Article

Environment and Planning A

Differentiating pathways of neighborhood change in 50 U.S. metropolitan areas

Environment and Planning A
2017, Vol. 49(10) 2402–2424

DOI: 10.1177/0308518X17722564
journals.sagepub.com/home/epn
SAGE

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Abstract

Rapid transformations sweeping the United States over the past 50 years have necessitated a reassessment of longstanding theories on how the neighborhood change process has unfolded. This article builds upon recent methodological advancements aimed at understanding longitudinal dynamics by developing a workflow that blends the self-organizing map and a sequential alignment method to visualize pathways of change in a multivariate context. It identifies the predominant pathways in which neighborhoods have changed according to their racial, ethnic, socioeconomic and housing characteristics in the largest US metropolitan statistical areas from 1980 to 2010. The distribution of these pathways is subsequently examined between metropolitan statistical areas and the spatial clustering of these trajectories within cities is analyzed. Results reveal a white-flight type process, the establishment of a multiethnic neighborhood, densification of single-family neighborhoods, gentrification in relatively diverse neighborhoods, upgrading of white single family neighborhoods, and the most frequent pathway of all: no change. High-poverty minority and wealthy white neighborhoods are most spatially compact and expanding in a contiguous manner, while multiethnic neighborhoods are relatively dispersed. Six groups of metropolitan statistical areas are identified based upon the similarity of their neighborhood composition. Parallels are drawn between the formation of enduring high-poverty black neighborhoods in Northern and Midwestern cities and the emergence of clusters high-poverty Hispanic neighborhoods in Hispanic destination cities.

Keywords

Classification, neighborhood change, self-organizing map, sequential pattern mining

Introduction

Longstanding theories on neighborhood change dating back to Chicago School sociologists of the early 1900s have recently come in to question in light of significant demographic transformations that have swept the United States over the past fifty years (Logan and Zhang, 2010). Rapid Hispanic and Asian immigration to American cities have offered the

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possibility of new types of processes that extend beyond the traditional invasion-succession or life-cycle models that have largely formed the backbone of neighborhood change studies. In addition to immigration, demographic shifts, economic restructuring, suburbanization, migration from industrial cities to southern and western destinations, and back to the city movements, all offer the potential to alter pathways of neighborhood change and potentially warrant the re-examination of these traditional theories.

While a rather large body of literature has been devoted to various aspects of neighborhood change, few have embraced a multidimensional vantage point that enables neighborhood dynamics to be understood in terms of its housing, demographic, racial and ethnic, and socioeconomic complexion in concert. Studies that have undertaken analyses from this perspective have largely been case studies on a single city (Mikelbank, 2011; Morenoff and Tienda, 1997), comparative studies on a few cities (Delmelle, 2015, 2016; Foote and Walter, 2016), or they have not examined metropolitan variations in neighborhood pathways nor spatial patterns of change within cities (Wei and Knox, 2014). The purpose of this article is to bring together the various streams of literature to more fully understand the pathways in which neighborhoods have evolved throughout the United States and how these pathways differ both within and between urban areas. Specifically, this article addresses three research questions:

1. What are the predominant ways in which neighborhoods have change in terms of their racial, ethnic, socioeconomic, and housing characteristic in the largest US metropolitan areas?
2. How do pathways of change vary across metropolitan areas?
3. What is the spatial arrangement of neighborhood trajectories within cities? In other words, are certain trajectory types more likely to be spatially clustered than others?

The analysis is performed on neighborhoods in the 50 largest metropolitan statistical areas (MSAs) in the United States from 1980 to 2010. In order to address these research questions, this article capitalizes upon recent advancements in the neighborhood change literature to classify longitudinal sequences into similar groups (Delmelle, 2016). However, given the large number of potential pathways of change, a visualization method is introduced that summarizes these trajectories on a single figure in such a way that the 30-year sequences are ordered, revealing the longer-run dynamics of neighborhoods. This methodology blends a self-organizing map methodology for arranging neighborhoods on a two-dimensional space based on similarity, a *k*-means clustering algorithm for grouping these neighborhoods, and a sequential alignment method that emphasizes the ordering of events. This latter step produces a set of sequence clusters that are subsequently analyzed between cities by grouping the 50 MSAs based on the similarity of their neighborhood composition, and within cities, by performing a spatial clustering analysis on neighborhood sequence classes.

The remainder of this article is organized as follows. First, a review of the literature identifies existing thoughts and empirical evidence on the potential pathways of change and where they are most probable to occur. The methodological workflow is then outlined and described followed by results, a discussion and conclusions.

Background

The traditional narrative of neighborhood change, and in particular, decline, has centered on long-standing ecological models first proposed by Chicago School sociologies at the turn of the 20th-century. The invasion-succession model, and other related variants including the life-cycle (Hoover and Vernon, 1959) and filtering model (Hoyt, 1933) describe a general progression of neighborhoods transitioning from predominantly white, of a higher socioeconomic status and possessing a newer housing stock toward a largely minority population, lower socioeconomic conditions, and an aging and deteriorating housing stock. Hoover and Vernon's (1959) life-cycle model describes five stages of development beginning with new, low-density, residential development occupied by residents of a high socioeconomic status, followed by a transitional phase characterized by an increase in housing density with a stable or declining socioeconomic status. The third stage features a change in the racial, ethnic, and/or income composition of the neighborhood as older homes are used at a higher density that their initial design. A thinning out of the neighborhood occurs in the fourth stage and the average age of neighborhood residents rises, and finally, the door for renewal is opened in the fifth stage where the neighborhood may return to stage 1 or 2, or it may undergo an increase in new multifamily housing (Schwirian, 1983).

Empirical evidence for this type of linear downgrading process, or invasion-succession of one dominant racial group, socioeconomic status, or housing composition giving way to either a minority or lower-income group has been documented in the literature at both a nation-wide scale (Wei and Knox, 2014) and for various individual metropolitan areas. Some evidence has suggested that this particular process is more prevalent in older, Northern and Midwestern industrial cities such as Chicago and Buffalo (Delmelle, 2015, 2016; Foote and Walter, 2016) – or those cities that developed around similar transportation-eras and where the post-war suburban neighborhood featuring low-density, single family homes provided an alluring respite for many upper-class families to center-city decline. These cities largely served as destinations for blacks during the Great Migration where they settled in spatially compact, center-city neighborhoods as whites increasingly migrated to newer suburbs, and they have subsequently undergone either population declines or stagnations as de-industrialization drained their economic engines. It is in these cities, therefore, that the invasion-succession/filtering model is most likely to continue to conform to the observed process of neighborhood decline and where the friction for change remains the highest. Entrenched patterns of racial segregation in neighborhoods and a legacy of housing discrimination has served as an impediment to the development of new pathways of change in Northern and Midwestern cities (Wilson, 2008). This is especially true in the case of high-poverty minority neighborhoods whose persistence has been well documented (Hwang and Sampson, 2014; Lichter et al., 2012; Morenoff and Tienda, 1997; Sampson, 2009) and for very affluent neighborhoods whose reputation helps stabilize their status (Durlauf, 1996; Solari, 2012).

In newer, more rapidly growing cities, however, the potential for deviations from this well-established path is the greatest. The influx of immigrant populations, coupled with housing and population growth, offers the opportunity to overcome historical neighborhood racial segregation potentially leading to the rise of racially integrated neighborhoods (Ellen et al., 2012; Frey and Farley, 1996). Specifically, the presence of Hispanics or Asians in a neighborhood is thought to provide a 'buffer' against white flight, enabling the establishment of a stable, racially integrated neighborhood, given that whites have been historically less segregated from Asians and Hispanics. Following this reasoning, Logan and Zhang (2010) contend that in the current era of rapid Hispanic and Asian immigration, two processes of neighborhood racial and ethnic change are likely to coexist: the traditionally held notion of white flight and replacement by minorities – now including both Hispanics and Asians in addition to blacks, and a second pathway that features the emergence of a racially diverse population. This latter neighborhood type is argued to represent a stable intermixing of residents, not as a temporary composition as the neighborhood continues its way to becoming dominated by one group. Their empirical study on racial change in 24 metropolitan areas between 1980 and 2000 finds supporting evidence of both of these processes, and other analyses have also reported on the increasing number of diverse neighborhoods across the United States (Ellen et al., 2012; Lee and Wood, 1991; Walker, 2016; Wright et al., 2014). In a follow-up nation-wide analysis, Zhang and Logan (2016) emphasize that increasing diversity is primarily the result of minority entry into white neighborhoods whereas declining diversity hails from the diminishment of white residents below a certain threshold. Regional variations in integration trends across metropolitan areas suggest that the emergence of such multiethnic neighborhoods is more probable in cities experiencing an increase in the share of minority residents, but as Ellen et al. (2012) suggest, too large of a minority population then opens the door to the segregation of these groups. Western US cities were identified as a harbinger for the establishment of stable, integrated neighborhoods as early as 1970–1980 (Lee and Wood, 1991) and, along with Southern US cities, have since undergone increases in racial integration (Ellen et al., 2012; Iceland et al., 2013; Lee and Wood, 1991).

