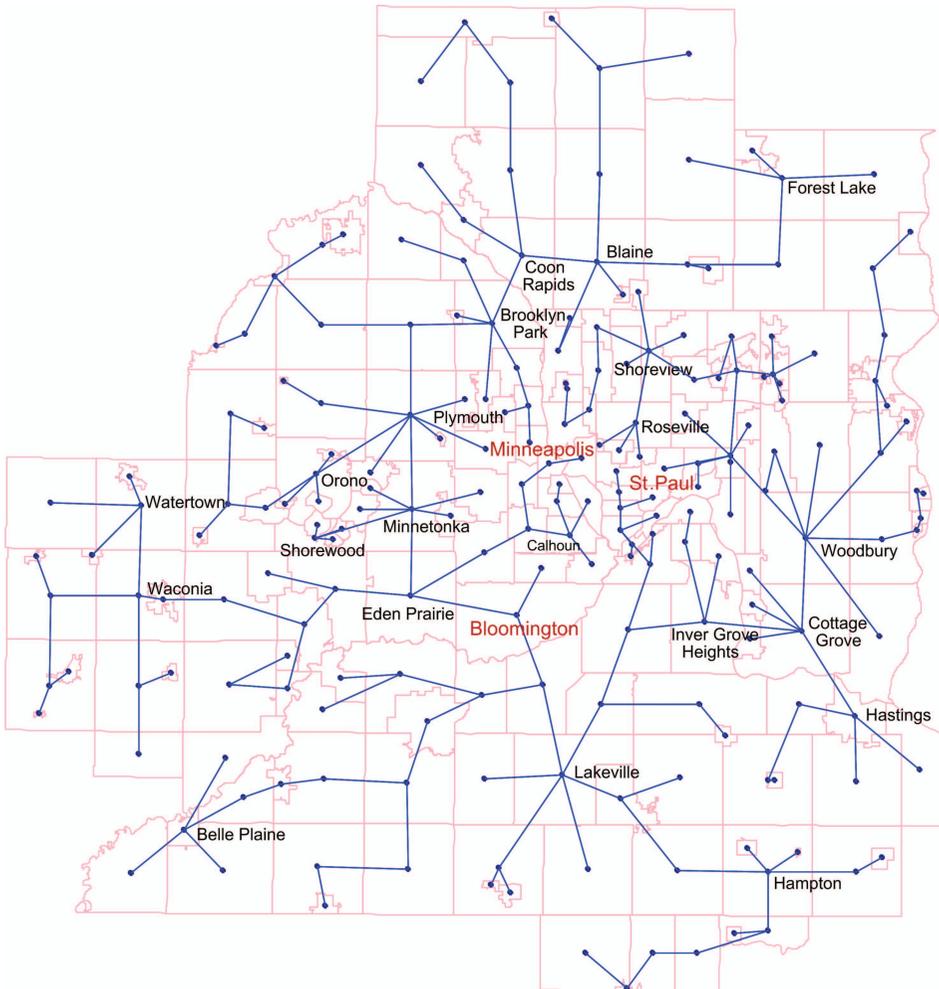


Fig. 3. The minimum spanning tree (MST) systematically links the closest nodes together as constructed from real estate marketing areas, revealing sectoral structures in neighborhoods defined by migration.

balancing conflicting forces acting on each unit (Fig. 4B). This migration-based distance illustrates a different pattern of regionalization than that defined by in situ approaches such as preexisting segmentation (e.g., such as base units defined as just low-level realtor zones) or MST alone.

The advantages of migration-based networks are clear in how they identify significant clusters that are not evident in geographic distance-based networks and how they highlight spatial features of segmentation identified by MST. The entire metropolitan area can be divided into two large clusters centered on Minneapolis and St. Paul, which we term West and East TCMA, respectively. The South metro grows out of the West TCMA, whereas the north metro area (e.g., Blaine, Arden Hills, Linwood Township, Andover) is located between these two main clusters, implying that they have almost equal connections with

