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SMALL AREA CLASSIFICATION IN URBAN GEOGRAPHY: A REVIEW OF MULTIDIMENSIONAL METHODS

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ABSTRACT: *Regional analysis methodologies continue to evolve in geographical scholarship, and one contemporary example is classifications of neighborhoods within metropolitan areas. Fourteen articles published from 1997 to 2021 demonstrate methodological progress using multivariate statistical analysis to produce multidimensional classifications of the small area statistical units that are commonly used to analyze neighborhoods in metropolitan areas. This review traces the theoretical context, development of analytical techniques, and key findings. The 14 articles identify neighborhood categories by multidimensional analysis and describe them with subjective nomenclature derived from classical urban land use studies. Census tracts are commonly equated with neighborhoods. The line of research is consistent with the Area Studies tradition of geography in concept and objectives; it uses modern statistical techniques to update the regional analysis methodology of the 20th century. The trend is to assume path dependency, but some studies find abrupt changes independent of previous neighborhood status. Therefore, the analysis of small areas should test path dependency and analyze alternative explanations such as accessibility, policy, spatial interaction, and urban structure. The conclusion suggests three avenues for continued analysis of small area categories: cross-sectional comparisons of spatial association, analysis of political/administrative units in addition to or in conjunction with census tracts, and non-parametric techniques appropriate to the accuracy and distributional characteristics of available data.*

KeyWords: *Classification, Multivariate Analysis, Neighborhoods, Regional Analysis, Urban Geography*

INTRODUCTION

Restructuring of American metropolitan areas has prompted concern for the character, socioeconomic status, and stability of urban neighborhoods. Regional analysis is a venerable strategy of geographers for the study of areas, metropolitan or otherwise, with the objective of context and perspective. The subject of this review is studies that, at a neighborhood scale, implement the definition of regional analysis by applying classification criteria to areas "throughout which there is some kind of homogeneity" (James and Martin, 1981 p. 372). Neighborhood studies appear in a variety of disciplinary and interdisciplinary journals, but they are geographical in content and purpose. Regional analysis is the methodology and an understanding of areas is the purpose, thus the studies reviewed here are continuations of the Area Studies tradition of academic geography (Pattison, 1964). Small area classification, a set of techniques frequently employed in neighborhood analysis, has made progress involving refined statistical methods coupled with increasing availability of data. The trend is to use classification of neighborhood types to describe temporal sequences, but results indicate broader applicability. The condition of small areas affects the whole, and Schachner (2022) reviews a body of literature analyzing a broad range of neighborhood conditions that might affect the development prospects of a metropolitan area. Furthermore, small areas are the geographical scale where outcomes of urban policy and metropolitan development strategies are realized. Their classification provides a baseline for understanding the relationship between economic geography and governance.

Small area regional analysis involves two challenges: definition of the geographical units that represent neighborhoods and selection of the variables that best describe them. This review concerns studies whose primary focus is on the second of these although it is necessary to include some discussion of the implications of geographical areas and the limitations of data available for them. Studies fall on a continuum from those focused on a single dimension of closely related variables, such as poverty, to those attempting contextual analysis of multidimensional conditions. Both are useful, with the more specific studies addressing a particular problem of neighborhoods in depth (Guo and Bhat, 2007; B. Lee et al., 2024; Song and Knapp, 2007; Trudeau, 2013). Division between the two objectives is arbitrary in the continuum of approaches, but it is useful to distinguish relatively more unidimensional and more multidimensional studies. This review analyzes studies emphasizing the more general objectives of context and perspective for the metropolitan area. The research methodology reviewed here is applied in more specific topical studies by adaptation to the analysis of accessibility, land use, public perceptions, and spatial interaction (Bucholtz et al., 2020, Sarzynski et al., 2014).

This review covers small area classification research as presented in 14 articles over the past three decades. It identifies significant achievements in describing contemporary metropolitan areas and recommends avenues of future research to overcome limitations thus far encountered. Methodological developments fall within the spectrum of statistical techniques called multivariate analysis (Everitt and Dunn, 2001). Statistical texts outline the strategy and tactics: "the underlying theme of much multivariate analysis is simplification" (Chatfield and Collins, 1980 p. 6). Consistent with that theme, most of the 14 studies under review employ either principal component (PCA) or discriminant analysis, to extract dimensions from a complex set of variables. Most then use dimension characteristics as variables and employ cluster analysis to classify observations by type. Much of the innovation in methodology lies in the sequence of statistical techniques rather than invention of new ones.