Within metropolitan areas, changes to the location of diverse neighborhoods are also underway. Ehrenhalt (2012)'s great inversion hypothesis contends that the traditional model of central city diversity surrounded by suburban homogeneity is in the process of being replaced by an increasingly white and wealthy urban core surrounded by more diverse and impoverished suburbs. Empirical evidence does support the idea that neighborhood diversity is on the rise in neighborhoods at a distance from the center city, a trend that is particularly acute in cities of the Sun Belt (Walker, 2016). Traditional suburban neighborhoods are also ever more destinations of new immigrants to cities (Farrell, 2016; Wilson and Singer, 2011). More than half of all foreign-born residents lived in suburban locations by 2010 (Wilson and Singer, 2011), especially in the immigrant-rich metropolitan areas of California, Texas, and Florida (Frey, 2011). These changes in settlement locations point to the potential emergence of a neighborhood trajectory from mostly white and single family, or those with more stereotypical suburban characteristics, towards an increasingly foreign born population. This type of transition fits under the umbrella of Zhang and Logan's (2016) minority entry into white neighborhoods, but more specifically identifies foreign born or immigrant entry into white, single-family neighborhoods (or traditionally suburban traits).

A second major change sweeping US metropolitan areas that may alter traditional notions of neighborhood trajectories is a shift in residential building practices away from single family residences toward multifamily, condominiums, and mixed use designs. Low-density, single-family residential developments that were the norm following World War II were largely fueled by population growth, rising incomes, highway expansion, and a consumer preference for low-density developments (Wheeler, 2008). However, more recent trends have indicated a shift in these practices attributable to several factors. First, the demographic composition of the nation is increasing in its share of those over the age of 65 and in single-person households. Both of these groups have different housing needs than the large number of households raising families that helped shaped the American suburban landscape (Nelson, 2009). Second, there has been a perceptible shift in residential preferences of Americans toward more walkable, mixed use neighborhoods (Russonello and Stewart, 2011). The result of these changes has been an observed reversal in building trends toward dense developments in the nation's city centers (Thomas, 2010), with a large nation-wide increase in condominium construction (Rosen and Walks, 2013) as well as a densification and increase in multifamily housing in more stereotypical suburban, or low-density single family neighborhoods, toward what could be described as 'New Urbanist' or 'New Suburbanist' designs (Larco, 2009). Such trends have been observed in some of the fastest growing cities such as Las Vegas (Wheeler, 2008), Phoenix (Atkinson-Palombo, 2010), and Charlotte (Delmelle et al., 2014) where demand for housing is the greatest and developers seek to maximize profits by building compactly as they capitalize upon shifting demographics and preferences.

Delmelle's (2015) multivariate study on neighborhood change in four U.S. cities identified one neighborhood type as 'New Starts' or those characterized by high levels of multifamily housing, an influx of recent in-movers, a highly education population, and few children. Charlotte and Portland saw the largest number of neighborhoods transition into this group, and they tended to transition from struggling neighborhoods with low socioeconomic traits, and, in the case of Charlotte, also from blue collar neighborhoods with single family housing. Likewise, a similar analysis of Chicago revealed two processes of renewal leading to a similar dense, well-educated population: one from the most struggling neighborhoods and a second from neighborhoods with blue collar characteristics (Delmelle, 2016). Both processes suggest a form of gentrification featuring an influx of highly-educated residents into lower socioeconomic neighborhoods, but the former is more likely to occur in center city neighborhoods while the latter process may be more dispersed throughout the metropolitan area, including in suburban location. An increase in multifamily housing is consistent with the final neighborhood renewal stage of Hoover and Vernon's (1959) life-cycle model.

The study by Delmelle (2015) did not include race in its analysis, however, there is some evidence regarding the racial composition of a neighborhood and its propensity to undergo socioeconomic ascent. Hwang (2016), for instance, found the early presence of Asians in a neighborhood to be most foretelling in predicting gentrification, while those with a concentration of blacks and Latinos have been shown to be less likely to experience an influx of upper- and middle-class whites (Hwang and Sampson, 2014). Likewise, in Delmelle (2016)'s analysis of neighborhood change in Chicago and Los Angeles, neighborhoods transitioning into a 'Young Urban' category like the aforementioned 'New Starts' category had increasing shares of Asians and higher overall levels of diversity than other neighborhoods in the city. Those neighborhoods that remained struggling on the other hand had high and increasing shares of blacks in the case of Chicago and Hispanics in the case of Los Angeles (Delmelle, 2016). Therefore, neighborhood socioeconomic ascent that most closely fits traditional notions of gentrification are expected to occur in relatively diverse neighborhoods and/or those with a presence of Asians, and less likely to occur in impoverished neighborhoods featuring a high concentration of blacks or Hispanics.

Finally, rounding out the literature on potential pathways of change, aside from the previous two examples of pathways of neighborhood ascent, a third category includes the improvement in socioeconomic conditions in white suburban neighborhoods. Owens (2012) found this to be the most prominent pathway of ascent for all neighborhoods across the United States and Delmelle (2016) identified it as the sole form of neighborhood upgrading in Los Angeles.

To summarize, in comprehending neighborhoods as a multidimensional bundle of housing characteristics along with their corresponding socioeconomic, demographic, and racial and ethnic profiles, the literature has provided evidence of the following potential pathways of change:

1. A white-flight/filtering type process characterized by an aging housing stock, followed by the diminishment of whites and gradual replacement by minority groups. This likely most prevalent in Northern and Midwestern cities.

2. The establishment of a multiethnic type of neighborhood largely born out of minority entry into white neighborhoods.
   a. Immigrant or foreign born entry into traditionally white, single-family neighborhoods. Both processes are likely in newer cities with recent housing construction that have seen an increase in immigrants and minority groups such as Western and Southern cities.
3. The densification of neighborhoods from single family housing toward multifamily dwellings, populated by either wealthy or younger, childless residents. This is expected to be more prevalent in faster growing cities.
4. Gentrification of neighborhoods, most likely in neighborhoods with an Asian presence or racial and ethnic diversity and not likely to occur in primarily black or Hispanic neighborhoods.
5. White single-family neighborhoods upgrading to higher socioeconomic status.
6. No change – a process of stability, likely most acute for high-poverty minority residents and for affluent neighborhoods.

The spatial arrangement of neighborhood types according to their multivariate profiles and associated dynamics has generally been apprehended in a descriptive manner with cross-sectional maps portraying the distribution of classes within each metropolitan area shown over time (Delmelle, 2015; Foote and Walter, 2016; Mikelbank, 2011). Some observations from this work reveal a propensity for pockets of racially concentrated disadvantage to be most spatially clustered within cities (Delmelle, 2016), for newer, faster growing cities to change in a manner that results in the relative dispersion of neighborhood types throughout cities (Delmelle, 2015; Foot and Walter, 2016), and for neighborhood gentrification to expand in a spatially contiguous fashion (Guerrieri et al., 2013).

Data and methods

Data

This analysis is performed on neighborhoods belonging to the 50 largest MSAs across the United States from 1980 until 2010. Census tracts are used as proxies for neighborhoods and data are obtained from the Longitudinal Tract Database (Logan et al., 2014) which interpolates census tract variables through time to the 2010 boundary files. This dataset uses decennial census data for 1980–2000 and 2006–2010 American Community Survey data for 2010. There are 37,479 census tracts in the 50 MSAs, and with 4 time stamps (1980, 1990, 2000, 2010), this creates an initial input dataset of 149,916 records. Eighteen variables are selected to describe a neighborhood's racial and ethnic, housing, socioeconomic, and demographic profile at each point in time. These variables are selected based upon prior studies in the literature and they enable the characteristics previously identified as potential pathways of change to be evaluated. Two relevant variables are omitted because of a large number of missing records in the earlier years of the analysis: median rent and median household income. Each variable is normalized relative to its own metropolitan area, each year by computing a *z*-score. This way, home values in Oklahoma City in 2000, for example, are relative to the mean of that city in that year and not compared to the absolute value of home values in New York City.

