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GIScience and neighborhood change: Toward an understanding of processes of change

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Abstract

Processes of neighborhood change are the result of the unfolding of events and decisions by multiple actors operating at varying spatial and temporal scales, enabled and constrained upon an unequal urban landscape. The contributions of GIScience toward understanding these processes have evolved from the simple mapping of static, cross-sectional maps toward an embrace of novel data and methods that enable longitudinal trajectories to be extracted and neighborhood futures to be predicted. In this article, I review these advancements and chart a course forward that considers a future research agenda that is critically cognizant of the potentials and perils of new data sources and method, is representative of the full spectrum of processes operating both visibly and invisibly that give rise to observed neighborhood outcomes, and considers their varying spatial and temporal scales.

1 | INTRODUCTION

As GIScience sought to become an intellectual field of study distinct from the use of the systems themselves, the University Consortium for Geographic Information Science (UCGIS) defined this burgeoning field as "the development and use of theories, methods, technology, and data for understanding geographic processes, relationships, and patterns…" (Mark, 2003, p. 2). Nearly two decades later, while the growth of GIScience has blossomed, the bulk of progress has been made in understanding relationships and patterns, while advancements toward understanding processes have lagged (Goodchild, 2004, 2013). Processes present a more arduous challenge for GIScientists as they imply an unfolding of events through time—and a seamless integration of the temporal dimension within

GIS has yet to be achieved (Andrienko, Andrienko, Demsar, et al., 2010; Goodchild, 2013). Nonetheless, progress has been made and creative solutions have blended new and emerging space-time datasets with statistical, machine learning, and new visualization techniques in an effort to better understand temporal processes across space. In this article, I review this progress with respect to processes of neighborhood change and chart a research path forward.

Changes in neighborhoods involve shifts in the physical and social characteristics of some cohesive geographic unit (Schwirian, 1983). The processes driving these changes are the product of decisions and actions on behalf of multiple actors including, but not limited to: residents, developers, lenders and financial institutions, urban policies, public and private investments, and demographic and economic forces at play beyond the city in which the neighborhood is situated. These factors operate on varying spatial and temporal scales to produce the changes we observe at different snapshots in time and space. Some elements of this process are observable and measurable—changes in the demographic or socioeconomics of a neighborhood, for instance, are both an observable outcome of these processes, and also part of the process itself. Other considerations are less visible or measurable, but play an important role in shaping how a neighborhood will evolve over time. The actions of residents in collectively accepting or resisting changes is one such example (Temkin & Rohe, 1996).

The use of GIS and contributions of GIScience to understanding the various facets of these multi-scalar, multi-temporal, and multi-dimensional processes have been diverse. First, GIS has been instrumental in the creation of spatial variables used in longitudinal statistical models to tease out causal mechanisms and key explanatory variables behind changes. As examples, this body of research has produced knowledge on the importance of the share of vacant housing in a neighborhood as an early indicator of decline, precipitating a white-flight process (Sadler & Lafreniere, 2017) and has demonstrated that the racial profile of a neighborhood, its proximity to downtowns, and a large share of historic housing foretell the likelihood of gentrification (Rigolon & Németh, 2019). Cross-lagged models, though not without limitations, are particularly apt in disentangling causal indicators across simultaneous or reciprocal neighborhood processes (Pandey & Coulton, 1994). The inclusion of spatially lagged variables can further provide insights into the spatial dynamics of neighborhood changes as a contiguous process (Delmelle & Thill, 2014; Hipp, 2010).

Second, agent-based and cellular automata models have been developed specifically to simulate neighborhood outcomes as complex processes emerging out of individual decisions and actions (Boeing, 2018; Jackson, Forest, & Sengupta, 2008; Liu & O'Sullivan, 2016; Torrens & Nara, 2007). These models can evaluate how certain conditions or decision rules recreate empirically observed landscapes and they can identify complex or non-linear effects that result from the collective behavior of individuals. For example, research has revealed "tipping points" or threshold values at which the change process intensifies when enough new residents of a certain race or income move into a neighborhood (O'Sullivan, 2009).

