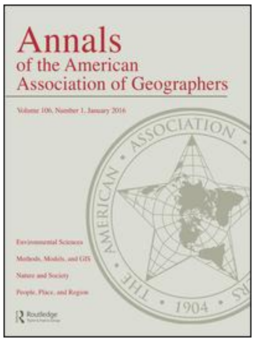

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Mapping the DNA of Urban Neighborhoods: Clustering Longitudinal Sequences of Neighborhood Socioeconomic Change

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The spatial pattern of longitudinal trends in neighborhood socioeconomic dynamics has long been implied by traditional urban models dating back to the Chicago School; however, empirical studies beyond the mapping of change between two points in time are surprisingly limited. This article introduces a methodology to the study of spatial–temporal patterns of neighborhood socioeconomic change. The approach first involves establishing discrete classes of neighborhoods following a *k*-means clustering procedure and then applies a sequential pattern mining algorithm to determine the similarity of longitudinal sequences. Sequences are then clustered to derive a typology of neighborhood trajectories. The method is employed in an empirical analysis of neighborhood change from 1970 to 2010 for all census tracts in the cities of Chicago and Los Angeles. In Chicago, this time period was marked by a sustained process of center city revitalization through two distinct upgrading processes, whereas in Los Angles, neighborhood upgrading largely came in the form of suburban upgrading. The spatial structure of neighborhood dynamics in Chicago resembled patterns described by Chicago School theorists, whereas the dynamics of Los Angeles deviated from this ordered regularity. *Key Words: cluster analysis, GIS, neighborhood change, sequential pattern analysis.*

邻里社经动态的纵贯趋势之空间模式，往往意味着追溯至芝加哥学派的传统城市模型；但超越绘製两点间随着时间改变的经验研究，却出人意料地相当有限。本文引介一个研究邻里社经变迁的时空模型之方法论。该方法首先依循K方法的集群过程建立不连续的邻里类别， 接着应用序列模式探勘演算法来决定纵贯序列的相似性。序列接着进行集群，以取得邻里轨迹的类型学。该方法应用于 1970 年至 2010 年间，芝加哥与洛杉矶城市所有人口统计区的邻里变迁之经验分析。在芝加哥，此一时期以透过两造相异升级过程所展现的持续性市中心复苏过程为特徵； 在洛杉矶，邻里提升则大幅以郊区升级的形式发生。芝加哥的邻里动态空间结构，近似于芝加哥学派理论家所描绘的模式，而洛杉矶的动态，则偏离了此般具有秩序的规律性。 *关键词： 集群分析，地理信息系统，邻里变迁，序列模式分析。*

Desde hace mucho tiempo el patrón espacial de las tendencias longitudinales en la dinámica socioeconómica vecinal ha estado implícito en los modelos urbanos tradicionales originarios de la Escuela de Chicago; sin embargo, los estudios empíricos que vayan más allá del mapeo del cambio entre dos puntos a través del tiempo son sorprendentemente limitados. Este artículo presenta una metodología para el estudio de patrones espacio-temporales del cambio socioeconómico de los vecindarios. Primero, el enfoque implica establecer clases discretas de vecindarios por medio de un procedimiento de conglomerados de k-medias, para luego aplicar un algoritmo secuencial de minería de patrones para determinar la similitud de secuencias longitudinales. Enseguida, las secuencias son agrupadas para derivar una tipología de trayectorias vecinales. El método se emplea en un análisis empírico de cambio vecinal de 1970 a 2010 para todos los distritos censales de las ciudades de Chicago y Los Ángeles. En Chicago, este período de cambio estuvo marcado por un proceso sostenido de revitalización del centro a través de dos procesos distintos de renovación, mientras que en Los Ángeles la revitalización ocurrió en gran medida en términos de renovación suburbana. La estructura espacial de la dinámica vecinal en Chicago trae a la mente los patrones descritos por los teóricos de la Escuela de Chicago, mientras que la dinámica de Los Ángeles se desvía de esa regularidad ordenada. *Palabras clave: análisis de conglomerados, SIG, cambio vecinal, análisis secuencial de patrones.*

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When Chicago School sociologists developed the first formal models describing the spatial, socioeconomic urban landscape of humans and their activities in the form of concentric zones (Burgess 1925), sectors (Hoyt 1939), or multiple nuclei (Park, Burgess, and Roderick 1925; Harris and Ullman 1945), they depicted a cross-sectional view of the spatial sorting of residents, housing, and businesses. Accompanying these models were theories describing how the socioeconomic composition of neighborhoods changes over time, emphasizing residential competition for space. Initially couched in ecologically derived terms of "invasion and success" (Burgess 1925) and later explained as a supply-and-demand function of aging housing and new residential construction on the outskirts of cities (Hoyt 1939) or a trade-off between transport and land costs (Muth 1969), early models of neighborhood change depicted a gradual downgrading process of neighborhoods close to the urban core as wealthier residents were drawn or pushed—depending on the theoretical vantage point—to the outer extent of urban areas. The spatial configuration of these dynamics was thus implied to exist along a linear gradient away from the urban core as neighborhoods composed of the oldest housing eventually became occupied by residents of a lower socioeconomic status. Beginning in the 1960s, the countering trend of the renewal of previously disinvested center-city neighborhoods began to receive attention in the context of gentrification (Glass 1964). As the oldest, most centrally located neighborhoods possess housing that is arguably most prime for redevelopment (Brueckner and Rosenthal 2009), the more traditional spatial pattern of decline away from an urban core has since been revisited to suggest that the oldest suburban neighborhoods, or the inner ring neighborhoods—those inaccessible to amenities and composed of relatively undesirable housing—are the most prone to decline (Hanlon and Vicino 2007; S. Lee and Leigh 2007). Hoover and Vernon (1959) synthesized these processes as a part of their life cycle model, which suggested that neighborhoods transition through a set of five stages from development to renewal. To contrast these notions of regular urban spatial structures, those adhering to the so-called Los Angeles School have proposed that postmodern cities are no longer arranged neatly around a central core. Rather, the periphery determines the core in a highly decentralized, chaotic urban form (Dear 2002).

Whereas the spatial configuration of neighborhood dynamics has long been inferred throughout the large body of neighborhood change research, there has been remarkably little research that has actually sought to map the long-term, socioeconomic trajectories followed by neighborhoods, beyond the mapping of change between two points in time (e.g., Randall and Morton 2003; Kitchen and Williams 2009; Teernstra and Van Gent 2012; Wei and Knox 2015). In fact, the overwhelming majority of studies on neighborhood dynamics more broadly have also overlooked the longitudinal paths followed by neighborhoods to determine what the most common pathways of change are over the long term, considering multiple points in time. Does empirical evidence support the idea that neighborhoods cycle through a series of stages as proposed by Hoover and Vernon (1959)? Are there additional pathways of change besides the more commonly discussed downgrading and upgrading? Such questions have been posed previously in the literature (Owens 2012; Teernstra and Van Gent 2012), but the methodological approaches to neighborhood analyses employed thus far have restricted studies to investigating snapshots of change between two points in time, rather than capturing the longer sequence of events through which the neighborhood change process unfolded.

This article therefore addresses these gaps in the literature by proposing a methodological approach to the study of neighborhood trajectories. A sequential pattern mining procedure is applied to four decades (five time stamps) of neighborhoods classified according to their socioeconomic, housing, and demographic characteristics. The resulting trajectories are then mapped to determine the spatial configuration of neighborhood dynamics and can therefore be used to scrutinize longstanding theories of where neighborhood changes are implied to take place. Initially developed by biologists for the study of DNA sequences, sequential pattern mining procedures are popular in many social science contexts, including the analysis of life course events (Barban and Billari 2012) or career pathways (Fuller and Stecy-Hildebrandt 2015). In geographic research, spatiotemporal analysis can be considered from two perspectives: space-in-time and time-in-space (Andrienko et al. 2010). The first deals with movements in space over the course of time, whereas the latter reflects changes in the attributes of spatially situated units. In respect to space-in-time analysis, sequential alignment methods have been used as a method for classifying or summarizing human movements and activity patterns and mapping these trajectories in the geographic space (Wilson 2006; Shoval and Isaacson 2007; Kim 2014; Kwan, Xiao, and Ding 2014). Stehle and Peuquet (2015) recently applied it to the analysis of spatial–

temporal patterns of political and diplomatic events. This article introduces sequential pattern mining as a means of performing time-in-space analysis on changes in neighborhood socioeconomic complexions over the long term.

The proposed methodology is employed in an empirical analysis of neighborhood change from 1970 to 2010 for all census tracts in the cities of Chicago and Los Angeles (and their corresponding counties)—two cities that have followed distinct development trajectories and serve as the namesake of two contrasting schools of thought on urban form. The following research questions are addressed:

1. What are the dominant trajectories of neighborhood change observed over the course of a forty-year time span?
2. What is the spatial arrangement of neighborhood dynamics? How do they compare between the two cities?
3. How do racial and ethnic changes map onto socioeconomic, housing, and age dynamics?