Methods

The methodological workflow to address the stated research questions is outlined in Figure 1. The procedure begins by classifying census tracts at each decade from

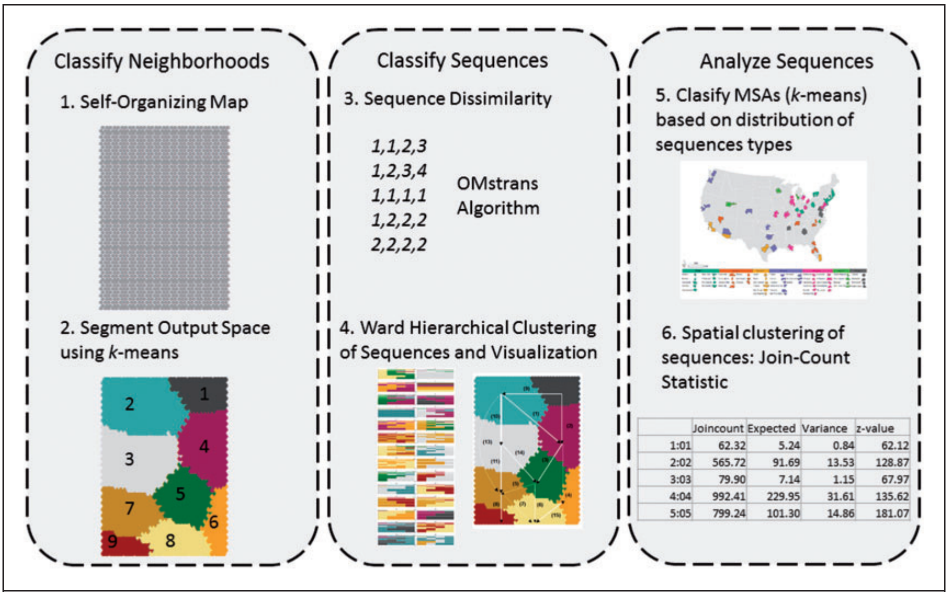

Figure 1. Methodological workflow.

1980 to 2010 according to their similarity across the 18 variables. Sequences of classes are subsequently created for each tract that depicts its longitudinal signature. These sequences are then classified according to their similarity, and finally, an analysis is performed on the distribution of sequences between MSAs and on the spatial clustering within MSAs. The crux of this analysis builds off previous work that employed sequential pattern analysis to classify neighborhood sequences (Delmelle, 2016), but it makes two important improvements to that technique to make it more suitable for larger, more complex datasets. The first is that rather than categorizing neighborhoods into discrete classes based upon a multidimensional set of characteristics using a *k*-means algorithm, in this analysis, a preliminary step organizes neighborhoods based upon their similarity onto a two-dimensional output space using a self-organizing map algorithm. This initial step is shown in Figure 1: the two-dimensional output space is represented as a grid on which neighborhoods are arranged according to their similarity across all 18 variables. This output grid is then partitioned using a *k*-means approach (shown in step 2 of Figure 1) to demarcate the most similar groups of neighborhoods. This additional step has the benefit of providing a platform to visualize the dominant pathways of change according to a multivariate set of characteristics and helps aid in the interpretation of results for a large number of neighborhoods and potential trajectories (Step 4 in Figure 1). The second methodological improvement is in the sequential pattern alignment method. In the Delmelle (2016) article, a commonly used Optimal Matching (OM) algorithm was used to determine the similarity between sequence types. In this work, a method that better emphasizes the ordering, or sequences between events and is therefore more appropriate for examining neighborhood transitions is used: OMstrans (Step 3 of Figure 1). Both improvements are discussed in more detail below along with the remainder of the steps illustrated in Figure 1.

Classifying neighborhoods. The neighborhood classification step begins by arranging neighborhoods according to similarity across their multiple attribute dimensions on a two-dimensional output space using a self-organizing map algorithm (Kohonen, 1990). This neural network-based procedure works by first establishing the output space, comprised by a set of nodes, or neurons. Each of these nodes consists of an n-dimensional weight vector, corresponding to each of the n input variables or dimensions in the study (in this instance, $n=18$). Weight vector values of the output space are initially randomly assigned and updated as the algorithm progresses. The procedure works in an iterative fashion where in each step of the process, an observation (neighborhood) is presented to the output space, and nodes 'compete' for that neighborhood based on the similarity of its vector of attributes and each of the neuron's weight vector values; similarity is assessed by computing the Euclidean distance between all input variables of the neighborhood and the output nodes. When the best matching neuron is identified, the neighborhood is assigned to that node, and the weights of the node are updated to more closely approximate the assigned neighborhood. Weights of nearby neurons are also updated to become more like the newly placed neighborhood. Multiple observations may be assigned to each node while some nodes may have no neighborhoods assigned to them, however, their weight vectors will be similar to surrounding neurons. The ultimate result of this procedure is an ordered output grid so that all neighboring neurons have similar weight vectors. For more details on the algorithm, readers are pointed to Skupin and Agarwal (2008) for an introduction and applications to spatial problems.

The SOM toolbox in Matlab is used for this step in the analysis (Vesanto et al., 2000). The number of output nodes is set to 1904 – this value is obtained via the SOM toolbox heuristic (5*dlengthˆ0.5) where dlength equals the number of records.

The second phase in the process is to group the output nodes into discrete classes using a k-means approach. As the attributes of the nodes have been updated to account for similarity, adjacent nodes will be assigned to the same group. This stage essentially demarcates the output space into the most homogeneous group of nodes for an easier interpretation of results. The number of clusters is determined by examining 2–15 different cluster solutions and selecting the one that results in the largest average silhouette width, a measure of the overall strength of group membership. Characteristics of each cluster are obtained by examining the mean z-score of each of the input attributes, or weight vectors, of all nodes assigned to the cluster.

Classifying sequences. Once each neighborhood has been assigned a class at each point in time, a sequence can be created for that neighborhood, depicting its temporal trajectory. In order to classify sequences based on their similarity, the first, and perhaps most crucial starting point, is determining how to assess their similarity (or dissimilarity). Studer and Ritschard (2016) provide a comparative analysis of various methods for determining sequence dissimilarity for social science applications. They distinguish five distinct ways in which sequences may differ from one another: (1) *experienced states*, or the distinct elements present in the sequence; (2) *distribution*, the total time spent in each state, (3) *timing*, the date at which each state appears, (4) *duration*, the consecutive time spent in the same state, and (5) *sequence*, the order in which states are experienced. Given this application, the most important criterion in determining similarity is according to the sequence in which neighborhoods have transitioned through various states. Considering the authors' critical assessment of several dissimilarity metrics and their appropriateness in capturing each of the aforementioned properties, the Optimal Matching between sequences of transitions (OMstrans) method developed by Studer and Ritschard (2016) is employed. This variant of the popular OM algorithm, which evaluates the minimum total cost to completely transform one sequence into another via inserting, deleting, or substituting elements in the sequence, computes the OM distance between sequences of transitions. In other words, each state is joined with its previous state to form two-period long subsequences (the sequence ABCD would be converted to AB–BC–CD), and the OM procedure is applied to these subsequence pairs. This overcomes the traditional OM algorithm's insensitivity to ordering. In the cost formulation, the sensitivity of OMstrans to sequencing is governed by the parameter, w, an origin-transition tradeoff parameter. When w=1, OMstrans is equal to the classical OM algorithm, while a lower w value gives more importance to the transition type and therefore more importance to the sequencing of events. In this case, a value of 0.1 is given, stressing the importance of sequencing. A value of 3 is given as the insertion and deletion costs; values greater than one minimize the time warping of sequences, and substitution costs are derived from the transition rates between classes. The package Seqdist2 is R is used to derive the dissimilarity matrix, while TraMineR is used to visualize sequences (Gabadinho et al., 2011). A full overview of the dissimilarity metrics and parameters as implemented in Seqdist2 can be found in Studer and Ritschard (2016).