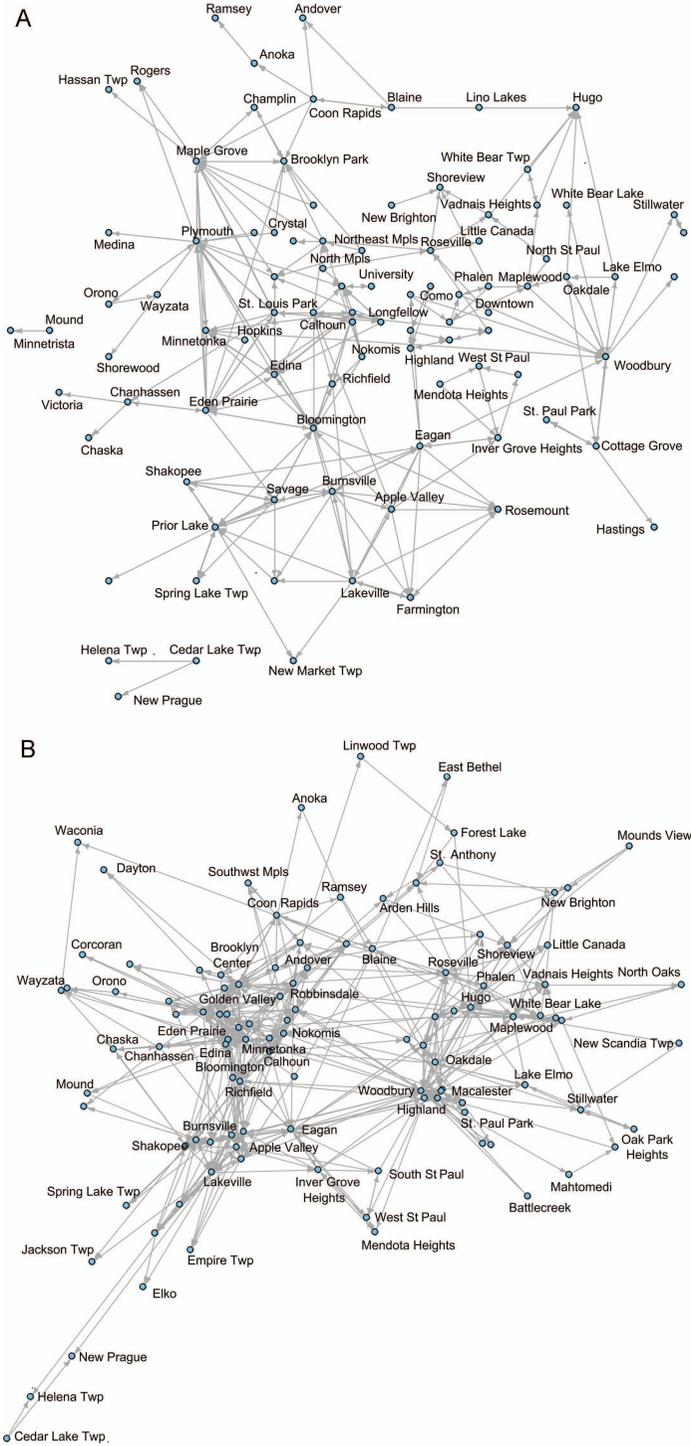


Fig 4. Network based on geographic distance (A) and migration flows (B).

Minneapolis and St. Paul despite having a broad spatial distribution in reality. Each main cluster has a secondary cluster lying to the south, in the west with Minnesota River Valley communities (e.g., Burnsville, Shakopee, and Savage) and in the east with what is locally often called South St. Paul just across the Mississippi river (e.g., West St. Paul, South St. Paul, and Inver Grove Heights). These southward extensions add further evidence to the MST-based finding that migration is sectoral outward from the core cities.

Migration-based networks highlight a number of neighborhood dynamics in addition to clustering and sectoral bias. First, rendering of migration-based distance highlights the pervasive effects of the natural barrier of the river, which despite ample bridge connections, serves to isolate them from the main clusters centered on Minneapolis and St. Paul. This approach confirms the existence of a “river effect” that has been suggested as existing in other metropolitan areas (Tirtiroglu and Clapp, 1996), as well as highlighting the “sibling rivalry” effect noted above. Second, it captures pervasive socioeconomic differences that are not evident in the geographic-distance networks. The west TCMA has three sub-clusters—east, north, and southwest—that each have a coherent identity that supports previous research. The eastern cluster has long been a working-class neighborhood and home to recent immigrants, the northern cluster is typically perceived as home to persistent poverty, and the southwest to high-profile suburbs. Finally, migration-based networks capture local peculiarities. In West TCMA, for example, there are distant exurbs such as Cedar Township that are further out in migration space than geographic distance would suggest, while in East TCMA, there are suburbs that directly adjoin St. Paul but lie far closer to Minneapolis in terms of migration. These suburbs were initially occupied by workers in meat packing plants and more recently by Mexican immigrants, giving it a distinctive personality that contrasts with the upper-middle class neighborhood to the north (Adams and VanDrasek, 1993). A migration-based network is necessary to highlight how actual neighborhoods and migration have a character that is not spatially bounded.