ARTICLE SELECTION PROCESS

Not all small area classifications are regional analysis, and not all regional analysis concerns small areas. The selection process for this review seeks articles that are both. Candidate articles are found in keyword searches, title searches, and a cumulative thread of citations. Informal terms such as 'neighborhood', 'central city', 'inner city', and 'suburb' are operationalized with formal units of census geography such as tracts, places, or traffic analysis zones. Both informal and formal terms are used in searches to compile a long list of studies which is refined based on topical content that includes a data reduction-classification-verification procedure, emphasis on context or perspective, and the use of multidimensional data. The list is refined further by tracing paths in the development of small area classification methodology through cross-references (Table 1). Morenoff and Tienda (1997) is seminal in that it clearly addresses the unidimensional/multidimensional dichotomy and advocates the latter for neighborhood analysis. All of the subsequent articles use the multidimensional approach, four cite Morenoff and Tienda directly, and others can be traced through indirect citations. It is curious that a book entitled *Multivariate Statistical Analysis for Geographers* is only indirectly cited research that does just that (Griffith and Amrhein, 1997). Mikelbank (2004) cites the source and is cited in turn by seven others that prove to meet the other criteria of this review. Another article classifies central cities, but uses a statistical technique cited in six neighborhood classification studies and

Table 1. Small Area Classification Literature Citations

Article	Thread Refs City / Cited by	Subsequent Citations[1]	Influential References
Morenoff and Tienda 1997	0 / 4	54	Wilson 1987
Mikelbank 2004	0 / 7	112	Griffith & Amrhein 1997, Hill et al. 1998
Leigh and Lee 2005	0 / 2	1	Bollens 1988
Lee and Leigh 2007	1 / 2	58	Burgess 1925, Hoyt 1939, Hoover & Vernon 1959
Vicino 2008b	2 / 7	41	Burgess 1925, Bollens 1988, Hill et al. 1998
Hanlon 2009	3 / 4	76	Bollens 1988
Mikelbank 2011	3 / 6	47	Hill et al. 1998
Owens 2012	2 / 4	136	Burgess 1925, Wilson 1987
Wei and Knox 2014	4 / 4	68	Burgess 1925, Hoyt 1939, Hoover & Vernon 1959, Hill et al. 1998
Delmelle 2015	6 / 4	78	Burgess 1925, Hoyt 1939, Hoover & Vernon 1959
Delmelle 2016	8 / 1	65	Burgess 1925, Hoyt 1939, Harris & Ullman 1945, Hoover & Vernon 1959
Foote and Walter 2017	5 / 1	18	Hoyt 1939
Li and Xie 2018	9 / 0	26	Burgess 1925, Harris & Ullman 1945, Hoover & Vernon 1959, Hill et al. 1998
Kinahan 2021	5 / 0	5	Wilson 1987, Hill et al. 1998

[1] Citations in Web of Science online search, August 1, 2024.

emulated by others (Hill et al., 1998). Disciples of Morenoff and Tienda use hierarchical agglomerative cluster analysis while followers of Hill et al. prefer K-means clustering—the contrast between these two variants is discussed later. Both articles provide a rationale for the value of classification and conceptual inspiration for subsequent methodological developments.

The search yields 14 small area classification articles that qualify as modern regional analysis variants of the Area Studies Tradition of geography because they use cartographic presentation, the assignment of interpretive labels to specific intra-metropolitan areas, and/or the use of geographic information systems. An interlocking web of cross-references indicates common interest in refining neighborhood classification methodology and in using it to understand urban restructuring. The 14 further share a concern for urban governance and public policy. They reference central cities, suburban political entities, issues of over- or under-bounding, regional coordination, and growth management.

This article proceeds as follows. A discussion of literature as context summarizes a selection of articles that document the relevance and significance of small area classification to issues of urban development and structure. These are frequently cited contemporary articles and classical models of urban land use and socioeconomic geography that obviously inspire this thread of research. That is followed by chronological content summaries documenting the sequence of methodological developments. Then a discussion section in four sub-sections points out conceptual insights gained, and some limitations, in the 14 articles. The conclusion suggests contributions to the understanding of urban affairs that could be realized by further development of small area classification research and methodological avenues to facilitate this.

LITERATURE AS CONTEXT

The need for spatial context is demonstrated by problem-oriented studies that require multidimensional analysis of small area geographies. Specialized studies influence and are influenced by the methodology of regional analysis. For example, empirical studies document that residential development or deterioration responds to the geographical distribution of commercial development (Ding and Bingham, 2000; Galster et al., 2003). In some, however, the firm location decisions that determine metropolitan spatial structure are influenced by neighborhood quality (Wu, Wei, and Li, 2020). The classification scheme devised by Vougaris et al. (2017) and employed by Schouten (2022) rivals the best of the comprehensive multivariate studies in conceptual and methodological sophistication. Their treatment of income and poverty as independent of neighborhood type, however, is contrary to most interpretations of status even though it serves well the objective of analysis of transportation policy questions. Comprehensive inventory of the distribution of neighborhood types could add useful information about the competitive interactions of job seekers (Shen, 1998). Recent efforts analyze job accessibility for specific populations defined by gender, occupation, or income (Hess, 2005; Kim et al., 2012; Sander and Testa, 2013).

Four classical sources are cited in the bibliographies of the 14 articles. They do not employ multivariate analysis but instead articulate the policy and theoretical issues that have inspired neighborhood classification. Burgess (1925) uses concentric zones to describe a dynamic process of neighborhood development that results in variation of character and quality and is basic to the succession theory of neighborhood analysis. Hoyt (1939) adapts Burgess' idea to a wedge-shaped geographical configuration of sectors radiating from the CBD. Harris and Ullman (1945) emphasize historical geography and multiple foci in urban morphology. All three view neighborhood character as a function of location and discuss processes of succession that have come to be known as filtering. Hoover and Vernon (1959) analyze communities in terms of three dimensions: job type, income level, and age composition of the household. They introduce the multidimensional concept—each dimension includes multiple variables—along with descriptive statistics such as employment-to-population ratios and location quotients. They also establish a four-area template: downtown, inner-city, inner-ring suburb, and outer-ring suburb that is apparent in subsequent research designs even when the source is not cited. All of the 14 small area classification articles use descriptive nomenclature reminiscent of, if not directly adapted from the vocabulary of the four classical studies. The more recent articles of the 14—since 2014—cite the classical studies more often and are more self-conscious of possible contributions to land use theory than are the studies published 1997-2012.