After the dissimilarity matrix is created between all sets of sequences, it is then input into a clustering procedure to derive a typology of sequences. In this case, a hierarchical ward's clustering procedure is used. A large number of cluster solutions are initially assessed (n=50), and clusters are subsequently merged and the cluster number is reduced until sequences following opposite trajectories (i.e. improving and declining) are grouped together. This is done via a visual inspection of the results.

Intra- and inter-urban analyses. Once the typology of trajectories is established, the distribution of each sequence cluster type within each MSA is analyzed by classifying MSAs based on the percentage of each trajectories type in the city. This is done via a k-means analysis and the number of groups is determined by selecting the partitioning that maximizes the average silhouette width.

Finally, to analyze the spatial distribution of trajectory types within each city, a multi-group join-count statistic is employed to test whether trajectories of the same type are more spatially concentrated than we might expect to see randomly. This metric of spatial autocorrelation is appropriate for categorical data such as trajectory classes. The statistic counts the number of 'joins', or adjacent neighborhoods belonging to each pair of classes and compares this value to an expected number to obtain a level of significance. Expected values are a function of the observed number of neighborhoods belonging to each class and variances are computed under non-free sampling (Bivand, 2017). A z-score compares the observed number of joins to the expected number; a higher z-score is indicative of a greater amount of spatial clustering between trajectory types while negative z-scores can be interpreted as a spatial dispersion between classes. The analysis is performed using the spdep package in R (Bivand, 2017) and is performed for all MSAs at once. Considering that the join-count statistic is conceptualized as a metric for analyzing spatially adjacent relationships, a queen contiguity weight matrix is used to operationalize these spatial relationships.

Results

SOM output and neighborhood classes

After the SOM is trained and all neighborhoods for the four time stamps have been sorted according to similarity on the output space, each node on that output space contains a final value for the 18 input variables (its weight vector). The distribution of each these variables can be visualized on that space to gain an understanding on the overall sorting of neighborhoods and their associated characteristics. These visualizations, called component

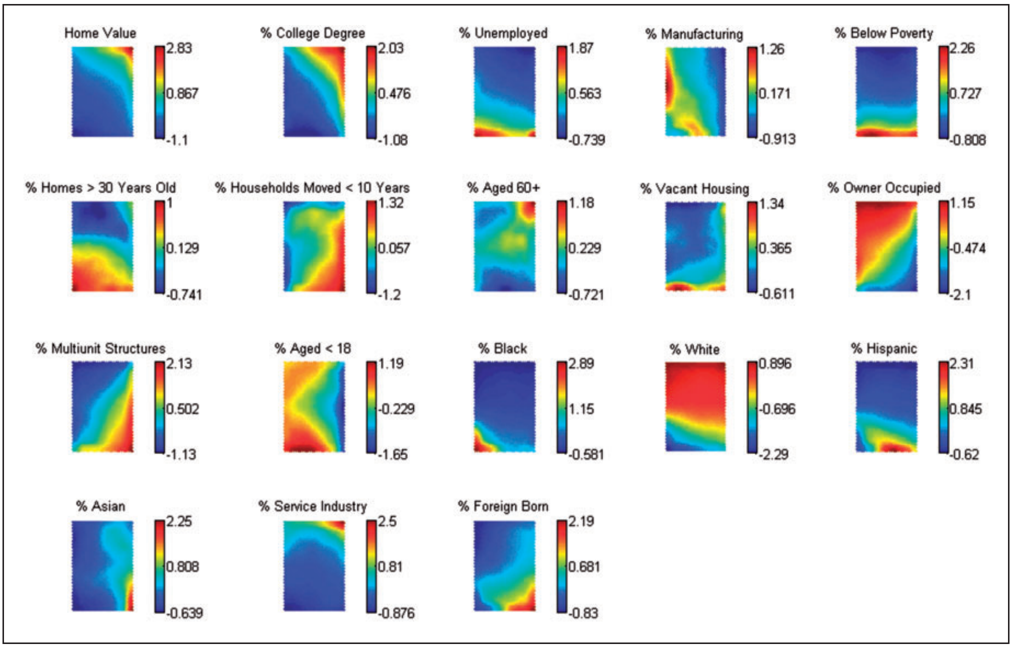

Figure 2. Distribution of 18 variables on SOM output space.

planes, are shown in Figure 2. In the figure, red colors indicate a high value for that variable, while blue indicates a low value; the values corresponding to each component plane's legend reflect the normalized values of that variable. For example, neighborhoods with the highest home values, the highest percentage of those with a college degree, and the oldest residents (% Aged 60+) are located at the upper-right corner of the plots. In general, neighborhoods at the top of the output space are largely white, and this gradually declines downward on the output space resulting in the highest concentration of blacks in the lower left-hand corner, Hispanics in the bottom center, and Asians in the bottom right. In terms of housing, the oldest homes can be found in the lower left corner, with a clear concentration of newer dwellings in the upper left corner. Owner occupancy and multiunit structures largely mirror each other in their gradients; neighborhoods in the upper left corner are largely single-family homes with high homeownership rates, while those in the lower right are multiunit structures with a larger share of renters.

This output space is next segmented using the values from the weight vectors of each node in k-means procedure to identify homogeneous groups of nodes. A nine-cluster solution is deemed to best fit the data based on the maximum average silhouette value and the segmentation of the output space is shown in Figure 3. It is helpful to keep in mind that this clustering solution is ordered so that neighborhoods belonging to cluster 1 are more similar to those in cluster 2 than those in cluster 9. Cluster descriptions are obtained by examining both the component planes in Figure 2 and the mean z-score of nodes belonging to each group; these values can be found in Table 1, and a brief description of each of the cluster types is provided in Figure 3. Of note in the nine clusters is cluster 8 which comes closest to the global neighborhood description by Logan and Zhang (2010) as these neighborhoods have the most even spread of all racial groups amongst all clusters, characterized by an above average concentration of both Hispanics and Asians, an approximately average number of blacks, and a slightly below average number of whites.

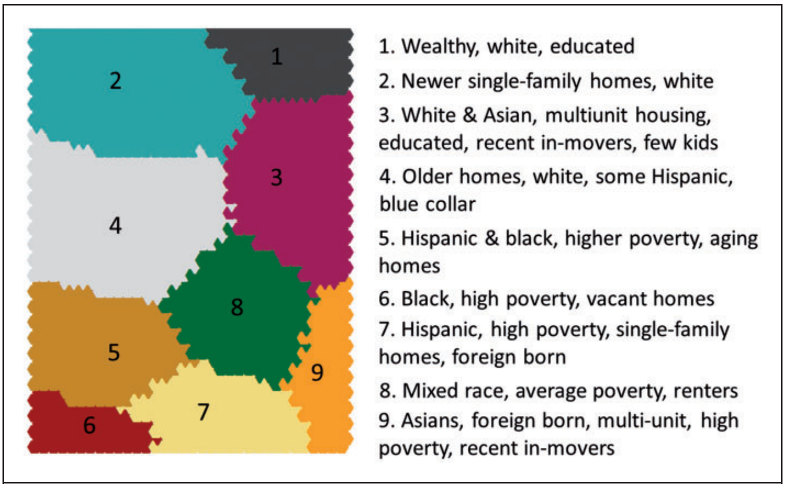

Figure 3. Segmentation of SOM output grid to 9 clusters and a brief description of each cluster type.

Table 1. Mean z-score of each cluster.