Spatial Patterns of Neighborhood Dynamics

There is a long history of research seeking to identify pathways of neighborhood change. Whereas early theories focused on neighborhood decline and its potential causes, more recent work has sought to identify the potential varied pathways of neighborhood upgrading, renewal, or ascent or to distinguish trajectories of neighborhood socioeconomic classes more generally. Initial downgrading processes are well documented in the literature, but to very briefly summarize and to contextualize the empirical analysis, explanations and associated spatial patterns of neighborhood decline date back to the early 1900s and the work of Burgess (1925), who conceptualized the idea of a spatial sorting of social and economic groups in the form of concentric rings around an urban core. Dynamics were played out through an ecologically based process of the invasion of one lower social group and the subsequent succession of the neighborhood's socioeconomic complexion. These concentric rings were later adopted by Muth (1969), but the underlying theory was replaced by an economically grounded explanation that reflected a trade-off between commuting costs and residential land consumption. Hoyt (1939) proposed an alternative spatial arrangement of residential groups in the form of sectors or wedges fanning out from an urban center where the highest income residents located on the outer extents far from the central business district and along waterfronts, consuming its natural amenity. Hoyt's theoretical basis rested on the relationship between neighborhood decline and housing age, or the filtering model. As housing demand increases with rising incomes, and new housing construction takes place on the fringes of his envisioned wedges, a depreciation of dwelling units occurs as housing age increases. Relatedly, economists Hoover and Vernon (1959) introduced some of the vernacular of neighborhood conditions that continue to be used today in their life cycle model of change. In this model, neighborhoods transition through a series of five stages: development, transition, downgrading, thinning out, and renewal. Accompanying a neighborhood's transition through these stages are distinguishable changes to some of its characteristics, including its demographic composition in terms of age and race, land use intensity, population density, and the quality and condition of housing. It is also important to note that not all neighborhoods were thought to evolve though an entire life cycle in chronological order; some will repeat steps or remain at one stage (Schwirian 1983).

Finally, rounding up the major thoughts on spatial patterns of change, Harris and Ullman (1945) offered that groups of similar socioeconomic status coalesced in spatial clusters, or multiple nuclei throughout an urban area. There has been some recent renewed interest in empirically testing the current validity of these models in light of postmodern critiques stemming largely from Los Angeles School advocates who resist the notion that regular spatial patterns and processes exist across urban landscapes. Empirical work challenging these postmodern arguments has examined the spatial distribution of incomes or populations throughout a number of North American cities and found that at various cross sections in time, Chicago School spatial regularities continue to be relevant in describing modern metropolises (Shearmur and Charron 2004; Hackworth 2005; Meyer and Esposito 2015).

An enormous body of research has also been devoted to the countering trend of neighborhood renewal, chiefly in the form of gentrification research. Although the underlying causes of gentrification have been a source of contention in the literature, Wyly and Hammel (1999) argued that regardless of the causes, this inherently geographic process represents a transformation of social classes in central-city neighborhoods that previously underwent devaluation, outmigration, and disinvestment. Thus, spatially, gentrification is expected to occur close to urban centers. This process is argued to be temporally uneven for neighborhoods within a city and has been described as exhibiting a spatially contagious pattern: Neighborhoods adjacent to wealthy or previously gentrified neighborhoods have a higher likelihood of gentrifying (Guerrieri, Hartley, and Hurst 2013). This spatial process, however, has been shown to be offset by the racial composition of a neighborhood: Those with a concentration of blacks and Latinos are less likely to experience the influx of middle- and upper middle-class whites that helps to define gentrification (Hwang and Sampson 2014).

Given the revitalization potential of neighborhoods close to urban centers, the initially held convention that neighborhood decline operates along a linear gradient from center cities has been reconsidered in light of a wealth of research that has documented the decline of so-called inner-ring suburbs (Hanlon and Vicino 2007; S. Lee and Leigh 2007; Vicino 2008; Hanlon 2009). These postwar suburbs arguably possess undesirable housing and are isolated from urban amenities, thus lowering their demand relative to other parts of a metropolitan area. One debatable issue regarding inner-ring suburban decline is a lack of consensus of where the spatial boundaries of this potential zone of decline exist. Empirical research to date has taken an a priori approach to delimiting this ring by classifying neighborhoods according to housing age or a set of socioeconomic variables (Cooke and Marchant 2006; S. Lee and Leigh 2007) or by using census-designated place boundaries to define the spatial location of these neighborhoods (Hanlon and Vicino 2007). Changes in one or more socioeconomic variables are then analyzed within the confines of this designated boundary. The methodology put forth in this article provides an alternative to this debate by grouping neighborhoods based on the similarity of their longitudinal profile; the spatial location of socioeconomic declines can then be ascertained from groupings of neighborhoods following similar trajectories.

Differentiating Neighborhood Trajectories

Aside from the spatial patterns of neighborhood dynamics, other research has sought to identify or differentiate the pathways through which neighborhoods change over time. Although downgrading and gentrification present two possible paths, Van Criekingen and Decroly (2003) challenged the convention that all types of neighborhood or urban renewal fall along a continuum, eventually leading to gentrification. Their research, based on an extensive review of the literature, established a typology of four distinct upgrading processes: gentrification, marginal gentrification, upgrading, and incumbent upgrading. Owens (2012) proposed a broadening of the debate on typologies of neighborhood ascent by characterizing types of neighborhoods throughout the United States that underwent improvements in residential incomes, housing costs, and educational and occupational attainment regardless of their initial socioeconomic standing. White suburban neighborhoods were identified as the most likely to ascend each decade between 1970 and 2010, but an increasing number of minority neighborhoods began experiencing socioeconomic ascent toward the latter end of their study time period.

Other research that has looked at pathways of neighborhood socioeconomic change more generally (rather than privileging either upgrading or downgrading) has used transition matrices to examine the frequency with which neighborhoods move between neighborhood ecological clusters (Morenoff and Tienda 1997; Mikelbank 2011; Wei and Knox 2014; Delmelle 2015). Morenoff and Tienda's (1997) study on neighborhood transitions in the city of Chicago was precedential in this line of research. They classified census tracts into four groups: stable middle-class, gentrifying yuppie, transitional working class, and ghetto underclass. Decennial transitions between these classes from 1970 to 1990 were examined, revealing that transitional working-class neighborhoods were the most fluid during this time span, either upgrading to stable middle class or falling into the underclass category. Neighborhoods at either end of the ecological spectrum were found to be very persistent in their classification through time. Racial and ethnic specific patterns of change were also uncovered.

Although offering an initial glimpse into the process of neighborhood change, ultimately, the use of transition matrices is limited in their ability to only examine change between two points in time (the probability of transitioning from one group to another from time i to time j). These first-order Markov-type analyses disconnect a singular transition from the larger sequence of events through which the neighborhood change process has unfolded, and are thus unable to differentiate the potential pathways that neighborhoods have evolved over the long term. Neighborhood change has further been shown to exhibit strong temporal dependence, as shorter term changes to neighborhoods are susceptible to reverting back to their prior condition following some exogenous shock (e.g., an investment in the neighborhood or fluxes in the business cycle); this consideration is overlooked in first-order transitions. Results might then give the impression that a neighborhood has changed course, when in fact that upward transition is an aberration in its overall trajectory (Galster, Cutsinger, and Lim 2007; Delmelle and Thill 2014).

A fully longitudinal perspective on neighborhood dynamics that looks at multiple time points has only very recently been considered by Wei and Knox (2014), who classified all of the metropolitan U.S. census tracts into six socioeconomic groups and subsequently listed the top thirty-nine two-decade sequences. Their results indicated that the top six sequences throughout the nation represented stability, and discerning any pattern from the remaining list of thirty-three is nearly impossible. The spatial patterns of these trajectories were not explored given the large geographic extent of the analysis. In a similar approach, Delmelle (2015) visualized the top ten longitudinal, categorical sequences followed by neighborhoods through five time stamps in four cities and subsequently mapped the cross-sectional cluster membership for each neighborhood at each time stamp (1970–2010). Although these two articles offer an initial step in considering longitudinal sequences beyond the analysis between two points in time, they are ultimately limited in their ability to show the spatial location of changes over the long term, and listing the most common sequences masks trends that might be gleaned from these trajectories, including information on the most common or similar trajectories over the long term.

There have been several other recent advancements in mapping and modeling longitudinal trajectories of neighborhoods. Séguin, Apparicio, and Riva (2012) investigated poverty rates through five points in time, from 1986 to 2006 for neighborhoods in Montreal utilizing a latent growth curve modeling approach. This type of trajectory clustering procedure discriminates neighborhoods according to their longitudinal trends, as discerned by their starting point (intercept) and slope over the time period. Neighborhoods belonging to each cluster were subsequently mapped, thus enabling a spatiotemporal investigation on poverty trends. This methodology, like other trajectory clustering approaches, offers one promising avenue when examining change according to a singular, continuous variable and when change can be assumed to follow an underlying trajectory over time.

The use of geovisual analytics for describing pathways of neighborhood change through multiple attribute dimensions has also received some attention. Skupin and Hagelman (2005) proposed an approach based on the computational technique of the self-organizing map to visualize longitudinal neighborhood trajectories. This method has been implemented in the exploration of neighborhood quality of life (Delmelle et al. 2013) and socioeconomic dynamics (A. C.-D. Lee and Rinner 2015).

The methodology proposed and implemented in this article is in the same spirit as Séguin, Apparicio, and Riva (2012) in that it seeks to identify the dominant pathways of change for multiple time stamps, but it operates on discrete socioeconomic classes and therefore considers the multidimensional nature of neighborhoods.

Method

The methodology developed to cluster and visualize longitudinal sequences of neighborhood change is outlined in Figure 1. As this technique is intended for clustering discrete processes, the first step involves creating cross-sectional typologies of neighborhoods. In this case, census socioeconomic, demographic, and housing data at the tract level from 1970 to 2010 obtained from the Longitudinal Tract Database (Logan, Xu, and Stults 2014) is used as the foundation. This data source interpolates four decades of census tract data to match the 2010 tract boundaries.