Third, GIS has been employed as a tool for community engagement in the planning process as a means of incorporating local knowledge and alternative hypotheses on the causal processes of change (Elwood & Leitner, 2003). Finally, recent developments have included data-driven methods for extracting and mapping historical trajectories of neighborhoods and forecasting techniques using novel data sources for predicting their future. A thorough review of each of these GIScience contribution areas to neighborhood change is not feasible in a single article, and so in this article I necessarily limit the scope of my review and discussion to the latter two, but also recognize the complementary nature that these various approaches play in constructing knowledge about the neighborhood change processes. The scope of the review also favors studies based on data from the United States—with some exceptions.

To begin a discussion of neighborhood change research and GIS, it is first necessary to define how a neighborhood is typically operationalized within a GIS. Galster's (2001) neighborhood definition of a "bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses" (p. 2112) has informed much of the recent scholarship on this subject as it emphasizes multi-dimensionality and the importance of spatial location. As per this perspective, neighborhood characteristics may encompass details on the buildings, infrastructure, demographics, and class status of residents, tax and public service packages, environmental, proximity, political, and sentimental traits. From a GIScience vantage point, modeling and mapping processes of neighborhood change therefore involve not only spatial and temporal dimensions, but must also consider multiple attribute dimensions as well. Andrienko, Andrienko, Bremm, et al. (2010) classified this type of spatio-temporal process, where temporal variation is distributed over space as “time-in-space,” in contrast to “space-in-time” changes where the spatial situation of some phenomena or object changes over time. In other words, with time-in-space changes, the spatial location remains fixed, but the characteristics of that place vary over time and so methods for analyzing attribute changes or trajectories are used. Space-in-time changes depict changes in the physical location over time, as is the case with movement trajectories. Processes of neighborhood change can therefore be described as multi-dimensional, time-in-space changes.

2 | LOOKING BACK: MAPPING AND DESCRIBING TRAJECTORIES OF NEIGHBORHOOD CHANGE

Traditional cartographic approaches to mapping time-in-space changes have used small multiple map displays at different time stamps. The handling of numerous attributes in these instances has typically been to classify neighborhoods into groups or bundles of attributes, frequently using a geodemographic classification approach such as *k*-means, for example (Delmelle, 2015; Mikelbank, 2011; Reibel, 2011). The use of variable-reducing techniques for describing neighborhoods can be traced back to Shevky and Bell's (1955) analysis of San Francisco's social structure using census data from 1940 and 1950. The resulting broader field of social area analysis ultimately sought to link socioeconomic urban structure and residential sorting patterns to processes of economic development and urban analysis. The closely related field of factorial ecology that emerged from this line of work continued in the tradition of applying statistical methods such as factor analysis or principal components to reduce place-based variables to a set of key explanatory variables (Berry, 1971). Collectively, these early data-driven analytical approaches attempted to identify the fundamental variables that gave rise to observed outcomes and were central to empirical analysis of the human ecological approach of the Chicago School. The fundamental difference between clustering or classification methods used in geodemographic studies today and factor analysis is that cluster analysis seeks to combine similar cases or neighborhoods based on multiple variables, whereas factor analysis combines variables into key factors or dimensions (Reibel, 2011). Geodemographic approaches therefore allow for the type of multivariate classification of neighborhoods that better aligns with Galster's (2001) neighborhood definition (Singleton & Spielman, 2014).

Figure 1 is an illustrative example of this traditional mapping approach of depicting change via a series of small multiple maps for the case of nine classes of neighborhoods in Buffalo (Erie County), NY. While easy to implement in off-the-shelf GIS packages, from a geovisualization standpoint, small multiples emphasize static state changes and spatial patterns over time rather than the unfolding of temporal processes (Andrienko, Andrienko, Demsar, et al., 2010).