Cluster Number	Median Home Value	% with 4-year college degree	% unemployed	% manufacturing	% below poverty	% homes built >30 years ago	% households moved <10 years ago	% > 60 years old	% service industry
1	1.39	1.45	–0.63	–0.55	–0.67	–0.21	–0.13	0.57	1.19
2	0.23	0.22	–0.45	0.02	–0.64	–0.62	–0.1	–0.12	0.26
3	0.36	0.74	–0.41	–0.46	–0.4	–0.26	0.53	0.23	0.03
4	0.4	–0.5	–0.13	0.31	–0.28	0.01	–0.22	0.12	–0.29
5	–0.71	–0.8	0.41	0.34	0.38	0.57	–0.32	–0.17	–0.56
6	–0.96	–0.01	1.35	–0.04	1.75	0.79	–0.12	–0.3	–0.78
7	–0.65	–0.82	0.68	0.28	1.17	0.54	0.66	–0.47	–0.58
8	–0.35	–0.3	0.03	–0.06	0.08	0.25	0.38	0	–0.4
9	–0.12	0.23	0.35	–0.54	0.73	0.26	1.07	–0.18	–0.42
Cluster Number	% vacant housing	% owner occupied housing	% multiunit structures	% < 18 years old	% black	% white	% Hispanic	% Asian	% Foreign Born
1	–0.04	0.6	–0.35	–0.38	–0.5	0.7	–0.52	0.27	–0.08
2	–0.35	0.85	–0.78	0.25	–0.47	0.66	–0.45	–0.14	–0.48
3	0.04	–0.43	0.65	–0.87	–0.36	0.44	–0.3	0.42	0.15
4	–0.2	0.3	–0.34	0.03	–0.3	0.32	–0.12	–0.19	–0.27
5	–0.07	–0.06	–0.19	0.5	0.54	–0.88	0.67	–0.3	0.24
6	0.84	–0.86	0.47	0.98	2.03	–1.85	0.34	–0.55	–0.21
7	0.39	–1.2	1.02	0.48	0.45	–1.14	1.48	–0.09	1.05
8	–0.01	–0.74	0.75	–0.31	–0.07	–0.12	0.26	0.3	0.48
9	0.41	–0.61	1.7	–1.05	0.11	–0.49	0.55	1.3	1.36

Note. Values shaded by intensity. Darker red signifies larger positive number, darker blue is a larger negative number.

Another notable group is cluster 3 which has many of the same traits as the New Starts (Delmelle, 2015; Mikelbank, 2011) and Young Urban (Delmelle, 2016) neighborhoods featuring a highly-educated population, high home values, an influx of recent residents, few children, and multifamily housing.

Longitudinal sequences

The next stage in the analysis consists of grouping trajectories of neighborhood change. The sequences are grouped into 34 trajectories and are visualized in Figures 4 and 5. In these

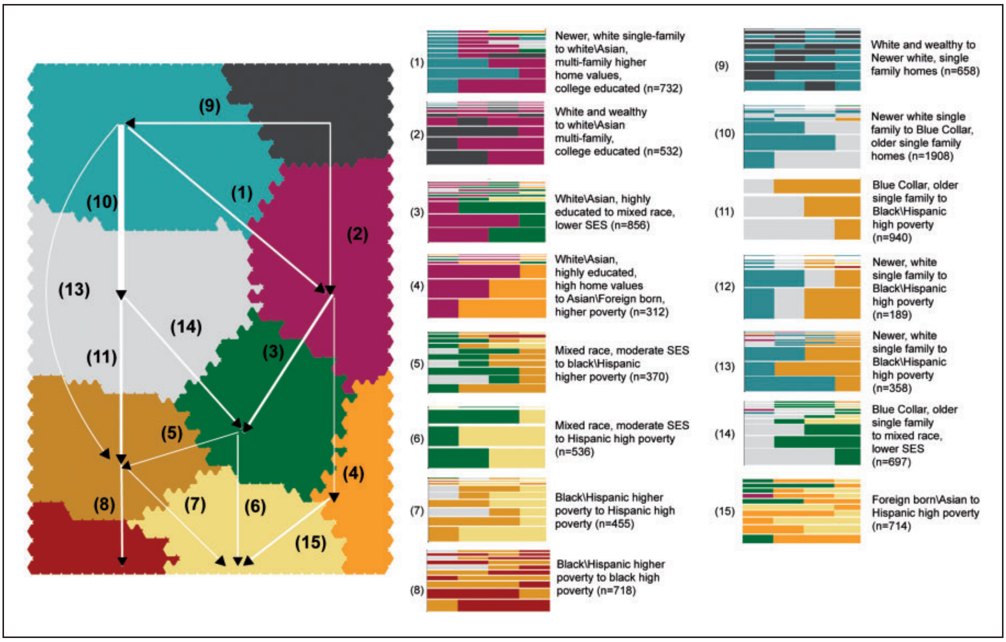

Figure 4. Pathways of neighborhood change 1: Descending trajectories.

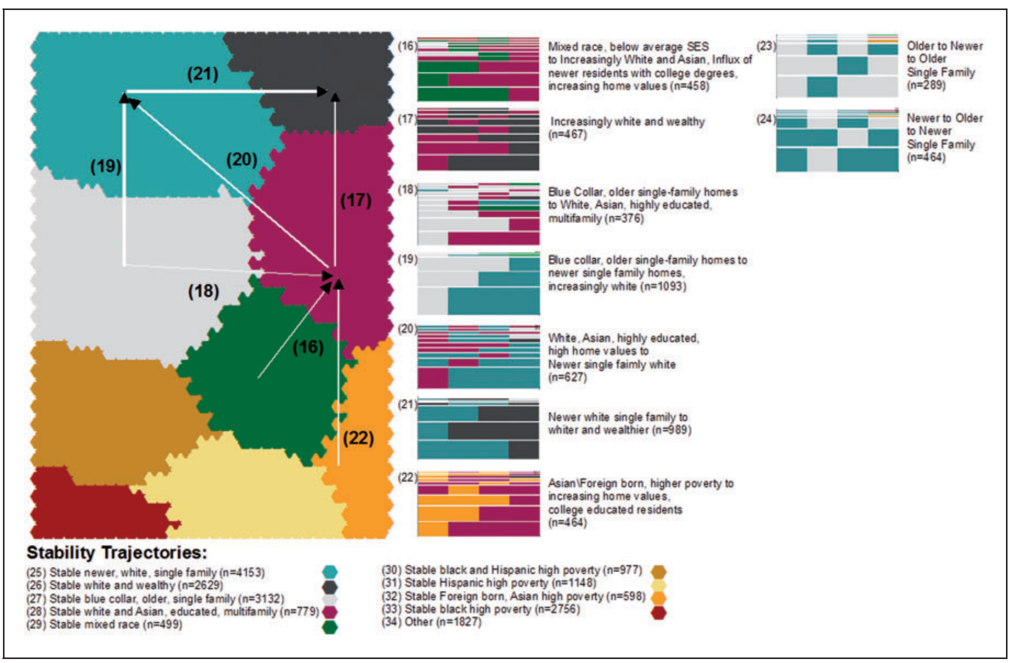

Figure 5. Pathways of neighborhood change 2: Ascending trajectories.

figures, the sequences belonging to each trajectory cluster are visualized to the right along with a brief description, and an arrow corresponding to the dominant pathway depicted in each sequence plot is visualized on the SOM output space to the left. The arrows are scaled by the share of neighborhoods belonging to that sequence cluster.

Figure 4 depicts pathways of change that follow a downward trend on the output space, generally representing a decline in socioeconomic status (as was apparent from examining the component planes in Figure 2). A clear pathway of linear decent can be followed down the left-hand portion of the output space, following trajectories 10–11–8. This pathway can be interpreted as a white-flight/filtering type process where newer housing and an overwhelmingly white population gives way to an aging housing stock coupled with a rise in vacant housing units, a gradual decline in the share of whites, and a diminishment of those moving into the neighborhoods. This is the most common pathway of change as indicated by the thickened arrows of trajectories 10 and 11. A less-common trajectory of socioeconomic decline follows on the right-hand portion of the output space. This pathway is not propelled by a population exodus, but rather by an influx of recent, largely foreign-born and Asian residents in neighborhoods characterized by a large share of multifamily housing and a high percentage of renters.

Two distinct pathways are also present into the mixed-race neighborhood type: the first follows trajectory 14, which shows an increase in recent in-movers with a rising share of Hispanics, Asians, foreign born residents, and, to a lesser-extent, blacks, coupled with a decline in white residents. This pathway features an increase in renters and a general decline in socioeconomic status. The second pathway follows trajectory 3 away from the highly educated, high home valued, multi-unit housing type neighborhoods with a mix of whites and Asians. This pathway features similar racial and ethnic changes, but is accompanied by a decline in recent in-movers, suggesting that the decline in whites is a result of out-migration.

Trajectory 1 shows a downward trend on the SOM output space, but is characterized by rising home values in conjunction with an increase in multi-family housing, a sharp rise in recent in-movers, a decline in children, and an increase in Asians. Thus, this depicts a movement away from more stereotypical suburban traits toward more urban characteristics, possibly in the form of new urbanist or suburbanist developments. Finally, it should also be noted that the pathways of decline shown in Figure 4 most frequently converge in the high-poverty, mainly Hispanic neighborhoods in the bottom center of the output space, showing numerous pathways into that group. The high-poverty black neighborhoods however, are a result of the white-flight type process.