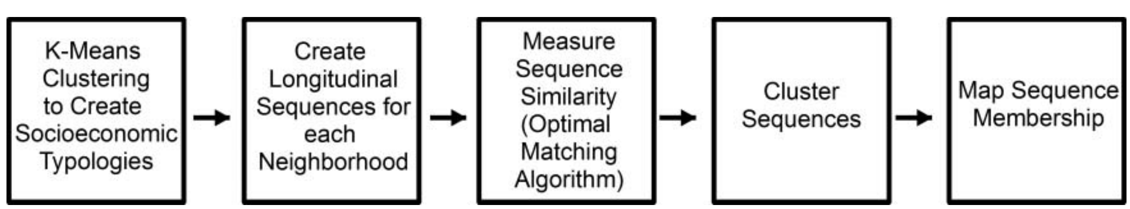

Figure 1. Sequence clustering and mapping methodology.

Cross-Sectional Typologies

A *k*-means clustering procedure on twelve input variables describing the demographic, socioeconomic, and housing characteristics of neighborhoods is used to establish initial typologies for all census tracts in the cities of Chicago and Los Angeles and their encompassing counties ($n = 1{,}318$ and 2,334, respectively). Counties are used as the spatial extent of the study area to better visualize the dynamics; outlying census tracts tend to be much larger and mask results of smaller, inner-city neighborhoods. It is recognized that these dynamics do play out beyond county boundaries. All variables are standardized by z score each year to control for different measurement scales and to compare changes across time; variables therefore represent a relative value compared to all other values in the city in that particular year. Variables selected for the cross-sectional clustering procedure are based largely on prior studies (e.g., Morenoff and Tienda 1997; Mikelbank 2011; Wei and Knox 2014, 2015; Delmelle 2015) and exclude variables that are highly correlated with one another and those with a large number of missing data values. Racial and ethnic composition is not included in this stage, despite its long history in factor ecology research because of the inconsistent manner in which these variables have been collected over time by the census. As an alternative, racial and ethnic changes to the resulting longitudinal clusters are considered in a complementary analysis following Morenoff and Tienda (1997). The inclusion of housing and age variables in addition to socioeconomic characteristics enables the emergence of a distinction between neighborhoods with more urban versus suburban characteristics and, in particular, neighborhoods possessing key indicators of gentrification.

This initial clustering procedure is performed separately for Chicago and Los Angeles, but in each case, neighborhoods for all five time stamps are entered into the clustering procedure at once at the start of the procedure. In the case of Chicago, fit statistics unanimously pointed to a five-cluster solution and the description of the resulting clusters largely resembled the results obtained by Morenoff and Tienda (1997) and Mikelbank (2011). Fit statistics for the case of Los Angeles were less decisive and suggested a range from four to seven; after a close inspection of the results, a five-cluster solution was also selected for this city. Although some similarity exists between the resulting cluster descriptions between cities, the groups do not match perfectly, as might be expected given their unique histories. In all, four of the classes are largely congruent, and a fifth is unique for each city. A brief summary of the resulting groups is provided next, and a complete table of the mean z scores of the variables belonging to each cluster is available in the Appendix.

The clusters for Chicago were as follows:

1. *Newer suburban*. These neighborhoods possess characteristics most commonly associated with the newest suburbs of a metropolitan area. They contain the newest housing and correspondingly, recent in-movers to the neighborhoods. There are a large number of families with young children, and the socioeconomic profile of these residents is high compared to the rest of the urban area.
2. *Older, stable suburban*. Compared to the newer suburban neighborhoods, older, stable suburban neighborhoods are composed of an older population who has resided in their single-family homes for a relatively long period of time (this group has the lowest average number of residents who moved into their housing unit fewer than ten years ago, compared to the rest of the city). These neighborhoods have low unemployment and poverty rates and can thus be thought of as the second oldest suburban neighborhoods.
3. *Blue collar (Chicago only)*. Blue collar neighborhoods contain a large share of workers employed in manufacturing industries. They have the oldest housing and home values below the mean of the city. Poverty rates are greater than the city average, and the share of residents holding a college degree is below the city mean.
4. *Struggling*. These neighborhoods represent those of the lowest socioeconomic class. The share of residents in struggling neighborhoods possessing a college degree is far below the city average, and poverty rates, unemployment, and the share of children under the age of eighteen are the highest in the city. Homeownership is low and the share of vacant housing is high.
5. *Young urban*. Young urban neighborhoods have a distinguishable set of characteristics that define the most highly educated residents, living in multi-unit dwellings with the highest housing values in the city. They have the largest share of recent in-movers to their neighborhoods and contain very few children under the age of eighteen. Thus, this set of attributes portrays many gentrification characteristics of the young, educated living in urban high rises.

The following were the clusters for Los Angeles:

1. *Elite (Los Angeles only)*. A distinct class of neighborhoods that emerged for Los Angeles contain residents of the highest socioeconomic status. These neighborhoods have the highest housing values but are largely made up of single-family structures and possess the largest share of residents over the age of sixty who have lived in their homes for a long period of time.
2. *Newer suburban*. Like Chicago, newer suburban neighborhoods in Los Angeles feature the largest share of recent construction along with a large number of recent in-movers. Homes are largely single-family, owner-occupied dwellings with values around the county mean.
3. *Older, stable suburban*. The older, stable suburban neighborhoods of Los Angeles differ slightly from those of Chicago. Although they contain older, single-family homes with a small number of recent in-movers, they also have a higher share of manufacturing employees and lower shares of college-educated residents. Home values are below the county average, but poverty rates and unemployment are low.
4. *Struggling*. Similar to the struggling neighborhoods of Chicago, in Los Angeles, these tracts are characterized by low levels of educational attainment, high poverty rates and unemployment, and home values below the county mean.
5. *Young urban*. In Los Angeles, young urban neighborhoods have a large share of multi-unit structures with housing values above the county average (but less than the elite neighborhoods). As with Chicago, they also have a large share of recent in-movers, above-average college education levels, and relatively few children under the age of eighteen.

Following the initial cross-sectional clustering procedure, each neighborhood is assigned one the aforementioned classes five times (from 1970–2010). A sequence for each neighborhood is then created that depicts its longitudinal, socioeconomic trajectory.

Measuring Sequence Similarity

The next stage in the sequential analysis procedure is to assess the similarity of each sequence. There are several possible methods for determining the similarity of categorical sequences including the longest common prefix (LCP), the longest common subsequence (LCS), and the optimal matching distance (OMA). Within the social science literature, OMA is the most frequently used method for sequence alignment, whereas space-in-time research has largely relied on ClustalG, a multidimensional approach that enables a far greater number of discrete classes compared to more traditional alignment metrics (Wilson, Harvey, and Thompson 1999; Kwan, Xiao, and Ding 2014). In this study, sequences are unidimensional, with only five discrete classes, and so the more traditional methods of LCP, LCS, and OMA were all initially tested, and OMA was found to produce the most intuitive results. This algorithm is essentially a string editing technique that computes the dissimilarity between two sequences as a function of the number of edits or steps needed to completely transform one sequence into the other. The implemented algorithm used in this study is part of the TraMineR package in the statistical software R (Gabadinho et al. 2011) and is based on Needleman and Wunsch's (1970) derivation.

Briefly, the algorithm assesses the cost of inserting, deleting, or substituting elements in one sequence to completely transform it into another sequence; the more steps needed to make two sequences equal, the greater the cost or dissimilarity between the two. Substitution costs can either be set as a constant, representing an equivalent value to change between socioeconomic classes, or they can be derived from transition rates between classes; the more infrequent the transition between classes, the higher the substitution cost. In this study, a transition rate substitution cost matrix produced the more favorable results. Substitution costs resulting from transition rates are calculated as follows:

$$2 - p(i|j) - p(j \mid i), \tag{1}$$

where $p(i|j)$ is the transition rate or probability of observing a transition between socioeconomic class from time t to time $t + 1$. In this case, t represents each decade between 1970 and 2010. The substitution cost matrices are shown in Table 1: A higher value indicates a less frequent transition and therefore a higher cost in the string editing method. For example, transitions between newer suburban and struggling neighborhoods in Chicago were relatively rare and so the maximum substitution cost is assigned to this transition. The transition between newer suburban and stable older suburban was much more common, so this transition receives a lower substitution cost.

These transition costs are then used by the OMA in assessing the similarity between neighborhood

Table 1. Substitution cost matrix: Chicago

$p(i\|j)$	Newer suburban	Stable older suburban	Blue collar	Struggling	Young urban
Newer suburban	0	1.68	1.92	1.99	1.94
Stable older suburban	1.68	0	1.83	1.99	1.93
Blue collar	1.90	1.83	0	1.78	1.87
Struggling	1.99	1.99	1.78	0	1.90
Young urban	1.94	1.93	1.87	1.90	0
Los Angeles					
Newer suburban	0	1.79	1.95	1.89	1.94
Stable older suburban	1.79	0	1.81	1.91	1.92
Struggling	1.96	1.81	0	1.96	1.82
Elite	1.89	1.91	1.99	0	1.90
New starts	1.94	1.92	1.82	1.90	0

sequences, ultimately leading to the creation of a matrix consisting of the minimum edit costs between sequences of all neighborhoods in the study area. As a simple illustrative example, suppose two neighborhoods, A and B, have the following sequences of neighborhood classifications from 1970 to 2010:

Neighborhood A: Suburban, suburban, stable older suburban, stable older suburban, blue collar.
Neighborhood B: Suburban, suburban, stable older suburban, blue collar, clue collar.

One way to completely transform Sequence B into A would be to substitute the first blue collar as stable older suburban. According to the substitution cost matrix in Table 1, the cost to make this transformation is 1.83. If this were then the minimum edit cost between these two sequences, that value would be recorded into the matrix. An alternative way to align the two sequences would be through the use of insertions or deletions. In the preceding example, the first sequence could be converted to the second by deleting the fourth element in Sequence A (stable older suburban) and inserting another blue collar at the end of the sequence. Costs for insertions and deletions help to govern the amount of time warping allowed and represents an understudied element of sequential alignment methods in social science research (Hollister 2009). Higher insertion and deletion costs lead to a better preservation of temporal ordering, whereas lower costs will prohibit any substitutions from occurring, forcing the algorithm to perform more closely to the longest common prefix. In this case, these costs are set at a value of 1, representing half the maximum substitution cost, which is a largely held standard in the literature (Hollister 2009).