Research over the past decade has therefore sought ways to more effectively communicate spatial changes across multiple time stamps, for several attribute dimensions. The purpose of these largely data-driven methods has been to inductively uncover how neighborhood changes have unfolded across multiple attribute dimensions, for multiple periods of time. Their aim has largely been to generate hypotheses on potential pathways, but they can also serve to validate the existence of theorized processes. One such method explored for this purpose is the self-organizing map (SOM), a highly visual artificial neural network that performs both data projection and quantization. In the case of neighborhood change, the SOM works by arranging neighborhoods on an output space (often 2D and rectangular) in such a way that those most similar to one another across all of their attribute variables are located near one another on the output space. To depict change, neighborhoods are entered into the

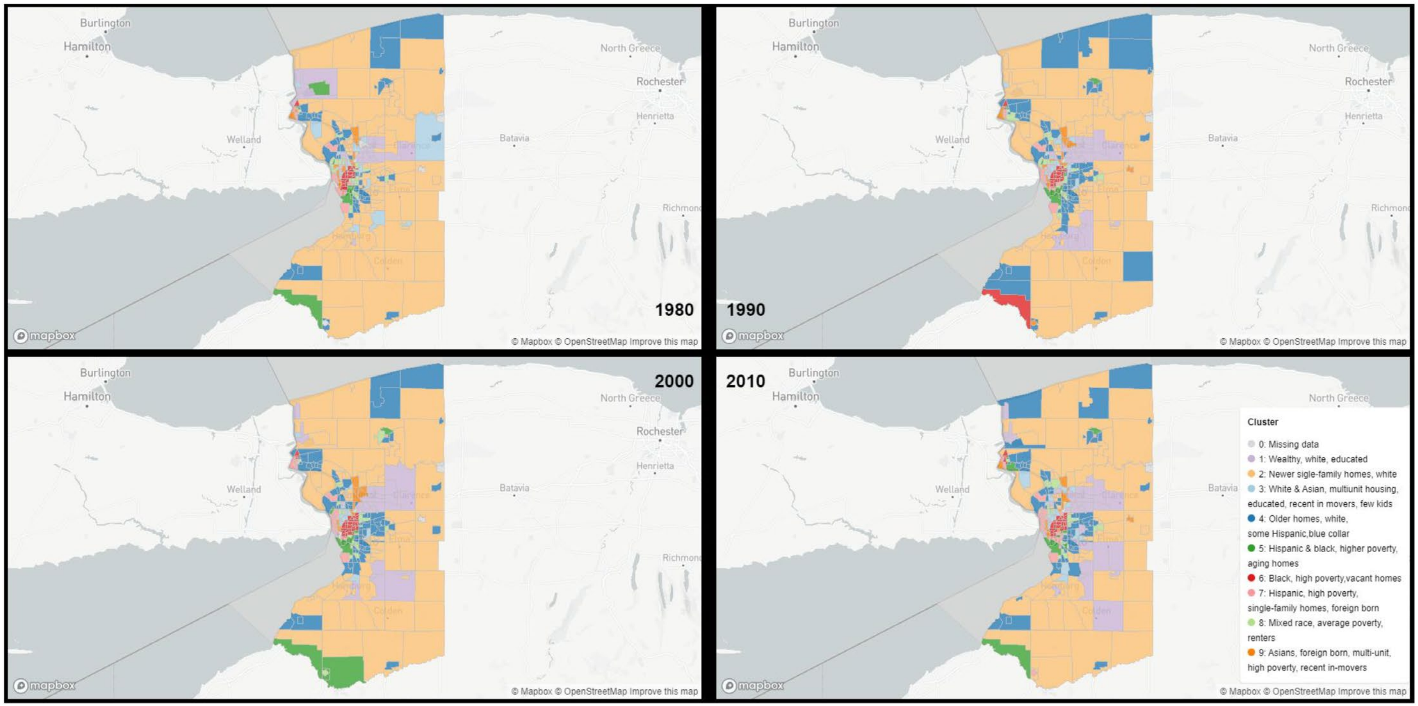

FIGURE 1 Small multiples of geodemographic classification changes, Erie County, NY 1980–2010. Map made at https://neighborhooddynamics.dreamhosters.com/nds/msa11com.html

SOM algorithm at multiple points in time and their location on the output space can be traced to depict its attribute trajectory of change (Delmelle, Thill, Furuseth, & Ludden, 2013; Lee & Rinner, 2015; Skupin & Hagelman, 2005).