A fifth work, a landmark book, sets neighborhood analysis as an occasion for concern about policy and social issues. Wilson (1987) stresses the complexity of urban extreme poverty and cites neighborhood change as a factor. Specifically, selective outmigration of middle class households from Black ghettos contributes to socioeconomic isolation for the population left behind. Wilson also stresses a macro-regional component; the severe economic restructuring in the Northeast and Midwest accompanies the most intense ghettoization in American cities. This analysis of humanistic implications and of temporal trends is implicit in the concerns of the 14. Bollens (1988) doesn't qualify as a classic because interest as expressed by number if citations waned after a flurry in the late 1990s. Nevertheless, it raises consciousness by documenting economic and fiscal decline of suburbs and dispels the notion that they consist of homogenous neighborhoods; both themes are pursued in the 14 articles beyond the three with direct citations. For comparison, Hoyt (1939) is cited by 3 of the 14, Hoover and Vernon (1959) by 4, Burgess (1925) by 6, and Wilson (1987) by 6.

CHRONOLOGICAL CONTENT SUMMARIES

Chronologically, the fourteen articles begin with a one-step classification of census data, apply progressively more complex analysis to more nuanced data sets, and conclude with Kinahan's (2021, p. 521) cautionary article calling for "additional qualitative work (to) contextualize the quantitative patterns" (Table 2). Morenoff and Tienda (1997) produce an early example of multidimensional neighborhood classification using 10 variables that cover economic, education, employment, household type, and migration dimensions. A hierarchical agglomerative cluster technique identifies four categories of census tract for 1970, 1980, and 1990. Clusters are named from descriptive statistics and are assigned ordinal socioeconomic status. Cook County, Illinois, census tracts are proxy for neighborhoods and are evaluated in terms of their progression up or down the scale.

Table 2. Small Area Classification Study Areas and Data Sources

Article	Study Area	Data[1.]	Variables/ Dimensions	Area Units
Morenoff and Tienda 1997	Chicago, Cook County	Census 1970 and 1990	10	Census Tracts
Mikelbank 2004	Non-central MSA places	Census x 3	47/4	Incorporated Places
Leigh and Lee 2005	Philadelphia	NCDB 2000	11/3	Census Tracts/ 4 subareas
Lee and Leigh 2007	Atlanta, Cleveland, Philadelphia, Portland OR	NCDB 2000	11/3	Census Tracts
Vicino 2008	Baltimore first tier suburbs	Census, NCDB 2000	49/6	Places 1970, Census tracts 2000
Hanlon 2009	100 largest US MSAs	US HUD, Census 2000	44/5	Census Places
Mikelbank 2011	Cleveland MSA	NCDB 2000	44/4	Census Tracts
Owens 2012	National, MSAs	NCDB 2000, ACS 2005-09	19/5 or 6	Census Tracts
Wei and Knox 2014	National, all metropolitan areas	LTDB 2010	16/3	Census Tracts
Delmelle 2015	Buffalo, Charlotte, Chicago, Portland OR	LTDB	12/3	Census Tracts
Delmelle 2016	Chicago MSA and Los Angeles MSA, central counties	LTDB	12/3	Census Tracts
Foote & Walter 2017	Austin, Las Vegas, Raleigh	NCDB 2010	26/3	Census Tracts
Li and Xie 2018	Detroit MSA	NCDB 2010	14/6	Census Tracts
Kinahan 2021	Central Cities: Baltimore, St. Louis, Cleveland, Philadelphia	NCDB 2010	23/4	Census Tracts, Central Cities

1. Data base abbreviations are: ACS-American Community Surveys 5-year samples, LTDB-U.S. Housing and Urban Development Longitudinal Tract Data Base, NCDB-Geolytics Neighborhood Change Database, and U.S.HUD-U.S. Housing and Urban Development 2006 State of the Cities Data System.

Mikelbank (2004) implements a multi-dimensional approach by extracting data from the Census of Population for 2000, the Economic Census for 1997, and the Census of Governments 1997. A national sample of 3,567 non-central-city places is classified based on 47 variables covering four dimensions: economic, demographic, fiscal, and spatial structure. Hierarchical agglomerative clustering minimizes squared Euclidean distance between observations within each group. Identification of 10-, 4-, and 2-cluster solutions permits analysis of the progression of clusters, that is which of the ten clusters are combined at intervening stages to produce the 4-cluster solution.