The final minimum edit costs matrix can then be used in a clustering procedure to establish groups consisting of the most similar sequences. In this case, a hierarchical Ward's clustering approach is applied to the data. To determine the final number of clusters, several different solutions were examined to assess whether or not meaningful distinctions in trajectories were being discerned. Ultimately, nine clusters for Los Angeles and ten for Chicago were selected. In the last step of the analytical procedure, neighborhood cluster memberships are mapped to visualize the longitudinal trajectories.

Results

The results of the proposed analytic approach are presented first for Chicago in Figures 2 through 4, followed by Los Angeles in Figure 5. Each map highlights neighborhoods that belong to the cluster of sequences shown in the plot below the map. That diagram, a sequence frequency plot, illustrates the longitudinal sequences assigned to each cluster, where the color corresponds to one of the five classes described earlier, and time progresses along the *x* axis from 1970 until 2010. The width of the sequences is scaled according to the frequency with which it is present in the cluster. The clusters are described next.

Chicago Sequence Cluster 1: Upgrading from Struggling

Neighborhoods in this first cluster have generally followed a gradual transition from a struggling classification early in the time period into either the young urban group, exhibiting characteristics typically associated with gentrification, or into the blue collar group, following a more marginal gentrification trend, according to Van Criekingen and Decroly's (2003) classification. These sixty-one neighborhoods, constituting 5 percent

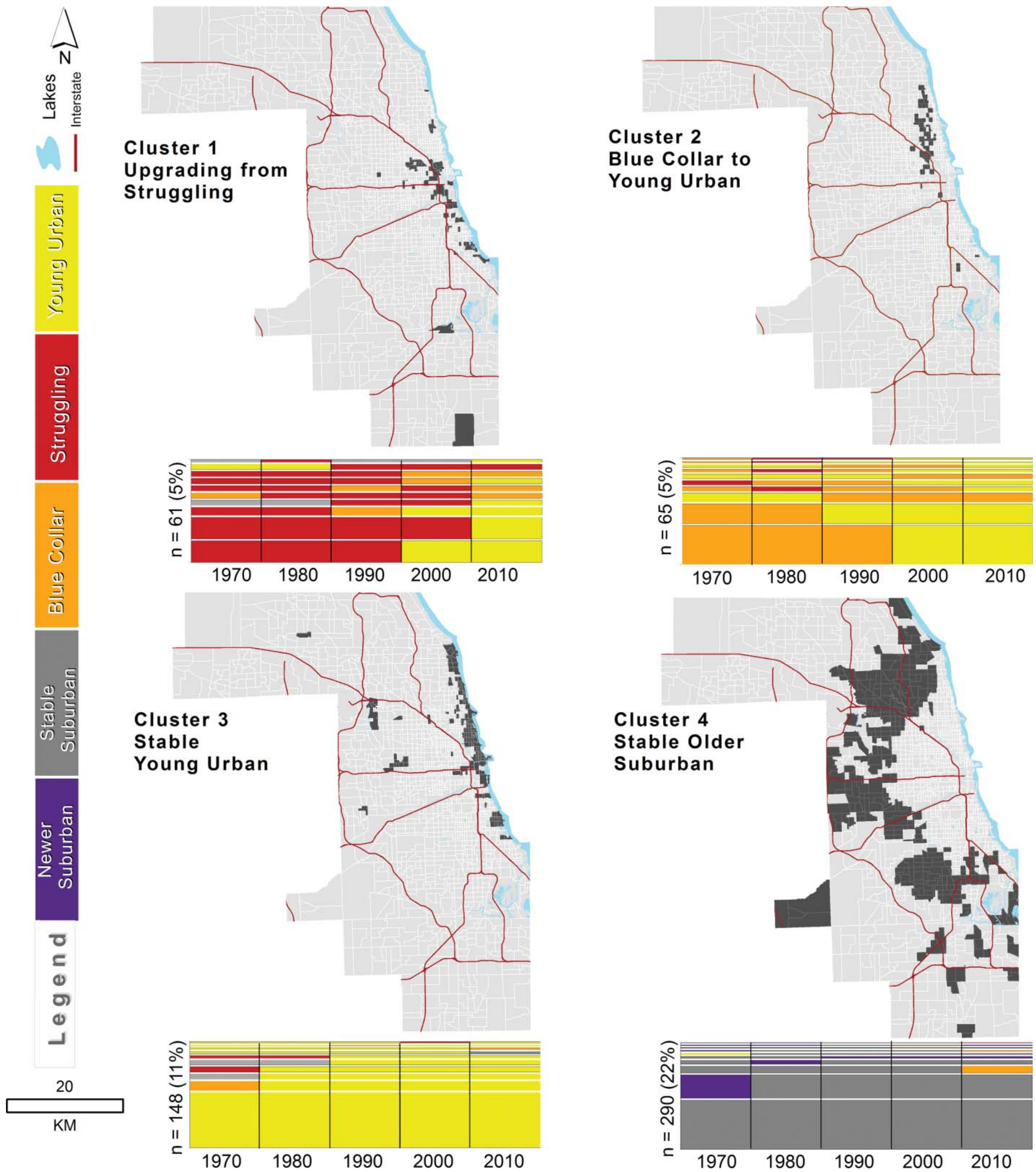

Figure 2. Chicago Sequences 1 through 4 and their spatial location. (Color figure available online.)

of neighborhoods in the study area, follow a spatial pattern largely contained within the inner core of the city, close to the shores of Lake Michigan.

Chicago Sequence Cluster 2: Blue Collar to Young Urban

This second group of longitudinal profiles generally constitutes neighborhoods that have followed a trajectory from blue collar to young urban, again signaling an upgrading process but transitioning in from neighborhoods that began with a different socioeconomic profile as compared to the first group. Spatially, the sixty-five neighborhoods comprising this group are to the north of the first group, and together these first two clusters complete a north–south ring or urban revitalization within the city's innermost ring, just beyond the waterfront neighborhoods.

Chicago Sequence Cluster 3: Stable Young Urban

These neighborhoods have either remained in the young urban class the entire time frame or for the majority of it. With a spatial location predominantly

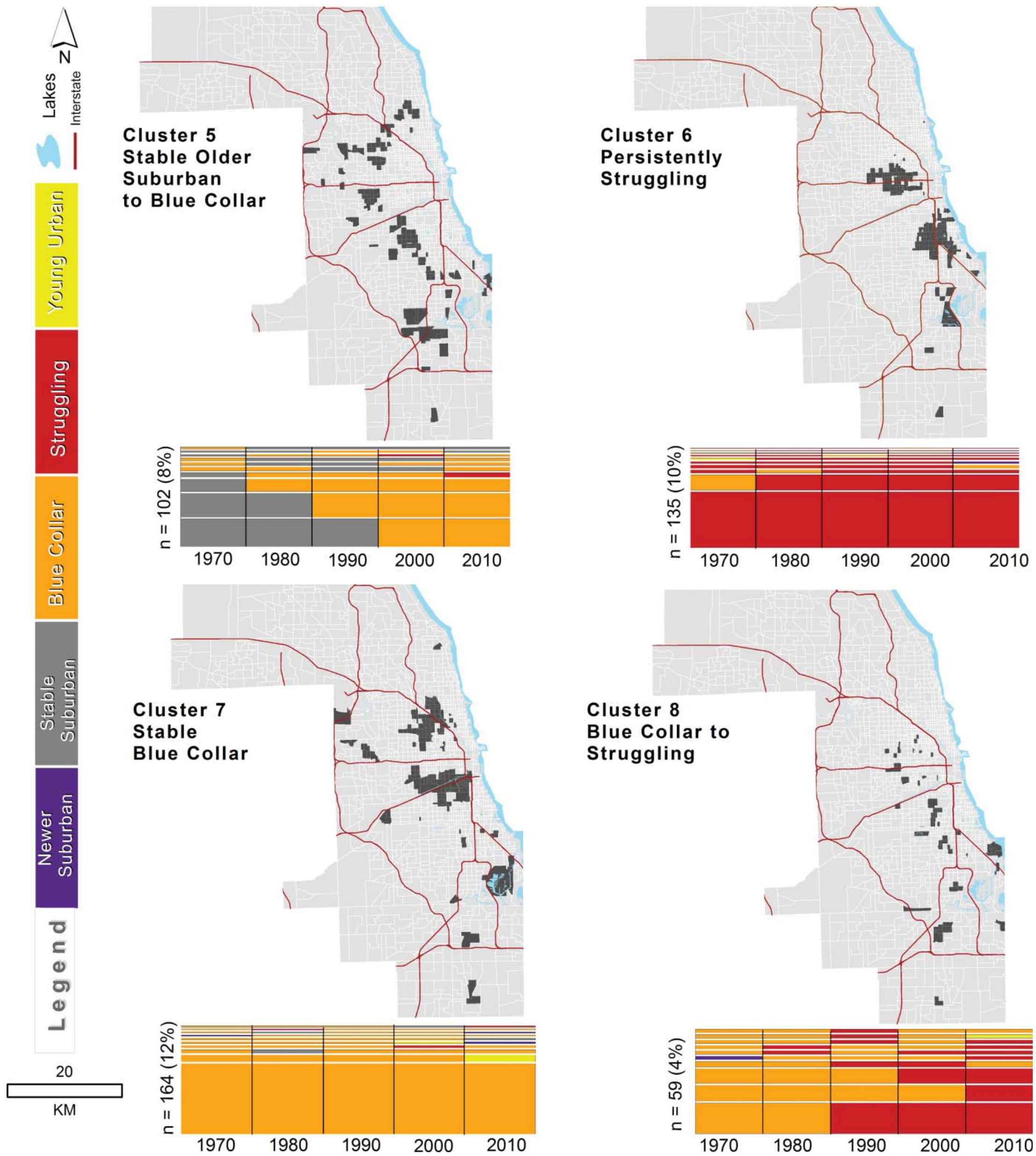

Figure 3. Chicago Sequences 5 through 8 and their spatial location. (Color figure available online.)

along the shore of Lake Michigan, these neighborhoods are characterized by the highest real estate values in the city and a consistent flow of recent and highly educated residents. They have maintained these characteristics over the long term.