Figure 2 illustrates this approach for a neighborhood north of downtown Buffalo, NY, highlighted in purple on the map on the left. The rectangular SOM output space is depicted in the right panel. In this example, the neurons of the SOM have been classified using a *k*-means algorithm to group clusters of similar nodes to aid in the interpretation. The trajectory for this neighborhood is shown in gray on the output space—it shows a small amount of change from 1980 to 1990 (light gray line), moving a few neurons to the left and then remaining in that spot until it experiences a larger change from 2000 to 2010, out of that cluster. In this example, the neighborhood was a relatively stable, upper-middle-class, suburban (mainly single-family housing) neighborhood until around 2000, when its census data showed indicators of change with an aging housing stock, a decline in White residents, and an increase in Hispanic occupants. Compared to simply examining changes in the *k*-means groups, the SOM trajectory can give some indication of the uneven magnitude of changes experienced by different neighborhoods, and has the advantage in that the resulting groups are ordered according to their similarity to one another.

The SOM technique has largely been used in an exploratory manner, describing or visually summarizing trajectories for different neighborhoods. Limited attempts have been made to subsequently classify the resulting trajectories. Ling and Delmelle (2016) applied a 3D *k*-means method in one such attempt—the results were largely intuitive when mapping neighborhoods with similar trajectories, but the results of the clustering method showed a large amount of heterogeneity around the individual trajectories assigned to each group.

Given the complexity involved in clustering trajectories, one avenue explored for simplifying the process has been to reduce the trajectory to a set of discrete events and use sequential alignment methods to classify sequences of change. This line of thinking is analogous to developments in activity space modeling that use similar techniques to abstract movement trajectories to a set of sequential activities to depict space-in-time changes (e.g., Furtado, Kopanaki, Alvares, & Bogorny, 2016). Similarly, there is a history of applying sequence analysis to sociological applications such as life course analysis. Abbott (1995) describes sequence analysis not as a particular technique, but “rather a body of questions about social processes and a collection of techniques available to answer them” (p. 93). In the context of neighborhood dynamics, neighborhoods are first categorized into discrete bundles of attributes using an attribute clustering method such as *k*-means. A neighborhood's longitudinal sequence then follows its change in classification through time, thus representing a neighborhood's process of change with a beginning, middle, and end. Of course, in these examples, the beginning, middle, and end time points are artifacts of the available data used in the analysis. Sequential alignment methods such as the optimal matching algorithm and its derivations then group the sequences according to their similarity (Delmelle, 2016, 2017; Kang, Rey, Wolf, Knaap, & Han, 2020; Li & Xie, 2018; Patias, Rowe, & Cavazzi, 2019). Neighborhoods belonging to similar sequence groups can then be mapped on a single map, overcoming some of the aforementioned limitations of using small multiples for visualizing trajectories of change. An example of a neighborhood's sequence is shown in Figure 2, below the SOM output space. The highlighted neighborhood remained in the same class in the first three time periods before transitioning to a different class in the last time period. The sequence simplifies the information contained in the SOM trajectory method by reducing change to a set of discrete transitions.