Two methodologically transitional studies classify census tracts by location as “downtown”, “inner-city”, “inner-ring”, or “outer-ring” based on the age of housing and a contour mapping procedure (Leigh and Lee, 2005; Lee and Leigh, 2007). They use the Neighborhood Change Data Base (NCDB) for census tract boundaries standardized over multiple census years. In the earlier of the two, analysis of variance (ANOVA) means tests document divergent trends of four subareas in the Philadelphia metropolitan area 1970-2000. The latter study compares four MSAs with a more elaborate method. Analysis of 10 socioeconomic variables for census tracts yields 3 factors, and the factor scores become the dependent variables in a regression analysis with dummy variables for location, time, and interaction as independent variables.

Controversy about neighborhood status emerged in the sociology literature of the late 20th century, whether suburbs should be considered stable—the persistence model—or constantly changing—the human ecology model. An effort to resolve the issue uses a combination of principal components and cluster analyses on large data sets, 152 census tracts, from metropolitan Baltimore (Vicino, 2008). The procedure is complex. First 49 variables are reduced to six by principal components analysis (PCA) and are then assigned qualitative names for both 1970 and 2000. The six components of the former year are not identical to the six of the latter. The component scores for each tract in each year are then used as variables in cluster analysis yielding five categories for 1970 and six for 2000—again not strictly comparable. Results are interpreted as support for the human ecology thesis of change. Methodologically, the innovation is to use PCA to reduce a large number of variables to a manageable and rigorously defined set of dimensions. The authors say nothing about the cautions in statistical texts regarding the sensitivity of PCA to irregularities in the data.

Hanlon (2009) classifies 1,765 places in the 100 largest U.S. MSAs using 2000 decennial census data. The focus is inner-ring suburbs defined as places adjacent to the central city or in contiguous topological position such that all have greater than 50 percent of their housing units constructed before 1969. Principal components analysis reduces 44 variables to five, indicating the dimensions to be analyzed, followed by a k-means cluster analysis—using component scores of census tracts—that tests 4, 5, and 6-cluster solutions. The 5-cluster solution is deemed the most useful for descriptive purposes, but the results are qualified. The five principal components explain only 59% of the variance between census tracts.

An analysis of the Cleveland MSA examines decade-to-decade change using consistent category definitions (Mikelbank, 2011). This is achieved by applying one cluster procedure to all census tracts for all years. The classification examines 848 census tracts, standardized to 2000 boundaries over census years 1970, 1980, 1990, and 2000. It proceeds directly from selection of 44 variables to hierarchical agglomerative clustering. The first substantial change in the coefficient of variation (within groups) occurs at five clusters, and subsequent discriminant analysis results indicate the specific variables that evoke descriptive nomenclature. Depending on the cluster identity, 74 – 91% of census tracts remain within the same cluster for at least ten years. Indications of change are locally relative because z-scores are calculated to MSA means for each of the four census years.

Development of standardized area units facilitates study at a national scale (Owens, 2012). The study analyzes 51,448 census tracts in MSAs using 19 variables over five time periods—the four decades of the NCDB plus American Community Survey (ACS) data from 2005-2009 5-year estimates. These are reduced to five principal components, and that guides K-means clustering for each of the 5 time periods. A technical contribution is discussion of the discontinuity between ACS post-2000 data and the Decennial long form survey of previous decades. The long time frame and change in databases presents technical difficulty as only three types are consistent across all 5 time periods. Suburban types particularly require modified definitions from year-to-year and composition is uncertain. For example, a “Hispanic/Asian immigrant” cluster identified only for 2005-2009 includes census tracts that are mainly Hispanic, census tracts that are mainly Asian, and census tracts of mixed ethnicity including non-Hispanic non-Asians.

In the past decade, change trajectories have become the major interest of neighborhood classification studies. This is facilitated by the Longitudinal Tract Data Base (LTDB) compiled by the U.S. Department of Housing and Urban Development (Wei and Knox, 2014). Using LTDB for 1990, 2000, and 2010 with standardized 2010 tract boundaries, this study creates a pooled national sample that includes nearly 60,000 metropolitan census tracts for each of the three years. It calculates z-scores of 16 variables to national means for each year. The classification is a K-means cluster analysis that reveals 49 types of change for each of two transition periods, and 343 possible sequences of which 280 are actually observed. Ninety percent of the 60,000 census tracts follow one of the 39 most common sequences. The use of a clustergram, a visualization technique for evaluating different K-means solutions, leads this study to a best-fit number, seven instead of the customary four or five, and that in turn appears to reduce the misclassification error detected by discriminant analysis to only 7.2 percent. Furthermore, four discriminant functions explain 85 percent of the variance between census tracts, a big improvement over previous studies.

Delmelle (2015) follows Wei and Knox by developing a method to classify transition sequences. The results are empirical compare-and-contrast sequences in four metropolitan areas with two, Buffalo and Chicago, representing slow-growth and two, Charlotte and Portland, representing rapid-growth scenarios. A series of fit statistics enhances the methodology by providing a systematic basis for the number of clusters for K-means classification. The solution is five confirming the judgement of four previous studies performed without the fit statistics. Classification of neighborhood type sequences is refined in a second study by Delmelle (2016). The methodological sequence is 1) cross-sectional typology of census tracts by K-means 5-cluster classification, 2) plotting of longitudinal sequence for each census tract, 3) an optimal matching procedure for sequences, 4) a cluster analysis of sequences, and 5) mapping and visual inspection of sequence cluster membership. The double-cluster analysis is new. Variables include income, housing cost, education, in-movers, percent of workforce in manufacturing, and age for the cross-sectional typology.