We combined the results of the three steps—self-containment, MST, and network spatialization—in a single hierarchical, nested neighborhood system for the TCMA. We visualize such a hierarchy of neighborhoods by varying boundary width and color (Fig. 5). The seven-county Twin Cities Metropolitan Area can be divided into three clusters at the highest level, namely West (Minneapolis), East (St. Paul), and South metro. The boundary of these three clusters clearly illustrates the effect of both social and natural barriers on people’s perception of neighborhood structure and their migration behavior. The West and East TCMA are mainly separated by the Mississippi River and the homeowners living south to the Minnesota River valley are inclined to move within the South metro.

In addition to demarcating large-scale divisions, this neighborhood segmentation illustrates features of neighborhoods at smaller, nested scales. Consider the neighborhood structure of the city of Minneapolis, where the base units in this analysis are 11 low-level realtor zones (Table 3). Segmentation shows that northeast Minneapolis is rather independent of other communities in the city, as it has tighter connections with neighboring communities in the East TCMA cluster (e.g., St. Anthony, Columbia Heights, and Roseville). The remaining 10 communities form the remainder of the Minneapolis cluster, which has two nested subclusters of north and south Minneapolis, and the latter can be further divided into southeast and southwest subclusters. North Minneapolis and Camden are traditionally a mixed working and lower-middle-class neighborhood, and together with Brooklyn Center and Brooklyn Park, forms the sector that has a high African-American

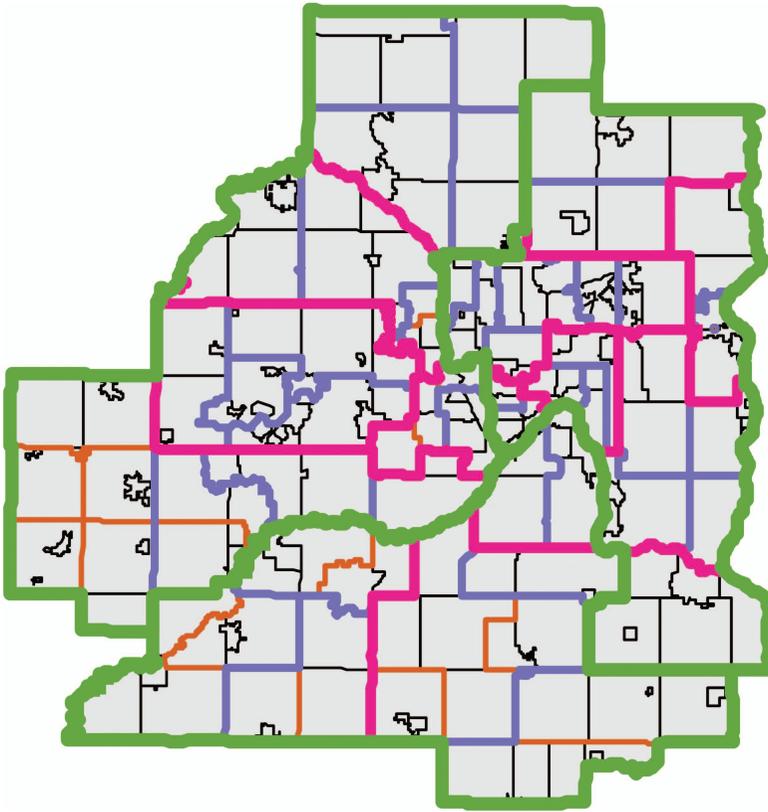


Fig. 5. Nested neighborhoods given by hybrid approach.

concentration. The southeast Minneapolis cluster, including Powderhorn, Longfellow, Philips, and Nokomis, has long been a self-contained working class community with modest housing (Adams and VanDrasek, 1993). The southwest cluster has two further divisions, the first being Southwest Minneapolis and Lake Calhoun, which feature scenic lakes and proximity to the downtown that has long made it a sought-after neighborhood that has much more socioeconomically in common with adjacent affluent suburbs such as Edina (Adams, 1991). The second southwest cluster is termed “business Minneapolis” because it is characterized by the downtown businesses and the University of Minnesota. In sum, the combination of MST and network spatialization provides an excellent way of demonstrating the multiscale and nested nature of neighborhoods.