The trajectories portrayed in Figure 5 show the general pathways of socioeconomic ascent, along with two non-linear trajectories likely depicting suburbanization processes (numbers 23 and 24), and processes of stability (trajectories 25–33). It should first be noted that nearly half of all neighborhoods in the 50 MSAs belong to trajectories of stability during the 30-year time period. The largest number of neighborhoods that remained the same class belonged to the newer, white, single family neighborhoods, followed by older, blue collar single family, black high poverty, and white and wealthy. The stable mixed race and higher poverty, foreign born/Asian neighborhoods contained the fewest share of neighborhoods of all the stability trajectories.

Pathways of ascent show a convergence toward the highly educated, multi-family, white and Asian type neighborhoods on the right-hand side of the output space. Neighborhoods that increased in these characteristics were either multiethnic in nature to begin with (trajectory 16), featured a large share of Asians and foreign born residents, but higher poverty rates (trajectory 22), or evolved out of older single-family, blue collar neighborhoods (trajectory 18), pointing again toward a densification and youthification movement. Trajectories 16 and 22 are most

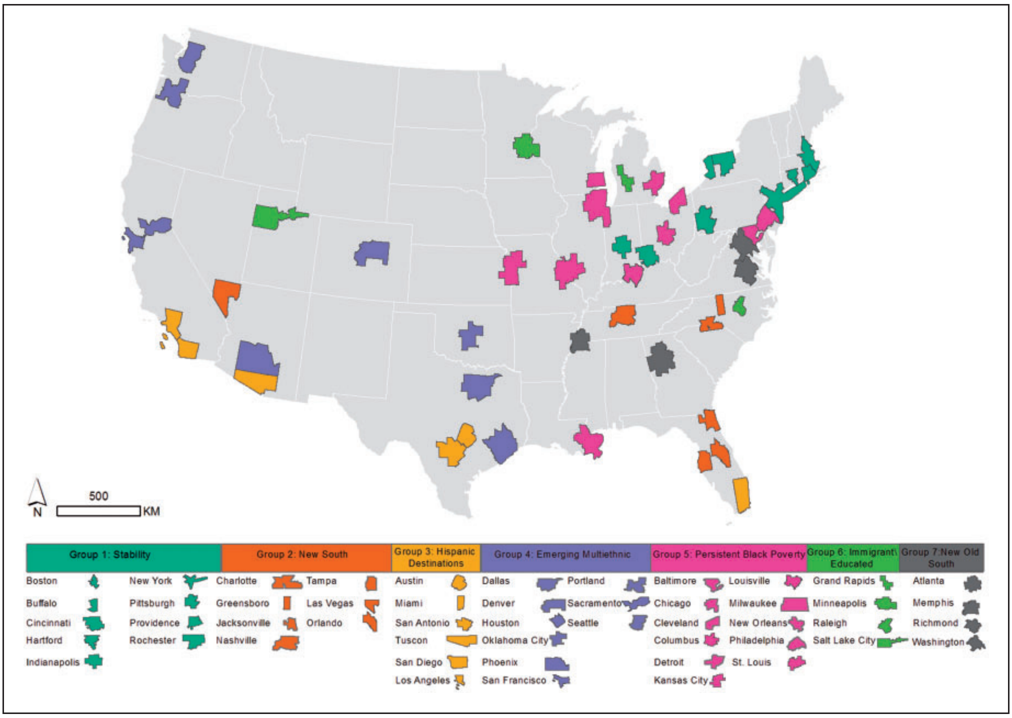

Figure 6. Classification of MSAs based on their neighborhood trajectory compositions.

characteristic of gentrification and support the notion that this process is most likely to occur in relatively diverse neighborhoods with a strong Asian presence (Hwang, 2016). Finally, trajectory 34 describes neighborhoods belonging to an 'other' category. These are a collection of trajectories that did not fit within any of the previous 33 dominant forms of change; they could not be represented by a singular trait.

Distribution of sequences by city

The distribution of each type of sequence within each city is summarized by grouping the MSAs according to the similarity of the percentage of each sequence type within each city. Based on the maximum average silhouette width, a seven-cluster solution is obtained. The cities belonging to each group are visualized in Figure 6, while the average percentage of each sequence type for the seven groups are summarized in Table 2.

The first group of cities named 'Stability' are in the Northeast and Midwestern United States and are characterized by high rates of stability including stable newer and older single family neighborhoods and those that have followed the first segment of the identified filtering or white flight process from newer to older single family neighborhoods. They also have the largest share of stable multiethnic neighborhoods and comparatively low levels of densification.

The second group, the 'New South', is comprised of rapidly growing Sunbelt cities such as Las Vegas, Charlotte, Nashville, Orlando, Tampa, and Jacksonville and feature a relatively large share of neighborhoods that have transitioned from single family towards the multi-family, highly educated group, likely reflecting the changing trend in residential construction and national demographic shifts. These cities also saw a large share of more traditional,

Table 2. Percentage of sequence clusters in city groups.

Group\Sequence Cluster	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1:Stability	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.02	0.07	0.02	0	0	0.02	0.03	0.01	0.01
2: New South	0.04	0.01	0.02	0.01	0.01	0.01	0.01	0.03	0.03	0.04	0.02	0	0.01	0.02	0.03	0.01	0.01
3: Hispanic Destinations	0.04	0.02	0.03	0.02	0.01	0.01	0.02	0.02	0.03	0.04	0.02	0.01	0.01	0.01	0.02	0.01	0.02
4: Emerging Multiethnic	0.03	0.01	0.03	0.01	0.01	0.02	0.02	0.02	0.02	0.06	0.04	0.01	0.01	0.03	0.02	0.01	0.02
5: Persistent Black Poverty	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.02	0.06	0.03	0	0.01	0.02	0.02	0.01	0.01
6: Immigrant and Educated	0.04	0.01	0.03	0.01	0.02	0.01	0.02	0.01	0.01	0.05	0.05	0.01	0.01	0.01	0.02	0.02	0.02
7: New Old South	0.03	0.02	0.02	0.01	0.02	0.01	0.01	0.04	0.01	0.05	0.03	0.01	0.03	0.01	0.03	0	0.02

Group\Trajectory Cluster	18	19	20	21	22	3	24	25	26	27	28	29	30	31	32	33	34
1:Stability	0.01	0.02	0.02	0.03	0.01	0.01	0.02	0.17	0.07	0.13	0.02	0.02	0.01	0.03	0.02	0.08	0.04
2:New South	0.02	0.05	0.03	0.02	0.02	0.02	0.02	0.08	0.07	0.13	0.01	0	0.01	0.01	0.02	0.07	0.1
3: Hispanic Destinations	0.01	0.02	0.03	0.04	0.01	0.01	0.01	0.1	0.09	0.06	0.03	0.02	0.08	0.05	0.01	0.05	0.06
4: Emerging Multiethnic	0.01	0.04	0.02	0.03	0.02	0.01	0.02	0.13	0.08	0.09	0.03	0.01	0.03	0.03	0.02	0.05	0.07
5:Persistent Black Poverty	0.01	0.03	0.02	0.03	0.01	0.01	0.01	0.12	0.08	0.12	0.02	0.01	0.01	0.02	0.02	0.12	0.04
6: Immigrant and Educated	0.02	0.1	0.02	0.04	0.02	0.01	0.01	0.11	0.07	0.11	0.03	0.01	0.01	0.02	0.04	0.04	0.03
7: New Old South	0.01	0.08	0.02	0.04	0.02	0.01	0.01	0.11	0.06	0.07	0.02	0.01	0.03	0.01	0.02	0.12	0.06

Note. Values shaded by intensity. Darker red signifies higher values, green indicates lower values.

newer single family, largely white neighborhoods with more stereotypical suburban traits and they contained the largest number of neighborhoods falling into the 'other' category, suggesting that in these fast-growing cities, alternate pathways of change are underway that do not fall under the trends dominated by the rest of the country.

The third group of cities, 'Hispanic Destinations', are the southernmost in the study and are dominated by Hispanic high poverty neighborhoods including the conversion of black and Hispanic neighborhoods to overwhelmingly Hispanic and the stability of Hispanic high poverty neighborhoods. They also have a relatively low share of the foreign born, Asian group. The fourth group, 'Emerging Multiethnic', includes the Western cities of Seattle, Portland, San Francisco, Phoenix, and Denver along with Dallas, Houston, and Oklahoma City. They are also fast growing destinations, but are distinguished from the 'New South' group by a larger share of neighborhoods transitioning into the mixed race or multiethnic group either from the older, white and Hispanic blue collar neighborhoods or from the white and Asian, highly educated class. They are not characterized by the single to multifamily transformations shaping the 'New South' cities.