While sequence and trajectory methods described above cannot identify all of the processes at play that give rise to the observed pathways of change, by examining the ordering of events for multiple attribute dimensions, at a minimum, they provide a means for empirically verifying the extent to which theoretical models of change have occurred in the past, and they provide a mechanism for generating new testable hypotheses on causal pathways. As an example, the study of multi-dimensional changes in census tracts using a blended SOM and sequence analysis method for the 50 largest Metropolitan Statistical Area (MSAs) in the country from 1980 to 2010, first identified six expected pathways of change based on past theoretical and empirical studies (Delmelle, 2017). The results of the analysis then confirmed the presence of many of those pathways, including a White-flight\house filtering process, the establishment of a multi-ethnic type of neighborhood, suburban densification, gentrification, especially in relatively diverse neighborhoods, socioeconomic ascent in

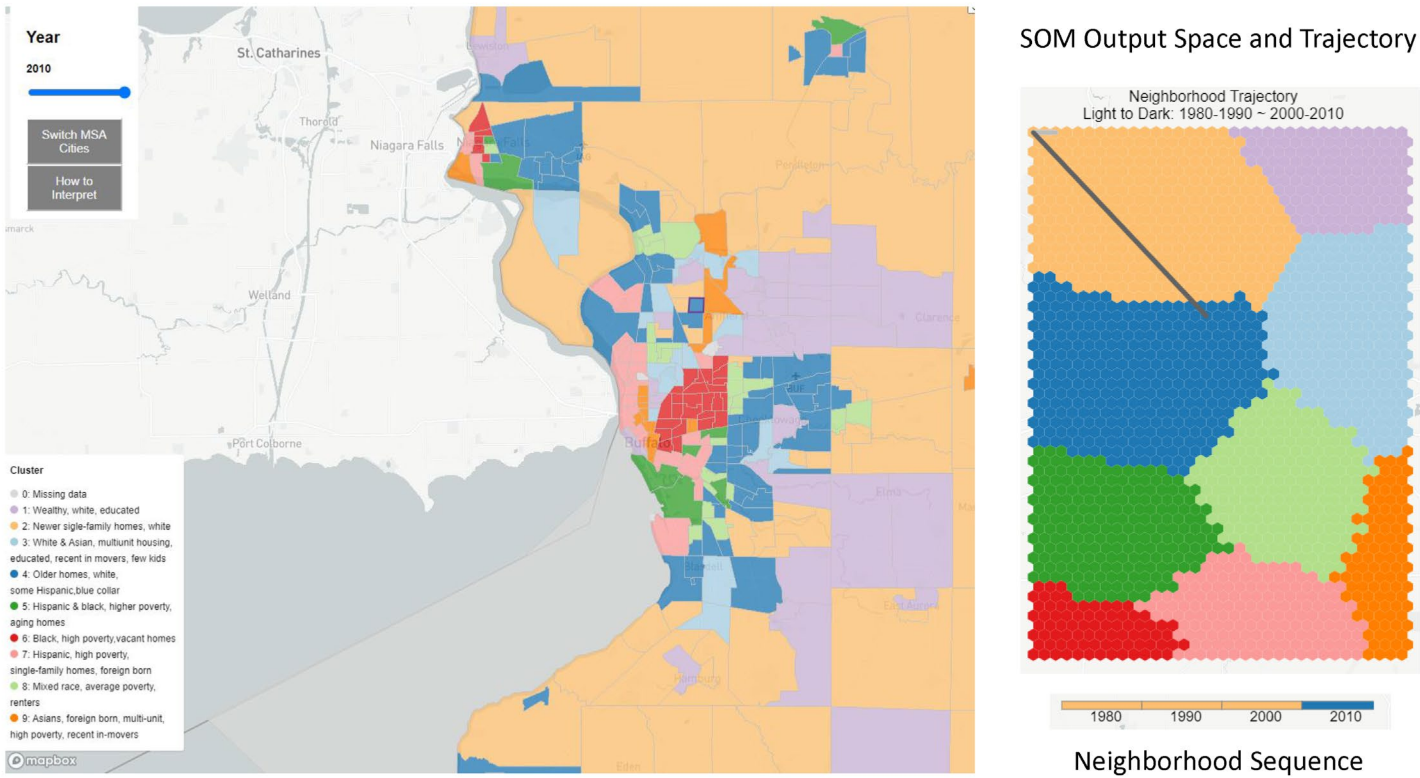

FIGURE 2 Example of SOM trajectory method of portraying neighborhood change for one neighborhood north of Buffalo, NY (highlighted on the map). Its trajectory of change is shown on the rectangular SOM output space on the right, while its sequence is shown below. *Source*: https://neighborhooddynamics.dreamhosters.com/nds/msa11barsom.html