Chicago Sequence Cluster 4: Stable Older Suburban

The stable older suburban class of neighborhoods cross-sectionally referred to older, single-family residential neighborhoods with residents who have stayed in their homes for a long period of time. The longitudinal sequence of the same name then refers to neighborhoods that have maintained this classification for the majority of the five decades under study. The 290 neighborhoods belonging to this cluster, the largest of all of the groups, follow a clear spatial pattern in a crescent toward the outer extents of the county but are not the farthest from the urban core.

Chicago Sequence Cluster 5: Stable Older Suburban to Blue Collar

These neighborhoods have followed a general transition to blue collar and represent a linear downgrading of older suburbs, one ring closer to

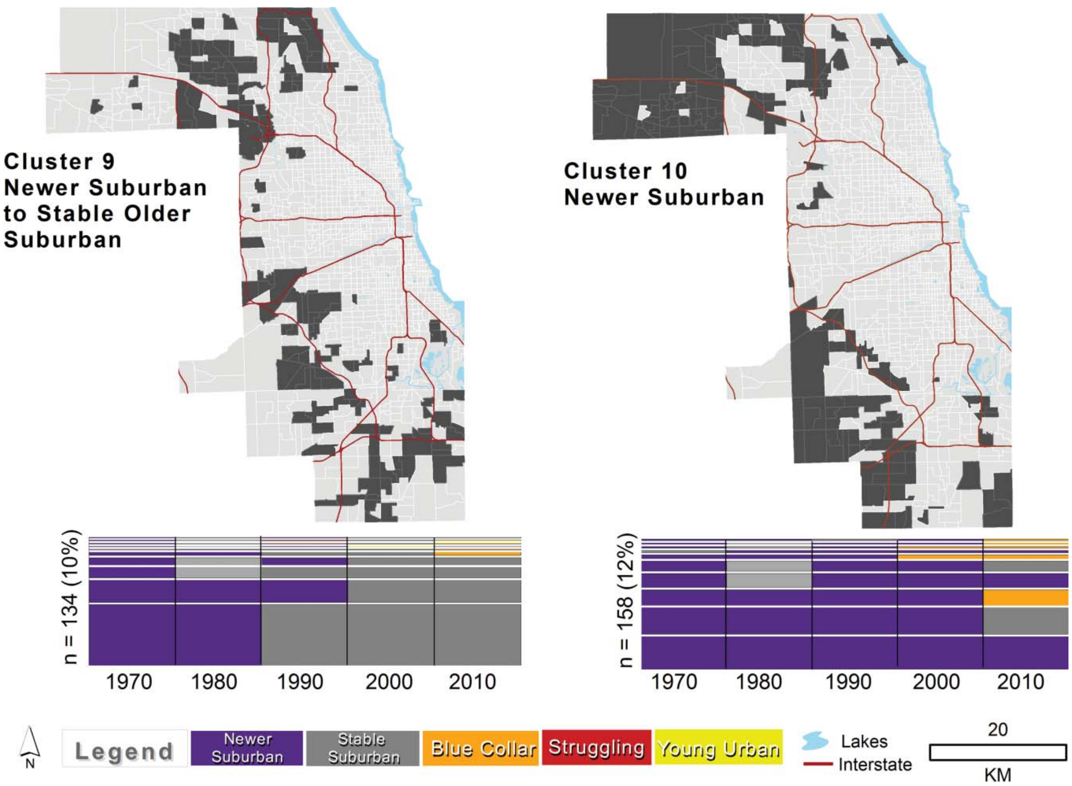

Figure 4. Chicago Sequences 9 and 10 and their spatial location. (Color figure available online.)

the city center as compared to the stable older suburban neighborhoods of Cluster 4. The 102 neighborhoods in this group appear to represent the spatial frontier of suburban decline.

Chicago Sequence Cluster 6: Persistently Struggling

The 135 neighborhoods assigned to this group represent those that have remained in the struggling class for the long term and are generally located in two distinct spatial clusters toward the south of the city.

Chicago Sequence Cluster 7: Stable Blue Collar

Neighborhoods in this group are largely located in spatially contiguous groups in the space between the persistently struggling neighborhoods of Cluster 6. The 164 neighborhoods in this group have largely remained blue collar for the duration of the five decades under study.

Chicago Sequence Cluster 8: Blue Collar to Struggling

Only fifty-four neighborhoods comprise this smallest cluster in the study area and they represent neighborhoods that have followed a downgrading trend from blue collar into struggling. These neighborhoods are less spatially compact than neighborhoods belonging to the other groups but are generally situated in the middle suburban ring.

Chicago Sequence Cluster 9: Newer Suburban to Stable Older Suburban

The 134 neighborhoods in this ninth cluster represent an aging from newer suburban traits in the first few decades of the study, toward an older population cohort consisting of residents who have lived in their homes for a long period of time. Thus, these represent the second newest suburbs in the study area.

Chicago Sequence Cluster 10: Newer Suburban

Located on the outermost spatial extent of the county, the 158 neighborhoods in this final cluster have consistently been characterized by traits depicting the newest suburban neighborhoods, with the highest median incomes and a large family presence.

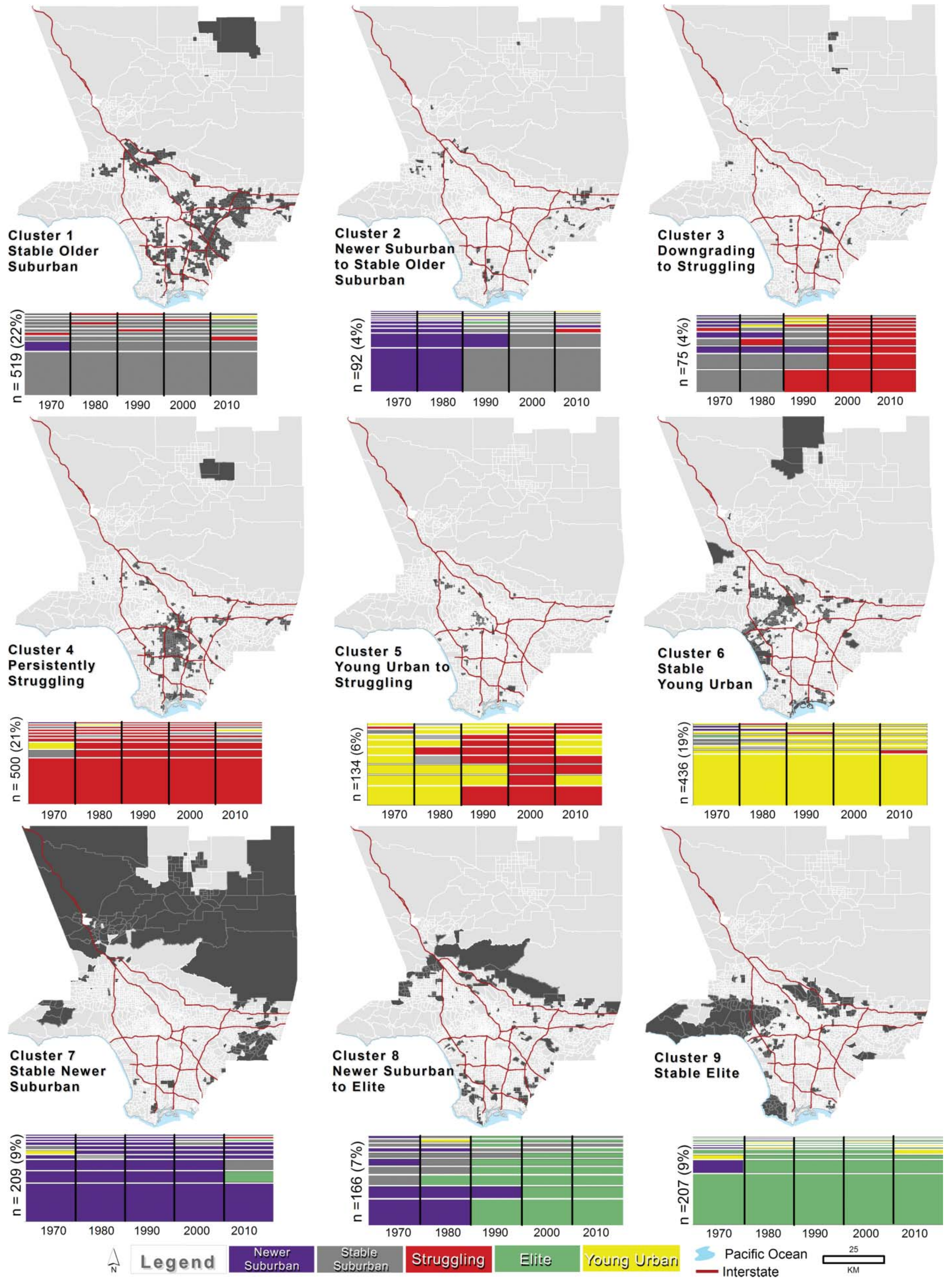

Figure 5. Los Angeles Sequences 1 through 9 and their spatial location. (Color figure available online.)