The fifth group, 'Persistent Black Poverty' is dominated by a large share of stable, black high poverty neighborhoods. Except for New Orleans, these cities were all destinations of the great migration and the patterns of racial segregation that were carved out during that period have proved durable through time. The sixth group, 'Immigrant and Educated', contains a seemingly diverse set of cities including: Grand Rapids, Minneapolis, Raleigh, and Salt Lake City. These four cities possess a relatively high share of stable foreign born and Asian, but high poverty neighborhoods, as well as a high share of the stable white and Asian, highly educated group, and a pathway from single to multifamily, white and Asian, and highly educated. These trajectories are in addition to a large share of the conversion of older, blue collar single family neighborhoods to newer and whiter single family neighborhoods. Thus, this group can be characterized by both immigration and a highly educated population in growing cities. Finally, the last group, 'New Old South', consists of Atlanta, Memphis, Richmond, and Washington D.C. Like the fifth group, they possess a large

Table 3. Spatial clustering between neighborhoods of same trajectory type.

Trajectory description (trajectory number)	Join count	Expected	Variance	z-value
Stable Black High Poverty (33)	799.24	101.30	14.86	181.07
Stable Hispanic High Poverty (31)	254.14	17.57	2.77	142.17
Stable Newer White Single Family (25)	992.41	229.95	31.61	135.62
Stable White & Wealthy (26)	565.72	91.69	13.53	128.87
Stable Black & Hispanic High Poverty (30)	171.19	12.72	2.02	111.49
Stable Foreign Born, Asian High Poverty (32)	92.33	4.76	0.77	99.85
Blue Collar Single Family to Newer & Whiter Single Family (19)	152.35	15.92	2.52	86.01
Stable Older, Blue Collar Single Family (27)	470.74	130.84	18.86	78.27
Asian Foreign Born to Asian & White Educated (22)	54.63	2.87	0.47	75.88
Asian Foreign Born to Hispanic High Poverty (15)	83.66	6.79	1.09	73.59
Newer White Single Family to Black & Hispanic Higher Poverty (13)	40.11	1.71	0.28	72.81
Black and Hispanic Higher Poverty to Black High Poverty (8)	82.29	6.87	1.10	71.81
Newer White Single Family to Asian & White Educated (1)	79.90	7.14	1.15	67.97
Asian & White Educated to Newer White Single Family (20)	62.32	5.24	0.84	62.12
Mixed Race to Hispanic High Poverty (6)	52.13	3.83	0.62	61.37
White & Wealthy to Newer White Single Family (11)	93.67	11.78	1.87	59.83
Newer White Single Family to White & Wealthy (21)	98.63	13.04	2.07	59.50
Mixed Race to Asian & White Educated (16)	41.35	2.79	0.45	57.26
White and Wealthy to Asian & White Educated (2)	48.24	3.87	0.63	56.07
Black and Hispanic Higher Poverty to Hispanic High Poverty (7)	40.03	2.76	0.45	55.71
Newer White Single Family to Blue Collar Single Family (10)	192.86	48.55	7.40	53.06
Blue Collar, Older, Single Family to Asian & White Educated (18)	30.74	1.88	0.31	52.12
Asian & White Educated to Asian & Foreign Born High Poverty (4)	24.37	1.29	0.21	50.16
White & Wealthy to Newer White Single Family (9)	52.56	5.77	0.93	48.55
Asian & White Educated to Asian & Foreign Born High Poverty (4)	61.08	8.09	1.30	46.56
Newer White Single Family to Blue Collar Single Family to Newer White Single Family (24)	33.85	2.88	0.47	45.30
Asian & White Educated to Mixed Race (3)	63.78	9.76	1.56	43.27
Stable Mixed Race (29)	33.68	3.32	0.54	41.42
Other (34)	148.58	44.51	6.81	39.89
Newer White Single Family to Blue Collar Single Family to Black & Hispanic High Poverty (12)	10.97	0.47	0.08	37.61
Blue Collar Single Family to Mixed Race (14)	39.29	6.47	1.04	32.18
Asian & White Educated to White and Wealthy (17)	22.58	2.90	0.47	28.66
Mixed Race to Black & Hispanic Higher Poverty (5)	16.57	1.82	0.30	27.06
Blue Collar Single Family to Newer White Single Family to Blue Collar Single Family (23)	12.48	1.11	0.18	26.67

share of stable, black, high poverty neighborhoods, but they have also undergone a process of improving socioeconomic status among white single family neighborhoods (to become both whiter and wealthier) and they have a relatively large share of neighborhoods that have transitioned from newer, white single family to black and Hispanic with a lower socioeconomic composition. Thus, these cities have maintained a piece of their southern history of racially segregated neighborhoods, but are more dynamic than their northern and Midwestern counterparts in experiencing growth in single family neighborhoods, and a changing racial composition of those traditionally white single family neighborhoods.

Spatial clustering of sequences within cities

Results of the spatial clustering analysis are presented in Table 3 which reports the spatial clustering of neighborhoods belonging to the same trajectory type. In other words, these

Table 4. Spatial clustering between neighborhoods of different trajectory types.

Trajectory 1 Description (trajectory number)	Trajectory 2 Description (trajectory number)	Join Count	Expected	Variance	z-value
Stable Black High Poverty (33)	Black and Hispanic Higher Poverty to Black High Poverty (8)	214.37	52.80	8.11	56.73
White and Wealthy to Asian & White Educated (2)	Stable White & Wealthy (26)	131.14	37.71	5.83	38.69
Stable Hispanic High Poverty (31)	Black and Hispanic Higher Poverty to Black High Poverty (8)	78.42	18.72	2.99	34.53
Stable Foreign Born, Asian High Poverty (32)	Asian Foreign Born to Hispanic High Poverty (15)	58.05	11.39	1.84	34.44
Asian & White Educated to White and Wealthy (17)	Stable White & Wealthy (26)	106.93	32.67	5.06	33.01
Asian Foreign Born to Asian & White Educated (22)	Stable Foreign Born, Asian High Poverty (32)	42.95	7.40	1.20	32.46
Blue Collar Single Family to Newer White Single Family to Blue Collar Single Family (23)	Blue Collar Single Family to Newer & Whiter Single Family (19)	44.28	8.43	1.36	30.79
Newer White Single Family to White & Wealthy (21)	Stable Newer White Single Family (25)	225.00	109.58	16.22	28.66
Newer White Single Family to Blue Collar Single Family (10)	Stable Newer White Single Family (25)	369.19	211.39	30.72	28.47
Asian & White Educated to White and Wealthy (17)	Stable Newer White Single Family (25)	36.00	6.72	1.09	28.06

results address whether neighborhoods of a given trajectory group are more likely to be located adjacent to neighborhoods of the same type than we would expect to see randomly. In the table, the join count value reports on the observed number of neighborhoods belonging to the same sequence group that are adjacent to one another. This is compared to an expected value, given the number of neighborhoods of that type in the study area. Finally, a *z*-score is used to determine statistical significance. According to the table, neighborhoods belonging to trajectories of stability are the most spatially compact of all trajectory types. This is most pronounced for those at either end of the socioeconomic spectrum – the highest poverty neighborhoods are the most spatially concentrated, followed by the largely white and wealthier neighborhoods. For transitioning neighborhoods, those that have moved into the white and Asian, educated class have done so in a spatially contiguous fashion; this is true regardless of the pathway it took to reach that class (i.e. either from the higher poverty, foreign born/Asian class or the white single family class) as have white single family neighborhoods that have become black and Hispanic. At the lower end of the spectrum, neighborhoods in the mixed race group that have either remained there for the longer term or transitioned into that group are comparatively spatially dispersed.

Table 4 indicates the co-location of trajectory types. For the sake of brevity, only the top 10 co-located sequence types are shown in the table. These results point to the prevalence of spatial spillovers of both wealth and poverty showing that, for example, neighborhoods which transition into the high black poverty group are largely located adjacent to existing black poverty neighborhoods and neighborhoods that increase in wealth do so on the periphery of existing wealthy neighborhoods.