White single-family neighborhoods, and finally no measurable change—the most commonly observed sequence, consistent with prior analyses (Wei & Knox, 2014). With respect to pathways leading to socioeconomic decline, two distinct processes were revealed: one consistent with commonly discussed White-flight\house filtering models of change featuring a gradual aging of the housing stock, increase in vacant housing and decline in new residents, coupled with a declining White population and lower socioeconomic indicators. The second process was not driven by an out-migration of residents according to the revealed ordering of events, but rather an influx of newer, largely foreign-born and Asian residents into neighborhoods with a larger concentration of rental and multi-family housing. Several different pathways of change led to the establishment of a type of neighborhood typically associated with gentrification—with a higher share of highly educated, recent in-movers, largely White and Asian, and more multi-family housing. One of these trajectories represented a shift from relatively racially and ethnically diverse, but lower-income neighborhoods, while the other depicted a change from previously suburban-type neighborhoods, especially in fast-growing southern and western U.S. cities (Delmelle, 2017). By revealing how neighborhoods changed, complementary approaches can then begin to theorize or empirically test why they changed and how they might change next.

Several studies have taken this next step by using the results of classification methods with confirmatory analyses to identify explanatory factors. Zwiers, Kleinhans, and van Ham (2017), for example, used a tree-structured discrepancy analysis linked with sequence analysis to achieve this. Greenlee (2019) further linked neighborhood sequences with disaggregate residential mobility data to apprehend a multi-scalar approach toward understanding processes of change. The development of historical trajectories linked with health outcomes is helping to advance research on neighborhood effects by taking a longitudinal perspective on both the place and the individual (Letarte et al., 2021).

While the sequence analysis approach has increasingly gained in popularity and utility, it is not without limitations—the optimal matching algorithm, for example, is sensitive to its choice of parameters and is theoretically disjoint from neighborhood change processes (Kang et al., 2020). To perform the initial multivariate, *k*-means classification, attribute values must first be normalized to construct dissimilarity matrices between variables on different measurement scales; therefore, these analyses really only examine relative, rather than absolute, changes. Innovations to the *k*-means algorithm have been developed to directly handle temporal neighborhood changes, applied mostly to case studies in the United Kingdom. In these approaches, the initial centroid of the clusters is not selected randomly but instead calculated from observations of the first or last time period. Observations of subsequent or prior time period are then assigned to these centroids and no iterations are performed, as is the case with traditional *k*-means (McLachlan & Norman, 2021; Singleton, Pavlis, & Longley, 2016). This enables insights into how much change has occurred within groups of similar neighborhoods over a specified time period.

There are other avenues of recent research that have taken alternative approaches toward classifying neighborhoods in a way that reveals something about their underlying processes. For example, work by Pan, Chen, Gao, Deal, and Liu (2020) takes advantage of individual residential movement data to classify neighborhoods based on their incoming and outgoing flows of residents according to their incomes—this is a clever application of an origin–destination clustering method that hones in on the individual movements that give rise to neighborhood changes. Several other studies have used growth curve models to classify and explain longitudinal trajectories—these are typically constrained to change according to a single variable and require at least three time stamps (preferably more) (e.g., Zwiers, van Ham, & Manley, 2018). Branic and Hipp (2018) blended a principal component analysis with a latent growth curve model to incorporate multiple variables into their neighborhood trajectory classifications. The use of growth curves to classify places has been more common in the criminology literature, but is deserving of more investigation for its potential for classifying neighborhood trajectories and incorporating the resulting trajectories into explanatory models to move this stream of research beyond descriptive mapping.