Los Angeles Sequence Cluster 1: Stable Older Suburban

The 519 neighborhoods belonging to this largest cluster for Los Angeles represent neighborhoods that have primarily remained stable older suburban for the past five decades. Several of these neighborhoods slipped briefly into the struggling category at one point during the time period but have otherwise remained stable. The spatial location of these neighborhoods in Los Angeles varies considerably from the concentric rings observed in Chicago but occupies a large swath of the eastern portion of the county.

Los Angeles Sequence Cluster 2: Newer Suburban to Stable Older Suburban

Generally located along the periphery of neighborhoods situated in the stable older suburban group of Cluster 1, Cluster 2 neighborhoods represent those that have transitioned into the stable older suburban cluster during the past two or three decades from the newer suburban group.

Los Angeles Sequence Cluster 3: Downgrading to Struggling

The seventy-five neighborhoods in this third group declined into the struggling category during the past two or three decades. Spatially disjointed, these neighborhoods generally share a suburban (older or newer) past but then underwent a decline that has persisted for multiple time periods.

Los Angeles Sequence Cluster 4: Downgrading to Struggling

This second largest cluster in Los Angeles (500) represents neighborhoods that have primarily remained in the struggling class for the duration of the time span. They occupy a large share of the center of the city of Los Angeles.

Los Angeles Sequence Cluster 5: Young Urban to Struggling

Los Angeles's fifth group of neighborhoods are those that generally began the time period in the young urban class and declined into the struggling class. Nearly all of these neighborhoods were in the struggling class in 2000, but some rebounded in 2010, whereas others have remained struggling. There are notable concentrations of these neighborhoods to the northwest of the city of Los Angeles.

Los Angeles Sequence Cluster 6: Stable Young Urban

Neighborhoods that have largely remained in the young urban class represent 19 percent of the sample and are largely located toward the northwest of the city, including a number of neighborhoods along the coastline.

Los Angeles Sequence Cluster 7: Stable Newer Suburban

As was the case for Chicago, neighborhoods that have remained in the newer suburban class occupy the outer extents of the county.

Los Angeles Sequence Cluster 8: Newer Suburban to Elite

The elite class was a distinct cluster for Los Angeles, representing the highest socioeconomic characteristics, single-family homes, and a stable and older demographic composition. Upgrading from newer suburban to elite is therefore unique to Los Angeles as compared to Chicago. The 166 neighborhoods that have made this transition exhibit a ring-like pattern, closer to the core of the city, as compared to the newest suburbs. This is largely the reverse of the pattern observed in Chicago, where this location represented a frontier of suburban decline; in this case we find a ring of suburban upgrading.

Los Angeles Sequence Cluster 9: Stable Elite

Neighborhoods that have remained in the elite class for most of the time period include those in the Hollywood Hills of Los Angeles County and are intermixed with the stable young urban neighborhoods of Cluster 6.

Discussion

The results presented in the previous section describe clusters of neighborhood socioeconomic trajectories and their spatial location throughout the cities of Chicago and Los Angeles and their counties over a four-decade time period. For the case of Chicago, of the ten clusters identified by the proposed sequential mining technique, five depicted trajectories of stability, with neighborhoods largely remaining in the same socioeconomic group throughout the duration of the analysis, two represented a downgrading process, and two portrayed neighborhood renewal processes. The spatial patterns of these clusters have, to some extent, cohered to the locations foretold by Chicago school theorists over a century ago: Wealthy urban elites have been and continue to be situated on

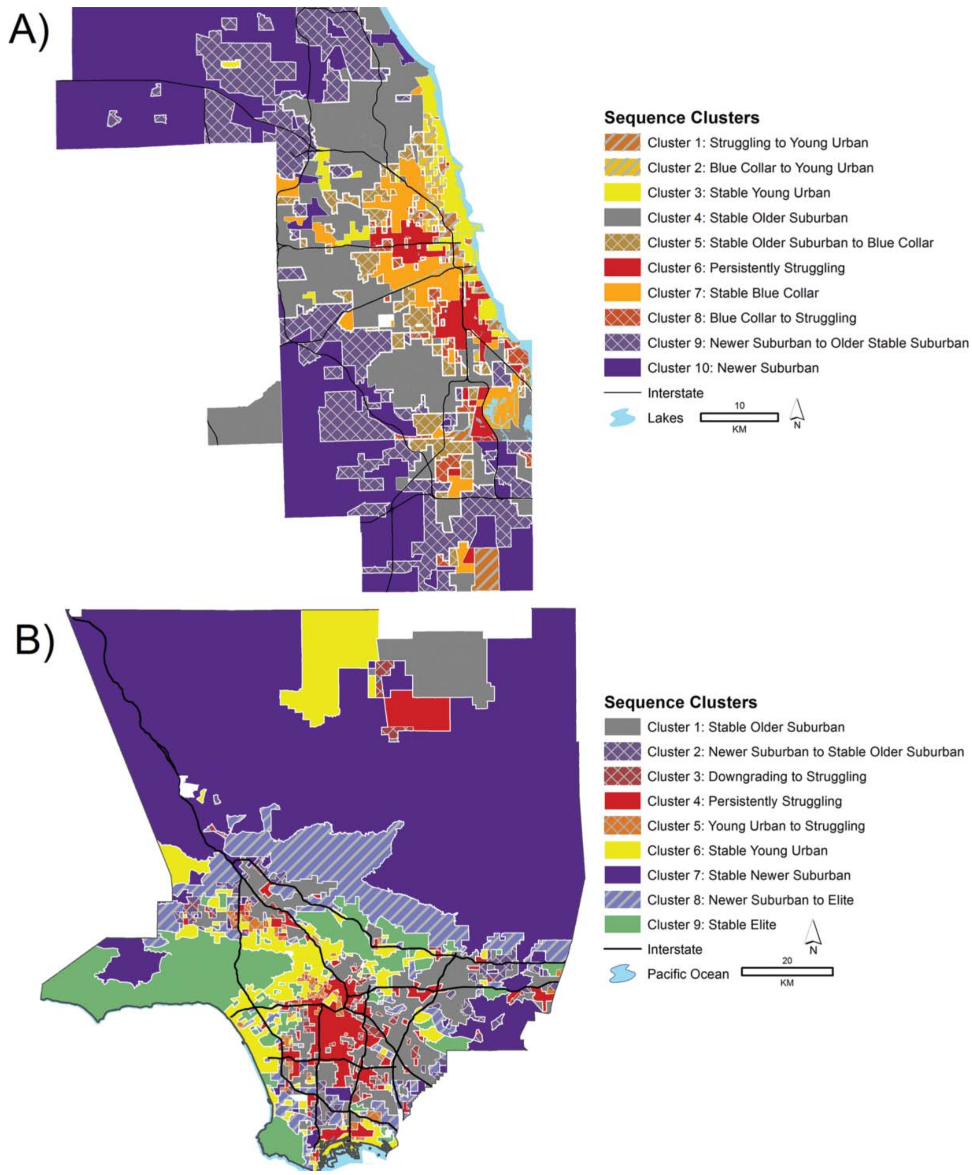

Figure 6. Contours of neighborhood dynamics: (A) Chicago; (B) Los Angeles. (Color figure available online.)

the banks of Lake Michigan, enjoying waterfront proximity, and the suburban wealthy have consistently occupied the outermost extents of the county. Inward from this outermost ring are neighborhoods that have transitioned from a newer suburban to a stable older suburban classification, signifying a natural aging of middle-class suburbs. Another ring closer toward the city is composed of neighborhoods that have maintained a stable middle-class characterization for the past four decades. A downward trajectory from this stable middle-class suburban classification to blue collar generally occupies the next ring toward the center; however, at this point, the spatial patterns begin to depart from a concentric-ring type model. Neighborhoods possessing stable blue collar or struggling trajectories are present in the same geographic ring but in distinct clusters away from each other, a pattern more akin to the multiple nuclei envisioned by Harris and Ullman (1945). In a more dispersed spatial arrangement scattered throughout this ring is the smallest cluster, those neighborhoods undergoing the second downgrading process from blue collar to struggling. One ring closer to the urban core and coastline from these three clusters are neighborhoods that have seen a gradual upgrading into the young urban class, thus undergoing some indicators of gentrification—a recent influx of highly educated, wealthier residents into previously disinvested center city neighborhoods.