Discussion and conclusions

This article has sought to understand the dominant trajectories of neighborhood change throughout the 50 largest MSAs in the United States from 1980 to 2010 from a multidimensional vantage point. An analytical approach was developed to visualize and classify neighborhoods into similar longitudinal sequences that subsequently enabled neighborhood trajectories to be compared between cities and within cities. The resulting analysis produced nine distinct cross-sectional classes of neighborhoods describing their racial/ethnic, demographic, housing, and socioeconomic composition, and 35 sequence clusters or trajectories depicting the predominant pathways of change. A review of the literature identified six plausible pathways of change based on existing evidence, and this analysis corroborated the existence of each of those including: a white-flight process, the establishment of a multiethnic type of neighborhood, the transition from single family to multifamily housing, gentrification in relatively diverse neighborhoods, upgrading of white single family neighborhoods, and no change.

To begin, it should be acknowledged that while this article is centered on change, more than half of the neighborhoods in the study belonged to sequences depicting stability during the 30-year time frame. Despite a wealth of literature devoted to the subject of change, the fact is that most neighborhoods remain the same, at least over the course of several decades. This finding that underscores work by others that have emphasized that the neighborhood change process is slow and that stasis is by far the most common trajectory (Wei and Knox, 2014). This is especially true for those at either end of the socioeconomic spectrum; the highest poverty black neighborhoods and the wealthiest and whitest neighborhoods are both temporally durable, and spatially compact. Analyzing the co-location of neighborhood trajectory types revealed that neighborhoods that transition into these groups do so in a spatially contiguous manner, thus furthering their spatial polarization.

The analysis of trajectory types by MSA pointed out that enduring high poverty black neighborhoods are most prevalent in Northern and Midwestern cities that served as destinations of the Great Migration (Sampson, 2009), many of which have witnessed heightened racial tensions in recent years. Several southern cities, identified as the 'New Old South' in this analysis, saw increasing concentrations of wealthy white neighborhoods as their cities otherwise became more racially diverse. This result bolsters evidence of increasing income segregation in the United States driven largely by the concentration of affluence (Reardon and Bischoff, 2011).

In respect to pathways of change, supporting evidence was found for the coexistence of two distinct trajectories of socioeconomic decline: one more akin to a white flight or house filtering model featuring an again housing stock and a gradual decline in whites and socioeconomic status, and a second that is the result of an influx of newer, largely foreign born and Asian residents into neighborhoods with a larger concentration of rental and multifamily housing. It was notable that all pathways of decline led to neighborhoods comprised of a largely Hispanic population coupled with high poverty rates and socioeconomic disadvantage. Parallels can be drawn to the formation of these neighborhoods and the high poverty black neighborhoods that were largely created prior to this study period: the Hispanic high poverty neighborhoods are generally located in cities receiving many Hispanic migrants and these neighborhoods are largely situated in a spatially compact manner and expanding in a contiguous fashion. So, while influxes of Hispanic and Asian immigrants to the country may allow for the emergence of multiethnic neighborhoods (Logan and Zhang, 2010), Ellen et al.'s (2012) hypothesis that too large of an increase in a minority group to a city sets the stage for the segregation of that group is an important caveat. Given the parallels with the formations of black high poverty neighborhoods in the north, the southernmost cities identified in this analysis as possessing these new and expanding pockets of poverty may be forewarned of the struggles facing their northern counterparts on concentrated, racially segregated poverty.

This analysis identified one relatively racially diverse neighborhood type; it was coupled with average to below average socioeconomic characteristics, and a higher than average share of renters and multifamily housing. This neighborhood type was established either via a white-flight processes out of a mixed Asian and white, highly educated class, or as a product of minority entry into older blue-collar neighborhoods with a white and Hispanic presence. These pathways are therefore supportive of a 'buffering' type process whereby the presence of Hispanics or Asians enables a larger share of whites and blacks reside together (Logan and Zhang, 2010). These neighborhoods are gaining in share in faster growing Western cities such as Seattle, Portland, and San Francisco, and are comparatively spatially disjoint than their single-race counterparts. The western locations conform to prior studies that have identified this region as a potential harbinger for the establishment of a new type of global neighborhood (Lee and Wood, 1991).

Several trajectories of socioeconomic ascent were uncovered in this analysis – it was notable that these pathways tended to converge in the establishment of a neighborhood type characterized by a highly educated population of recent in-movers, dominated by whites and Asians and with a relatively high share of multi-family housing and renters. These traits are often associated with gentrification and the movement into this group from relatively racially and ethnically diverse neighborhoods with lower socioeconomic traits, in a spatially contiguous manner supports current understanding on this phenomenon (Delmelle, 2016; Hwang, 2016; Hwang and Sampson, 2014). However, that was just one of the likely ways in which this neighborhood type was created. A second pathway followed neighborhoods out of a class comprised of single family housing – either slightly older with a blue collar composition, or newer with a higher socioeconomic profile to these multi-family, highly educated, white and Asian group. This latter trajectory conceivably portrays the development of new urbanist or suburbanist-type developments and was most prevalent in rapidly growing Sunbelt cities where this process developed alongside the establishment of neighborhoods with more stereotypically single-family suburban type traits. This trajectory fits the narrative of a shifting preference toward walkable neighborhood types and a growing presence of multifamily housing in traditionally suburban-type neighborhoods (Larco, 2009) and its presence in rapidly growing cities points to a diversification in the ways in which newer neighborhoods are constructed away from the single family mold that shaped the post-war landscape of older cities. The transition from single-family, white and relatively affluent towards dense and more diverse while maintaining higher socioeconomic traits is an aberration from Hoover and Vernon's (1959) life cycle model. Finally, it is notable that the 'New South' cities possessed the largest share of neighborhoods belonging to an 'other' category of trajectories that did not neatly conform to the 34 sequence clusters. So while this analysis uncovered dominant pathways of change that are largely consistent with the existing literature, a detailed scrutiny of these less frequent paths may reveal emergent trajectories of change that could warrant new theorizing of processes in very dynamic metropolitan areas. Future research should closely examine the trajectories contained in this group.

The absence of trajectories of socioeconomic ascent out of high poverty black, Hispanic and mixed black and Hispanic neighborhoods was conspicuous. Prior research has indicated that disadvantaged neighborhoods tend to undergo more volatile changes coinciding with the ebbs and flows of business cycles (Delmelle and Thill, 2014; Hincks, 2015; Williams et al., 2013). These short-term changes may register as improvements or declines when analyzing neighborhood dynamics from one time period to the next via transition matrices, but when viewing the full longitudinal sequences, a clear pathway of ascent fails to register as a predominant trajectory during this 30-year time frame. Results from this analysis could be used to identify neighborhoods that have made a sustained transition out of these groups to take a closer look at their characteristics.

The methodological workflow developed for this analysis offers a promising way of making sense of large, multidimensional, longitudinal datasets for understanding neighborhood dynamics. A visualization technique was developed that blends a self-organizing map's output space where neighborhoods are arranged according to similarity on a two-dimensional grid with a sequence clustering procedure for identifying dominant pathways of change. When the trajectories are visualized on the SOM output space, they allow for a more complete picture of longitudinal pathways to emerge than is depicted by each individual 30-year sequence cluster. The advantage of clustering sequences compared to analyzing transition matrices, as has largely been the norm in the literature thus far, is that it enables subsequent analysis to be performed on the distribution of neighborhood types between cities and within cities, as was done in this study. The developed method, however, is not without its limitation. Perhaps most foremost is that all variables were standardized across decades and MSAs which restricts its ability to gauge absolute changes. It therefore may not be appropriate for all studies on neighborhood dynamics. The empirical analysis was further limited by its inclusion of only the 50 largest MSAs which may omit important trajectories in smaller metropolitan environments. Future research could follow a similar approach in these metropolitan or micropolitan regions of the country to compare processes of change. It would also be worthwhile to take a closer comparative approach to analyzing spatial arrangement or clustering of neighborhood types within cities to complement the analysis in this study which grouped all MSAs together. Finally, while this analysis was descriptive in nature and featured only the most predominant pathways of change in the largest metro areas, the dataset of neighborhoods classified at each cross-section as well as the sequence clusters will be made freely available for researchers to further probe questions of causality or more close examine particular case studies.

Acknowledgements

Michael Widener deserves credit for suggesting the name 'New Old South' for one of the city cluster groups. Comments and suggestions from participants of the University of Toronto's Intersection's seminar, Elizabeth Morrell, and three anonymous reviewers were all valuable in finalizing this manuscript.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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