The studies reviewed thus far analyze a mix of variable types, including demographic, employment, housing, income, race and/or ethnicity all in the same data set. One innovative study separates variables of the socio-economic dimension, classifies neighborhoods using the other dimensions, then ranks the classes on a socio-economic index (Foote and Walter, 2017). The objective is to see if the non-economic indicators can provide a typology that will indicate economic change trajectories in fast-growing metropolitan areas. Three principal components of socio-economic variables explain 65% of the variance between census tracts. This yields the economic status index, and the ranked census tracts are sorted into quartiles. Demographic and housing variables are subjected to cluster analysis to yield five “neighborhood types” and these are assigned conventional descriptive names (Foote and Walter, 2017 p. 1212). The socio-economic index values are then assigned to neighborhood types to create a rank order of status. Class-type pairing tendencies are statistically significant in ANOVA but far from absolute.

Li and Xie (2018) attempt to refine the trajectory analysis procedure of Delmelle (2016). They similarly apply cluster analysis to each of five census years: 1970, 1980, 1990, 2000, and 2010 and rank the trajectories to identify 192 unique sequences of census tract progression across five transition periods. The procedural sequence is complex and justification is obscure. More fundamentally, this approach assumes path dependency, and that hypothesis should be tested rather than treated as axiomatic.

A recent study focuses on four shrinking central cities (Kinahan, 2021). Using NCDB covering five census years 1970-2010 and pooled census tracts, N=4,322, the study applies hierarchical agglomerative cluster analysis to 23 variables and selects a four-cluster solution based on change in the agglomeration coefficient. Then discriminant analysis identifies key variables whose names suggest cluster nomenclature. The cluster-discriminant sequence is then repeated for sub-samples: decade-specific for all cities and city-specific for all decades. It yields 36 comparisons—4 cities plus 5 census years times 4 categories—between sub-sample and aggregate cluster identity. Consistent classification is achieved for 75 percent or more of the cases in 21 of the 36 combinations. This test of stability seems weak, however, compared to conventional confidence intervals of 5 or 10 percent. That renders dubious the statement that the predominant pattern 1970-2010 is “no change” (Kinahan, 2021 p. 513).

Future research recommendations of the authors of the 14 studies should be taken seriously. Most are aware of the limitations of the methodologies employed and apply that knowledge to forthright observations about the quality of results. For example, Mikelbank (2011) is candid about the exploratory nature of his and previous results while Kinahan (2021) cautions that the methodology is descriptive and not definitive about causality. Despite such qualifications, the 14 articles reveal new empirical insights and suggest as yet unrealized theoretical potential.

DISCUSSION

Classification and Nomenclature

Both the robust findings and the limitations of the 14 articles can inform future research because they are examples of regional analysis at small conceptual scale. They treat neighborhood types as ensembles of variables, in contemporary jargon a "contextual analysis paradigm" (Spielman and Singleton, 2015 p. 1004). An index derived from the variables indicates nominal categories that sometimes have distinct ordinal connotations (Table 3). The words "suburban" and "stability" appear frequently in neighborhood type names with implications that are sometimes positive and sometimes negative. Other words used with either no or inconsistent ordinal implications are: diverse, minority, ethnic, new/newer, older/aging, young urban/yuppie. Words such as affluent/booming, wealthy, distressed, educated, elite, lower (income or class), struggling, and vulnerable have distinct ordinal meaning. Blue collar, laborer, manufacturing, and working seem anachronistic (Doussard et al., 2009). All 14 make quantitative comparisons with descriptive statistics, but only Foote and Walter (2017) attempt explicit quantification of relative neighborhood status. Morenoff and Tienda (1997) use the ordinal aspect of their classification to observe trends. Downgrading was prominent in the 1970s, upgrading prevailed in the 1980s, and both were influenced by immigration and intra-metropolitan re-location of demographic groups.

The cacophony of nomenclature provides descriptive interpretation but also qualifies mathematical rigor (Reibel, 2011 p. 308). Morenoff and Tienda (1997) infer ecological polarization: increased numbers of both "gentrifying yuppie" and "disadvantaged" neighborhoods with decreased numbers of "stable" and "working class" ones. Descriptive nomenclature is based on variables that have particularly high or low census tract means for each category. Owens (2012) argues, however, that gentrification is only one type of upward mobility for neighborhoods and that the term should be used judiciously with clearly specified definition. Contrary to claims of stability elsewhere, this study finds that change is the norm. Upward socioeconomic mobility may occur within neighborhoods that remain in the same type from decade-to-decade. Mikelbank (2004) uses discriminant analysis, with cluster type as the grouping variable, to identify the independent variables most responsible for the formation of each cluster. It is a methodological advancement, but the "manufacturing" cluster overlooks a low and declining percentage relative to other occupations. Vicino's (2008) "minority presence" is the most disadvantageous of the 1970 types while "Black middle-class" is one of the more successful in 2000. The author concludes that, compared to the MSA, 1970s suburbs were generally younger and wealthier than in 2000. The deterioration is associated with precipitous decline in "blue collar" employment. Other studies also find Black, Hispanic, immigrant, and white neighborhoods at various levels of an ordinal scale. That ethnic or minority identity signals failure in one instance and success in another emphasizes that multivariate techniques are "exploratory data analysis " whose best use is to raise questions that can be turned into hypotheses (Lattin et al., 2003; Reibel 2011, p. 307).