CONCLUSION

Defining urban segments is essential to a wide array of research and policy, ranging from studies of urban structure and housing price estimation to traffic demand analysis or understanding racial segregation. While the in situ characteristics of places, such as median housing value or household income, are useful in understanding how neighborhoods differ,

TABLE 3. NEIGHBORHOOD STRUCTURE OF THE CITY OF MINNEAPOLIS
REVEALED BY INTRAURBAN MIGRATION

Name	Clusters and subclusters			
	Level 1	Level 2	Level 3	Level 4
Northeast Mpls ^a	East TCMA	–	–	–
Camden	Mpls Cluster	North Mpls subcluster	–	–
North Mpls	Mpls Cluster	North Mpls subcluster	–	–
Powderhorn	Mpls Cluster	–	Southeast Mpls	–
Longfellow	Mpls Cluster	–	Southeast Mpls	–
Philips	Mpls Cluster	–	Southeast Mpls	–
Nokomis	Mpls Cluster	–	Southeast Mpls	–
University	Mpls Cluster	–	Southwest Mpls	Business Mpls
Central Mpls	Mpls Cluster	–	Southwest Mpls	Business Mpls
Calhoun	Mpls Cluster	–	Southwest Mpls	Southwest Mpls
Southwest Mpls	Mpls Cluster	–	Southwest Mpls	Southwest Mpls

^aMpls is a commonly accepted abbreviation of Minneapolis.

there is much to be gained by incorporating the dynamic nature of migration in urban segmentation. People change their place of residence based on their perception of urban space, and in turn, the housing decisions of people ultimately define neighborhoods.

Given the importance of intraurban migration in defining urban segments, we delineated the neighborhood structure of the TCMA by using a new dataset and a novel combination of approaches. We developed a nearly complete picture of homeowner migration data from tax parcel data and then used self-containment analysis to select the appropriate base units for urban segmentation. Although a different choice of base units may alter the results due to modified areal configuration, this choice would not likely affect the underlying effectiveness of combining MST and network spatialization and is rather instrumental in deriving a hierarchical system of urban segments. The neighborhood classification method combines a bottom-up procedure to construct an MST and a top-down procedure to partition the tree into hierarchical parts guided by network spatialization. A key advantage of this approach over others is that the “whole” is not overshadowed by any “parts” in these two procedures. Relatedly, tracing intraurban migration of homeowners, who generally make careful and informed decisions, can reveal important yet subtle changes and trends that may not be fully captured by generic survey data. Overall, applying a relational method to migration flows to represent real-world inter-neighborhood connections can well depict the intrinsic urban structure perceived by the local residents.

These data and approaches illustrate many features of urban segments of the TCMA that reaffirm the conceptual basis of intraurban migration and correspond with and expand on our existing understanding of neighborhoods in the region. This approach offers a useful way to build on existing regionalizations with migration data. The neighborhoods identified quantitatively and visually map onto what existing theories suggest and local experts observe, as described above for specific neighborhoods and general trends in the study site.

Urban structure is shaped by historical development trajectories, local cultural heritage, and physical characteristics that may not be included in quantitative segmentation analysis yet are clearly manifest in migration patterns. More specifically, the MST structure readily reveals the outgrowth of neighborhoods towards suburban areas per spatial filtering theories, while at the same time, it also reveals distinctive migration sectors and layers of hierarchy. This sectoral structure, while confirming existing theories on urban structure, can also potentially update what local experts have qualitatively derived from personal experience and historical analysis.

While incorporating intraurban migration into urban segmentation research offers many advantages, it points toward other challenges. We did not integrate intraurban migration data with in situ neighborhood metrics that form the basis for many segmentation approaches, and combining the two could offer even more sophisticated segmentations and attendant conceptual understanding of urban structure and function. In choosing the base units, there is room to use more sophisticated approaches, such as Monte Carlo testing, to assess significance. And, as noted above, while we sought to reduce false positives from the database, use of secondary information such as voting records or surveys could help reduce false negatives and increase sample size. We invoke a degree of homogeneity in the neighborhood populations in that we do not know anything about subpopulations, such as pockets of ethnic minorities nested within base units whose migration patterns may be lost in the overall flows among units. This mixing of in situ and relational data will likely require more complex statistical methods or simulation approaches such as agent-based models or spatial geosimulation. Finally, the approach developed here and many others still rely for the most part on set regionalizations to provide base units, which ignore the fuzziness integral to neighborhood boundaries.

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