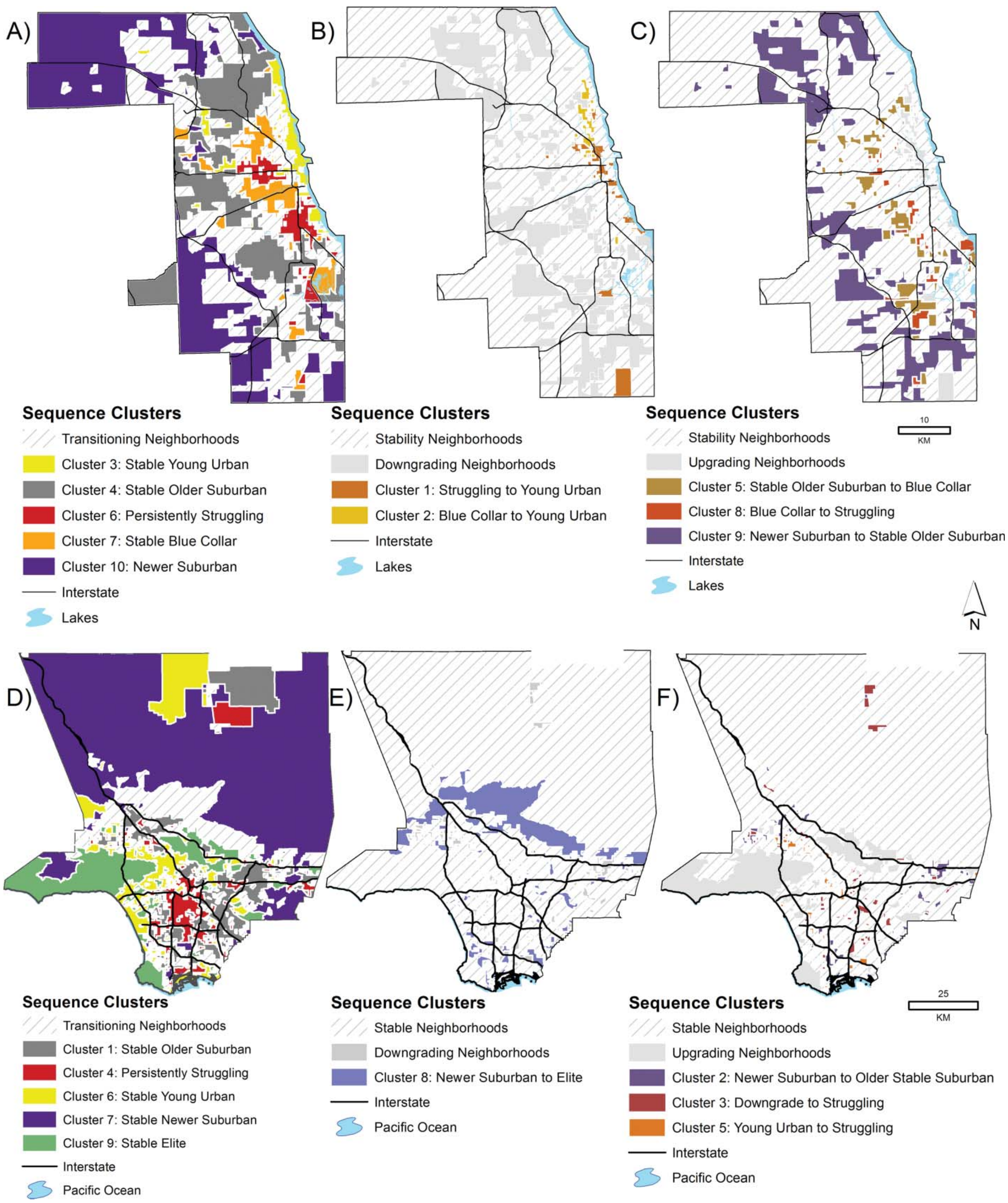

Figure 7. (A) Chicago stability neighborhoods; (B) Chicago upgrading neighborhoods; (C) Chicago downgrading neighborhoods; (D) Los Angeles stability neighborhoods; (E) Los Angeles upgrading neighborhoods; (F) Los Angeles downgrading neighborhoods. (Color figure available online.)

The sequence plots corresponding to the maps show that some of these transformations began in 1990, but they became more prevalent in the last decade, particularly in the case of the transition from struggling to young urban. The spatial contours of these dynamics are visualized in the map in Figure 6A, which portrays a composite perspective of the maps presented in the results section. The boundaries of contiguous neighborhoods belonging to the same cluster are dissolved to visually articulate the spatial arrangement of neighborhood dynamics; the resulting map highlights the observed concentric-ring and multiple nuclei patterns.

The case of Chicago's neighborhood dynamics and their corresponding spatial patterns neatly follows traditional theories and features the more commonly discussed neighborhood trajectories of a gradual decline away from the center city and more recent inner-city gentrification, to a large degree conforming to Hoover and Vernon's (1959) life cycle model of change. Los Angeles, on the other hand, offers some alternatives to this discourse. Of the nine longitudinal clusters revealed for Los Angeles, five represented processes of relative stability. Two of the sequence groups depicted a downgrading process: a gradual aging of the suburbs, as was present in the case of Chicago, and a decline from suburban-type neighborhoods into the struggling group—with a notable change, of course, starting in 2000. Like Chicago, neighborhoods that have transitioned to struggling in Los Angeles are spatially disjointed but tend to be located along the periphery of persistently struggling neighborhoods, suggesting some spatial spillover effects. A third type of trajectory represented neighborhoods that began the time period as young urban, saw a decade or two of decline into the struggling group in the middle of time period, but have shown some signs of revitalization back to young urban in 2010. Whether or not this improvement in 2010 represents a change in course or a temporary improvement remains to be seen. In contrast to Chicago, no strong revitalization trend of center-city neighborhoods of Los Angeles was uncovered during this time period. Rather, the dominant upgrading trajectory occurred in suburban neighborhoods, with a transition to the more elite suburbs. These patterns are illustrated in Figure 6B. An alternative visualization is presented in Figure 7, which isolates stability from transitioning neighborhoods for each city. Transitioning neighborhoods are further distinguished by whether or not their dominant pathway was one of improvement or decline. Figure 7 helps illuminate the ring of improvement toward the center of Chicago and its associated rings of suburban decline. It also serves to contrast the spatial patterns of neighborhood dynamics between these two cities: Los Angeles's dynamics feature an intermingling of declining, imp-roving, and stable neighborhoods more closely approximating the disorganized spatial landscape portrayed by Los Angeles School critics.

The first two research questions dealt with the identification of dominant trajectories and their spatial patterns. In recognizing that a neighborhood's racial and ethnic composition is not disjoint from its socioeconomic dynamics, the third research question considers how these dynamics have played out in tandem. Tables 2 and 3 depict the average share of racial and ethnic groups per cluster in 1970 and 2010 (1980 in the case of Hispanics). For Chicago, we can begin by examining changes in racial and ethnic composition for neighborhoods that began the time period in similar clusters but subsequently followed alternate trajectories through time. For instance, neighborhoods in Clusters 7 and 8 were both situated within the transformative middle ring and both started off in the blue collar class, but those in Cluster 8 eventually transitioned downward into the struggling classification, whereas those in Cluster 7 remained blue collar. Both of these groups saw rather dramatic declines in their share of white residents between 1970 and 2010 (from 91 percent to 20 percent for Cluster 7 and from 72 percent to 0.05 percent for Cluster 8), but the neighborhoods that remained blue collar underwent a doubling of their share of Hispanic residents during this time, whereas those that declined more than doubled their proportion of black residents. Neighborhoods that became blue collar from the stable older

Table 2. Average share of racial and ethnic groups per cluster: Chicago

	Proportion black		Proportion white		Proportion Hispanic		Proportion Asian	
Cluster	1970	2010	1970	2010	1980[a]	2010	1970	2010
1. Upgrading from struggling	0.49	0.50	0.47	0.26	0.23	0.17	0.02	0.06
2. Blue collar to young urban	0.05	0.12	0.92	0.62	0.30	0.19	0.02	0.09
3. Stable young urban	0.12	0.17	0.85	0.63	0.08	0.08	0.03	0.11
4. Stable older suburban	0.10	0.23	0.89	0.53	0.02	0.18	0.00	0.06
5. Stable older suburban to blue collar	0.09	0.34	0.90	0.19	0.06	0.42	0.00	0.04
6. Persistently struggling	0.78	0.89	0.20	0.03	0.05	0.06	0.01	0.01
7. Stable blue collar	0.07	0.12	0.91	0.20	0.30	0.60	0.00	0.07
8. Blue collar to struggling	0.27	0.66	0.72	0.05	0.25	0.28	0.00	0.01
9. Newer suburban to stable older suburban	0.03	0.20	0.96	0.63	0.03	0.11	0.00	0.06
10. Newer suburban	0.00	0.15	0.99	0.57	0.04	0.16	0.00	0.11

[a]The Hispanic population was not included as a separate ethnic group until the 1980 Census. This population was largely grouped with the white population in the 1970 Census.

Table 3. Average share of racial and ethnic groups per cluster: Los Angeles

	Proportion black		Proportion white		Proportion Hispanic		ProportionAsian	
Cluster	1970	2010	1970	2010	1980[a]	2010	1970	2010
1. Stable older suburban	0.11	0.09	0.85	0.15	0.35	0.62	0.35	0.13
2. Newer suburban to stable older suburban	0.04	0.08	0.93	0.23	0.22	0.51	0.02	0.16
3. Downgrading to struggling	0.12	0.12	0.85	0.11	0.37	0.71	0.03	0.07
4. Persistently struggling	0.30	0.12	0.66	0.05	0.50	0.76	0.03	0.06
5. Young urban to struggling	0.10	0.13	0.82	0.17	0.33	0.56	0.07	0.14
6. Stable young urban	0.03	0.07	0.93	0.48	0.16	0.23	0.03	0.21
7. Stable newer suburban	0.04	0.08	0.94	0.38	0.65	0.32	0.02	0.21
8. Newer suburban to elite	0.02	0.05	0.95	0.50	0.12	0.22	0.03	0.22
9. Stable elite	0.02	0.05	0.95	0.64	0.06	0.11	0.02	0.18

[a]The Hispanic population was not included as a separate ethnic group until the 1980 Census. This population was largely grouped with the white population in the 1970 Census.

suburban class (Cluster 5) also saw a large increase in Hispanic populations, with a similar decline in the share of whites. To an extent, these race-specific findings echo those revealed by Morenoff and Tienda's (1997) work, which suggested that Hispanic neighborhoods in Chicago evolved out of formerly middle-class white neighborhoods. Due to the longevity of this study, however, it was further able to distinguish the declining blue collar neighborhoods associated with a large increase in black residents. The spatially disjoint nature of these neighborhoods portrayed in the maps further raises the question of why those particular neighborhoods followed such a trajectory, although the composite maps do suggest a spatial spillover effect as they are located along the periphery of persistently struggling neighborhoods.