Methodological Insights

The variety of results is not surprising because, despite the common purpose of constructing a general context and perspective, small area classifications use a variety of data and analytical techniques. There are several ways to conduct a cluster analysis. The most basic distinction is between hierarchical and partitioning methods (Aldenderfer and Blashfield, 1984). Hierarchical agglomerative clustering (HA) starts with a number of clusters equal to the number of cases, then in each step combines the two clusters that produce the least increase in the coefficient of variation. The favorite partitioning method, K-means, starts with a prescribed number of randomly assigned centroids. Clusters are formed with each case assigned to the closest centroid. Then centroid locations are re-calculated for each cluster and cases are re-assigned accordingly. Iterations proceed until re-assignment of cases produces no further reduction in the coefficient of variation.

Four of the 14 studies use HA, 5 prefer K-means, and 3 devise analysis sequences that employ both. Two (Lee and Leigh, 2007; Leigh and Lee, 2005) use neither but define neighborhood types according to location classes similar to those of Hoover and Vernon (1959). The finding is a well-behaved progression of distress from downtown to inner city to inner ring with deterioration in suburbs proximate to central cities, but this is not surprising given the spatial smoothing of the GIS procedure. The authors acknowledge that "some inner-ring suburbs thrive" (Lee and Leigh, 2007 p. 161) and report a significant range of spatial differentiation within cities--Atlanta, Georgia has the highest and Portland Oregon the lowest. This is attributed to differences in planning policy.

Table 3. Small Area Classification Methodology and Descriptive Results

Article	Methodological Tools	Groups	Nominal Terms
Morenoff and Tienda 1997	Hierarchical Cluster, Descriptive Statistics	4	Middle Class, Yuppie, Working Class, Underclass
Mikelbank 2004	Hierarchical Cluster, Discriminant Analysis	10, 4, and 2	White Suburban, Manufacturing, Suburban, Working Diversity
Leigh and Lee 2005	Descriptives, ANOVA test of means	4	Downtown, Inner-City, Inner-Ring, Outer-Ring
Lee and Leigh 2007	GIS contour smoothing, Factor analysis, Regression	4	Downtown, Inner-City, Inner-Ring, Outer-Ring
Vicino 2008	PCA, K-means	5, 6	Minority Presence, Older Middle-Class, Blue Collar, Newer Middle-Class, Wealthy, Poor, Middle America
Hanlon 2009	PCA, K-means, Descriptives	5	Vulnerable, Ethnic, Lower Income and Mixed, Old, Middle Class
Mikelbank 2011	Hierarchical Cluster, Discriminant Analysis	5	Suburbia, New Starts, Stability, Struggling, Struggling African-American
Owens 2012	PCA, K-means	5	Minority Urban, Affluent, Diverse Urban, Booming, New White Suburbs, Hispanic, Upper-Middle-Class White Suburbs
Wei and Knox 2014	K-means with Clustergram, Discriminant Analysis	7	Middle-Class, White Lower, Mixed Renter, Black Poor, White Aging, Elite Immigrant
Delmelle 2015	K-means, Fit Statistics	5	Suburban, Stability, Blue Collar, Struggling, New Starts
Delmelle 2016	K-means, Census Tract Sequences, K-means sequences	5	Newer Suburban, Older Stable Suburban, Blue Collar, Struggling, Young Urban, Elite
Foote and Walter 2017	PCA, K-means	5	Suburban, Mixed New Starts, Immigrant Starts, Minority Concentrated
Li and Xie 2018	K-means, PCA, ANOVA, Hierarchical Clusters	5	Urban Elite, Suburban, Stability, Laborer, Struggling
Kinahan 2021	Hierarchical Cluster, Discriminant Analysis	4	Black Distressed, Lower Middle, Multifamily Educated, Turnover, Upper Middle

Data and Analytical Limitations

Social scientists are accustomed to working with imperfect data. This necessity requires as much knowledge as possible about the nature of the imperfections so they can be considered in the interpretation of research results. For neighborhood classification, data imperfections fall into the broad categories of sampling error and areal unit distortions. Sampling error of census data increases with the decrease in sample-size that accompanies the transition from decennial census to American Community Survey data. Random error is alleviated by combining variables whose positive and negative variances average zero to produce an average variance that is small relative to the collective means (Spielman and Singleton, 2015). Margins-of-error tend to be proportionally higher for variables with low absolute numbers. The 14 studies differ in the number of variables employed, ranging from 10 (Morenoff and Tienda, 1997) to 49 (Vicino, 2008), and the studies at the low end of that range often represent a dimension with only one or two variables. Increasing the number of variables in the analysis does not, by itself, eliminate the accuracy problem. More variables can mean inclusion of higher margins-of-error in a multivariate data set. Also, deep analysis of a census tract case study indicates that ACS error is not always random, and that types of bias may differ with neighborhood characteristics (Bazuin and Fraser, 2013).