Further innovations in extracting and mapping historical trajectories of neighborhood change may be found in the time-in-space or movement analytics literature. As noted by Zhang and Van de Weghe (2018), any method developed for the analysis of moving objects could theoretically be applied to the study of attribute trajectories. In the case of attributes, distance is constructed based on their similarity, often using Euclidean distance to construct similarity matrices—this can be used in lieu of geographic distance measurements. In the article by Zhang and Van de Weighe (2018), Reed graphs, similarity matrices, convoy, and mega-convoy methods were applied in an illustrative study on climate dynamics. This could be one starting point in advancing this line of work, but other approaches that borrow from current developments in movement analytics may also prove promising (e.g., Buchin, Dodge, & Speckmann, 2014; Li & Xie, 2018; Petry et al., 2019).

In addition to methodological advancements, the majority of prior studies that have constructed longitudinal trajectories or pathways of change in the United States have relied on census tract data as they are reliably collected, freely available, and contain multiple attribute dimensions. They serve as a convenient, yet imperfect proxy for neighborhoods. Given that census tract boundaries change over time, most empirical analyses have capitalized on datasets that have interpolated values to fixed or harmonized boundaries. Popular examples include the Longitudinal Tract Database (LTDB) from Brown University (Logan, Xu, & Stults, 2014), the Neighborhood Change Database (NCDB) from GeoLytics, Inc., and the National Historic Geographic Information System (NHGIS) standardized tract database. As estimates, none of these sources are free from error, an often-ignored reality in neighborhood change studies. Of the three popular options, the NCDB uses the simplest areal weighting procedure, while the LTDB and NHGIS use additional ancillary data to allocate population estimates and thus have generally smaller errors than the NCDB (Logan, Stults, & Xu, 2016). Longitudinal estimates of census block populations from 2000 to 2010 are also available from NHGIS (Schroeder, 2017), while more novel datasets for looking at historical trends—such as detailed building data from ZTRAX of Zillow—have recently been used to study urban evolution (Connor, Gutmann, Cunningham, Clement, & Leyk, 2020; Zoraghein & Leyk, 2019).

While convenient, the use of harmonized tract boundaries ignores the reality that neighborhood boundaries are not fixed in space; rather, they evolve over time, and data-derived boundaries rarely align with residents' perceptions of their neighborhoods (Coulton, Jennings, & Chan, 2013). The notion of a boundary itself is an artificial artifact representing space and place within a computer (Petrović, Manley, & van Ham, 2020). This is a fact that has largely been overlooked in the empirical neighborhood dynamics literature as it adds a further layer of complexity to the time-in-space mapping endeavor. With respect to moving beyond fixed-in-space boundaries, Dias and Silver (2021) make some inroads on this matter by suggesting that neighborhood polygons be transformed to a network model that frees it from the constraints of a fixed boundary. Dmowska, Stepinski, and Netzel (2017) developed a dasymetrically derived longitudinal (1990–2010) gridded population by race that enables racial segregation to be examined through time without the constraints of census boundaries. Beyond that, little if any research has explicitly modeled the complete process of neighborhood time-in-space and space-in-time change in an integrated fashion. Furthermore, while GIS has been used to measure and compare residential perceptions of neighborhood boundaries (e.g., Coulton et al., 2013), this body of research has yet to be integrated into neighborhood change modeling efforts as these data-intensive methods are tied to the data collection unit. Petrović et al. (2020) argue that new microgeographic data offer the opportunity to break away from the "tyranny of the neighborhood" administration unit—this opportunity will be touched upon in the next section.

The methods for mapping and classifying trajectories of neighborhood change reviewed thus far have centered on static map displays. However, the use of interactivity and the proliferation of online mapping capabilities offers another avenue for advancement on this topic. Cartographers have largely concluded that some degree of interactivity can help facilitate knowledge discovery in time-series data (Andrienko, Andrienko, & Gatalsky, 2001). While several interactive, web-based systems have recently been developed for visualizing neighborhood change (Dias & Silver, 2021; Lan, Delmelle, & Delmelle, 2021), these current systems do not enable users to upload their own data to generate or map trajectories, and have had limited formal evaluation of their effectiveness in communicating the results of potentially complex algorithms and in their ability to infer processes.