Other race-based patterns can be discerned from examining neighborhoods that remained in the struggling class that saw their share of black residents increase from 78 to 89 percent and the proportion of whites nearly vanish by 2010. The durability of racial inequality, particularly in the case of Chicago's predominantly black neighborhoods was discussed previously by Sampson (2009, 2012), who pointed to the prevailing influence of neighborhood racial and ethnic composition on residential selection decisions. In a recent examination of gentrification in Chicago, Hwang and Sampson (2014) concluded that black and Latino neighborhoods were less likely to undergo reinvestment and more likely to follow paths of decline. Although this durable inequality can certainly be seen here in the case of the most struggling neighborhoods, neighborhoods that remained in or improved into the young urban class indicate a relative stability in the share of black residents, and a decline in the share of whites. This finding stands counter to the popular narrative of gentrification depicting an influx of white residents and the exodus of minorities, but it is in agreement with several studies on the entry and exit of residents from gentrifying neighborhoods (McKinnish, Walsh, and White 2010; Ellen and O'Regan 2011). Neighborhoods that did upgrade from struggling, or those located in a linear crescent closer to the urban core (Cluster 1), began the time period with greater diversity as compared to the persistently struggling group and generally remained rather diverse by the end of the time frame.

Turning to the accompanying racial and ethnic dynamics for Los Angeles, declining older suburban neighborhoods are, as was the case with Chicago, associated with sharp increases in the share of Hispanic residents (Cluster 2), but in contrast to Chicago, the persistently struggling neighborhoods (Cluster 4) underwent a decline in their black population, in exchange for an increase in Hispanic residents. Neighborhoods that transitioned from young urban to struggling are illustrative of the complex multiethnic neighborhoods discussed in the rich neighborhood racial change literature (Denton and Massey 1991; Logan and Zhang 2010). Accompanying their declines in the share of white residents is an increase in blacks, Hispanics, and Asians. Elite, newer suburban, and young urban neighborhoods all saw overall increases in diversity with notable increases in their share of Asian residents.

Conclusions

A growing awareness of emergent and longitudinal data sources for examining the health and vitality of urban neighborhoods and cities has elevated the need for new analytical approaches for understanding the spatiotemporal dynamics (Arribas-Bel 2014). Although research on neighborhood change dates back over a century, the capabilities for exploring the spatial dimension of longitudinal dynamics has been limited to cross-sectional maps or reduced to examining change between two points in time. This article has offered a methodological approach to visualizing and summarizing longitudinal trajectories of neighborhood socioeconomic change based on sequential pattern mining techniques. Its aims were to classify the most common pathways of change and to provide a spatial linkage of where these dynamics occur within the urban environment.

The proposed technique was applied to a case study of neighborhood change in Chicago and Los Angeles from 1970 to 2010, as neighborhoods transitioned between discrete social classes: newer suburban, struggling, stability, stable older suburban, young urban, blue collar (Chicago), and elite (Los Angles). Ten longitudinal clusters were identified for Chicago and nine for Los Angeles; in both instances five of those represented a stasis pattern of remaining in the same socioeconomic class through the four decades. In Chicago, three trajectories described processes that could generally be described as downgrading—from blue collar to struggling, stable older suburban to blue collar and newer suburban to stable older suburban—and two represented neighborhood upgrading from struggling or blue collar. These resulting trajectories therefore fit within Hoover and Vernon's (1959) life cycle model of gradual decline followed by possible renewal. The spatial arrangement of these dynamics was reminiscent of the concentric rings first proposed by Burgess (1925) but also deviated from this configuration in neighborhoods situated in Chicago's middle ring: between the revitalizing center city and the stable outer suburbs. The results of this empirical case study therefore provide supporting evidence to the durability of Chicago School spatial patterns over the course of that city's development. Further investigation revealed marked racial differences in the longitudinal paths of neighborhoods, illustrating a reinforcement of racial inequality and poverty concentration and expansion. It also showed, however, that neighborhoods following pathways of gentrification maintained or saw increases in their share of minority residents over time.

Los Angeles showed considerable differences in neighborhood dynamics over time as compared to Chicago. Its lone trajectory of sustained improvement was in the form of suburban upgrading, notably situated in what could be considered an older suburban ring, to directly contrast with Chicago. Downgrading processes also represented suburban decline in two clusters but also featured a group of neighborhoods that underwent declines in the young urban class into struggling toward the midpoint of the time period, although several neighborhoods in that group rebounded by 2010 back to the young urban class. Should this later rebound persist, this would represent a distinct nonlinear trajectory not present in Chicago. The spatial structure of neighborhood dynamics in Los Angeles varied dramatically from the ordered concentric rings observed in Chicago, providing some credence to Los Angeles School critics who challenged the existence of these regularities in the postmodern city.

To date, the dominant methodological approach to examining multidimensional neighborhood change has relied on the use of transition matrices to quantify transitions between classes from one time period to the next. That technique ultimately separates a single transition from the larger sequence through which the neighborhood change process has unfolded. The approach put forth in this article offers an alternative by grouping neighborhoods according to a longer sequence of events and provides a mechanism for mapping these dynamics. Although not without its limits, it does offer some advantages that might ultimately help advance our understanding of neighborhood dynamics. For instance, in the case of Los Angeles, the method discerned one group of neighborhoods that shared a past history of largely suburban traits but saw a notable decline into the struggling class around the year 2000. What caused their trajectories to turn at that time? Future research could delve into this answer, but this analysis provides a way of identifying neighborhoods that have followed similar pathways that might be overlooked when examining a singular transition within that sequence. Likewise, to gain a more detailed perspective on local actions that could explain why some similar neighborhoods followed alternate pathways over time, this technique could additionally serve as a means for selecting neighborhoods for more in-depth qualitative research.

The methodology further enabled the identification of the spatial boundaries of neighborhood revitalization and decline, as defined by a similarity in longitudinal dynamics, as opposed to the a priori method of selecting neighborhoods based on a cross-sectional set of characteristics and subsequently investigating their changes. In this respect, the location of where such declines are occurring can more clearly be made evident and used in the strategic planning of place-based policy initiatives. In the example of Chicago, a clear ring of neighborhood decline was identified by the mapping approach; however, the sequential clustering technique separated two types of downgrading occurring within that ring. This differentiation might warrant alternate intervention or policy tactics in addressing these neighborhood transformations and is hence an advantage of this method.

As mentioned, the approach introduced in this article is not without limitations. As a clustering technique intended to reduce the complexity of a data set, some heterogeneity will inevitably remain in each cluster and thus information regarding unusual sequences followed by a small number of neighborhoods will consequentially be grouped with the more dominant trends in the data. This might pose a greater problem in cities where trajectories are more varied, such as those with large population influxes or newer cities. In a few instances, neighborhoods were assigned to longitudinal clusters for which they had an opposite pattern with the rest of the sequences in that group—more research on the optimal insertion and deletion costs is necessary, and alternate sequential alignment algorithms could also be evaluated. The initial set of cross-sectional clusters and input variables will also influence the ability of the method to detect longitudinal trends; future research could compare these results with a different number of clusters or using a larger set of variables. Racial and ethnic composition could be incorporated into the initial clustering by using an approach proposed by Timberlake and Iceland (2007) to estimate 1970 non-Hispanic whites, blacks, and Asians based on their 1980 proportions. Finally, this article centered on the analysis of decennial census data as a temporal unit of analysis, but neighborhoods' processes certainly play out at different timescales—suburbanization could be a relatively rapid occurrence in fast-growing urban areas, whereas gentrification might evolve over a much longer time span. A consistent time unit of analysis is not a prerequisite for this method; data at various intervals could be incorporated into an analysis to provide a richer understanding of the temporal unfolding of these processes.

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Appendix

Table A1. *Z* score means across clusters: Chicago

Variables	Newer suburban	Older, stable suburban	Blue collar	Struggling	Young urban
Socioeconomic					
% persons with at least a 4-year degree	0.41	0.02	−0.63	−8.84	1.33
% unemployed	−0.44	−0.42	0.24	1.50	−0.37
% manufacturing employees	0.23	−0.19	0.79	−0.50	−0.81
% below poverty level	−0.67	−0.57	0.21	1.90	−0.04
Housing					
% owner occupied	0.79	0.79	−0.42	−1.21	−0.92
% multiunit structures	−0.79	−0.76	0.46	0.93	1.08
Median home value	0.53	0.05	−0.57	−0.82	0.97
% structures built more than 30 years ago	−1.27	0.09	0.59	0.52	0.04
% household heads move into a unit less than 10 years ago	0.42	−0.96	0.08	0.33	1.02
% vacant housing	−0.30	0.61	0.06	1.39	0.26
Demographic					
% persons age 60 years and above	−0.68	0.74	−0.24	−0.37	0.16
% persons age 18 and under	0.50	−0.29	0.26	0.89	−1.47

Table A2. *Z* score means across clusters: Los Angeles

Variables	Elite	Newer suburban	Older, stable suburban	Struggling	Young urban
Socioeconomic					
% persons with at least a 4-year degree	1.43	0.25	−0.48	−0.83	0.58
% unemployed	−0.86	−0.42	−0.11	0.92	−0.17
% manufacturing employees	−0.79	0.09	0.26	0.66	−0.72
% below poverty level	−0.89	−0.71	−2.95	1.19	−0.04
Housing					
% owner occupied	0.97	0.98	0.50	−0.82	−0.95
% multiunit structures	−0.66	−0.77	−0.61	0.46	1.22
Median home value	1.48	0.03	−0.44	−0.67	0.43
% structures built more than 30 years ago	0.22	−1.41	0.34	0.28	0.03
% household heads move into a unit less than 10 years ago	−1.00	0.52	−0.78	0.47	0.70
% vacant housing	−0.33	0.15	−0.45	0.23	0.42
Demographic					
% persons age 60 years and above	1.07	−0.67	0.00	−0.68	0.60
% persons age 18 and under	−0.66	0.49	0.21	0.81	−1.20