A second source of error is in the geographical units used in the analysis. Some studies use units of local government. One such study of 2000 decennial census data classifies 1,765 places in the 100 largest U.S. metropolitan areas (Hanlon, 2009). Findings include considerable variation between categories in housing age, ethnicity, and immigration rates that are independent of socioeconomic status, and also stark contrast between high-employment places and more residential places. The aggregation does not account for variation in size of place--thus the cluster means that inspire qualitative nomenclature have aggregation error, and it is likely to be greater than if the study had used the more nearly standardized census tract data units. Furthermore, this study omits outliers, older suburbs that are not contiguous, and inlier older neighborhoods that have been annexed by the central city. The study notes that the latter is more common in southern and western states where annexation is legally easier, and thus is a source of regional bias in the findings. The most-commonly used areal units are the census tracts delineated by the United States Census Bureau. They generally nest within or encompass minor civil division boundaries, but in sprawling suburban areas a census tract often includes a variety of land uses including undeveloped land (Landis, 2016; Logan et al., 2014). Furthermore, census tract boundaries are modified for each decennial census, while time-series analysis requires consistent areal units. The Neighborhood Change Data Base (NCDB) uses areal interpolation to create standardized census tract boundaries. This method assumes that variables are distributed evenly and can be allocated proportional to area when census tracts split. Refinement with supplementary data is incomplete and imperfect (Logan et al., 2016). The Longitudinal Tract Data Base uses population-based interpolation augmented by areal interpolation in some cases. This produces better results but still assumes that the geographical distribution of other variables matches that of population distribution. Egregious exceptions are not hard to find (Logan et al., 2021). Twelve of the 14 studies use census tracts rather than census places—local municipalities or their equivalents—because the former are of more uniform size. Still, there is considerable variation in population and other variables between census tracts. Most of the 14 studies use arithmetic means of the census tracts in each type, and this is a source of aggregation error. Median or weighted values could provide more accurate characterization.

Analytical technique has evolved even more dramatically than data. Earlier studies use hierarchical agglomerative (HA) clustering while later studies tend to prefer K-means partitioning. The biggest advantage of HA is the ability to trace the progression of mergers of clusters with various characteristics (Mikelbank, 2004). The advantage of K-means is that it re-allocates once-classified cases at subsequent iterations and thus achieves lower coefficients of variation for a given number of clusters (Vicino, 2008). So there is tradeoff between qualitative information about the composition of clusters and their technical statistical accuracy. Recent developments provide rigorous means for choosing the best number of clusters (Reibel, 2011). Cross validation and cluster validity tests of hierarchical agglomerative cluster solutions provide measures of error not available in the customary practice of looking for a jump in the coefficient of variance. Results from a study using this refinement indicate regional orientation of sequence types, abrupt rather than gradual change in ordinal status for many census tracts, upgrading in all census tract categories, and poor predictive power of previous class identity for those that change (Wei and Knox, 2014). The time sequence is only 20 years, but the results suggest that hypotheses other than temporal explanations merit investigation.

Most of the studies use a linear transformation data reduction technique, either principal components or discriminant analysis, to simplify the complexity of the variable set. This is done either before the cluster analysis, in which case component loadings become the variables, or after the cluster analysis when cluster identities are the grouping variable in discriminant analysis. Vicino (2008) and Hanlon (2009) exemplify the former, Mikelbank (2004) and Wei and Knox (2014) the latter. Li and Xie (2018) use the results of PCA to calibrate a weighting formula for analysis of neighborhood trajectory types, but their characterization of three components is dubious. Housing vacancy and age variables load on a component called "Race-Poverty" and the median home value variable loads on the "Education-Employment" component, while the "Housing" component has only the multi-unit and owner-occupied variables. This counter-intuitive assignment indicates a limit for reliance on abstract statistical tests without careful selection of variables. It also indicates that future classifications of neighborhood type sequences won't mean much without clear statements of hypotheses.

The biggest shortcoming of the small area classification thread of research to date is inability to specify the relative importance of demographics, governance, industrial base, physical geography, and planning policy. The specification problem, combined with data uncertainty, qualifies findings of articles such as Mikelbank (2011) that deterioration of suburban communities around Cleveland indicates the potential for future community development and planning problems. The analysis is presented as candidly exploratory without any indication of causality. Figure 6 of a Detroit case study shows an uneven political landscape of central city, suburban municipalities, and unincorporated places, but no variable is included to represent these differences (Li and Xie, 2018 p. 1324). Kinahan (2021) contributes useful guidance for future studies by linking current neighborhood patterns to policy rather than to path-dependency. Categories produced by PCA or discriminant analysis sometimes defy conceptually useful dimensions of interest. This reflects shortcomings in both data and analytical technique. The problem is palpable in the assignment of nomenclature to categories (classes, clusters) of neighborhoods (census tracts, places) that doesn't seem to keep up with dramatic shifts in economy or society. Terms such as 'blue collar' or 'working class' have unclear meaning given sectoral shifts in the labor force. The studies document that meaning of 'minority' and 'suburban' are changing yet try to use those terms as benchmarks. The tendency of each study to adopt the terminology of predecessors does not resolve the issue.

Regional and Temporal Variation

Regional distribution of cases is uneven. Cities of the northeast get the most attention. Southern and western cities are less represented and, except for Atlanta and Los Angeles, tend to be smaller. The four studies of national samples suggest that this is a significant omission. One study of southern and western cases finds "an overall increase in their socioeconomic conditions" (Foote and Walter, 2017 p. 1220). This is most pronounced in suburbs while core areas remain low and outlying areas gain slowly. There are also structural distinctions between metropolitan areas--very high socioeconomic tracts appear clustered in Austin and Raleigh but dispersed in Las Vegas. All five neighborhood types have census tracts in all four socioeconomic categories in all years except for "suburban" where low and very low socioeconomic status become insignificant in 2010. Visualization on maps indicates that development is more attracted to highway corridors than to transit.

The indication in several studies that neighborhood dynamics differ in different types of cities begs the question—what is going on in big Sunbelt cities? One comparison of Chicago and Los Angeles is an exception, and its finding that they have different tendencies suggests the need for more cases (Delmelle, 2016). The analysis finds spatially disjointed down-grading of neighborhoods in Los Angeles but a distinct inner-ring tendency near Chicago. The conclusion is that there are two distinct upgrading processes: Chicago looks like the Chicago school model with a concentric progression of neighborhood filtering punctuated by center-city revitalization, and Los Angeles looks like the Los Angeles school with intermingling of declining, improving, and stable neighborhoods and little city-center revitalization. The implication for theory is that neighborhood condition may be more a result of exogenous factors than of prior status.

CONCLUSIONS

Regional analysis methodology using the statistical techniques of the 14 articles reviewed here is a powerful research tool. Three patterns of neighborhood dynamics emerge. One is variation by type of metropolitan area—size, age, and slow growth versus rapid growth. A second is variation by continental region. Third is a lack of continuity between census periods in the types of neighborhoods. This indicates unstable urban society in a state of change. Some of the studies claim significant findings of neighborhood stability, but this is hard to justify in a time frame of 20 or 30 years. One national study that covers a longer period makes no such claim (Owens, 2012). A more compelling finding is that neighborhood trajectories are highly specific to individual cases in four medium-sized metropolitan areas (Delmelle, 2015). The three themes of inconsistency and instability imply that progressively more mathematically complicated techniques for classifying temporal trajectories may yield diminishing returns. Furthermore, some of the findings suggest that macro-level trends in demographics and economics exert greater influence than historical status, and that policy is a major mitigating force for the macro-trends. Temporal study should not be abandoned, but it should be tied more closely to theory. The contributions are real and the relevance to previous threads of research—sequent occupance and path dependency—have not yet been explored. But it is time to give more attention to other perspectives. Three adjustments to the research agenda on regional analysis of urban neighborhoods seem appropriate. All three fall within established methodologies of urban geography. Only five of the 14 articles appear in nominally 'geographical' journals. The interdisciplinary interest in an intrinsically geographical theme is encouraging. It implies opportunity for research contributions by geographers in any combination of three forms.

First, small area unit classification is applicable to theory. It can be used to compare competing urban land use theories such as the concentric model of the Chicago school and the more dispersed model of the Los Angeles school (Delmelle, 2016). The results imply relevance to broad issues of urban structure that are independent of deterministic path dependency, so other theoretical constructs should be tested (Owens, 2012). Location and spatial association should receive attention as possible explanations of census tract status. An avenue of research emphasizing spatial rather than temporal statistics would be appropriate development and extension of the sub-regions approach (Leigh and Lee, 2005).

Second, future studies should reconsider the choice of areal units. Census tracts are not neighborhoods, despite their convenience as a surrogate, and political boundaries matter. Data for census tracts can be combined into municipalities or their component wards, and additional variables may be available for the larger places. A methodological benefit would be aggregation of census tracts to mitigate data inaccuracies of small geographical units (Bazuin and Fraser, 2013). At other times it might be advantageous to analyze distinctions within places using census block or block groups. The approaches of Kinahan (2021), Leigh and Lee (2005), and Vicino (2008) demonstrate that combination of census geography with political geography can enrich the analysis.

Third, future investigators should consider non-parametric statistics. Principal components analysis and discriminant analysis presume normal distributions and are sensitive to outliers, so logistic regression may be a useful alternative. Reibel (2011) dismisses the use of threshold analysis, and has influenced some of the more recent work, but the technique is promising given the tendency toward highly skewed data and the number of variables where outliers are not statistical mistakes but instead are crucial diagnostics of urban structure. The drawback of a non-parametric approach is loss of power for finding statistical significance, but texts on multivariate analysis recommend its best use as exploratory data analysis—EDA (Chatfield and Collins, 1980; Everitt and Dunn, 2001). The two most popular techniques in the 14 articles reviewed, principal components analysis and cluster analysis, are clearly identified as “exploratory” by Lattin et al. (2003 p. 10). Given that the objective of EDA is the discovery of new questions and formulation of hypotheses, the loss of power is an acceptable sacrifice for the gain of a technique better suited to the structure of the data and the current state of urban theory.

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