3 | LOOKING FORWARD: UNDERSTANDING CHANGES IN NEAR REAL TIME AND PREDICTING THE FUTURE

While understanding historical processes of change has important applications, there has been a longstanding interest in understanding changes in more real time and to potentially predict areas of increasing investment or disinvestment (Chapple & Zuk, 2016). The development of "early warning" systems for forecasting neighborhood change was motivated by the need for policymakers to develop place-based strategies prior to these changes becoming too entrenched, or their underlying processes accelerating. Thus, many municipalities began capitalizing on developments in GIS and the increasing availability of spatial data in attempts to create predictive systems. Nonetheless, according to Chapple and Zuk's assessment of the status of these systems in 2016, the "state of predictive analytics is poor" (p. 127).

Since then, predictive improvements have been made by capitalizing on machine learning methods and novel, especially user-generated or microgeographic, data sources. Efforts in "nowcasting" or associating gentrification with Yelp data reviews and business types (Glaeser, Kim, & Luca, 2018; Olson, Calderon-Figueroa, Bidian, Silver, & Sanner, 2021), Instagram postings (Han, Hong, & Lee, 2020), Foresquare check-ins (Arribas-Bel & Bakens, 2019), and restaurant reviews (Dong, Ratti, & Zheng, 2019) have advanced the recent state of the art. The use of more traditional government statistics has also been blended with more sophisticated methods such as random forests to better predict gentrification (Reades, De Souza, & Hubbard, 2019). Olson, Zhang, et al. (2021) build upon the clustering techniques discussed in the previous section to develop a predictive neighborhood clustering method using classification and regression along with integer optimization in a way that groups neighborhoods according to their predictive characteristics. Arguably, a case could be made that improved prediction via data-driven and machine learning methods does not provide new insights into underlying processes as they simply learn and replicate from the data they are fed. However, there has been a recent push for methods that improve both prediction and explanation (Gahegan, 2020). For example, similar to traditional parametric statistics, machine learning algorithms can inform which variables are most important in the predictive process, and allow for the incorporation of non-traditional data (like text) and enable the identification of complex, non-linear relationships without having to satisfy rigid model assumptions.

One of the potential advantages of these newer, user-generated data sources is that they can illuminate less visible processes of change that are at play before the movement of people and businesses give rise to observable changes later recorded in census surveys. As one illustrative example, real-estate listings are often advertised with a particular clientele in mind—usually one that will garner maximum profit for real-estate agents working on commission. Consequently, the words used to advertise properties may give an understanding of the less visible processes at play, or at least early indicators suggestive of the underlying process (Delmelle & Nilsson, 2021). Figure 3 is an example of a word cloud constructed from property advertisements for a neighborhood along a new light rail line in Charlotte, NC. After removing words common across all properties (e.g., bedrooms, bathrooms, etc.), the remaining words paint a fairly intuitive picture of what is occurring in that neighborhood. Words such as "renovated," "construction," "updated," "opportunity," "booming," and "new" all speak to an influx of capital investment in the neighborhood, while higher-end property amenities (granite, stainless) and urban amenities (restaurants, breweries, light rail, uptown) depict the type of homebuyer realtors are striving to attract to the neighborhood. Collectively, these words portray a near real-time process of gentrification occurring in this neighborhood and illustrate the promise of property advertisement texts as one such novel dataset that may help capture and communicate processes of neighborhood change (Delmelle, Nilsson, & Schuch, 2021).

Many novel datasets that show potential for communicating and predicting processes of neighborhood change, such as property listing data, require the handling and visualization of text data in geographic space. Geotext analysis and visualization is a developing area of research that, when done effectively, may overcome some challenges associated with communicating neighborhood change that use complex algorithms such as the SOM, discussed in the previous section. Solutions for linking natural language processing with geographical visualization

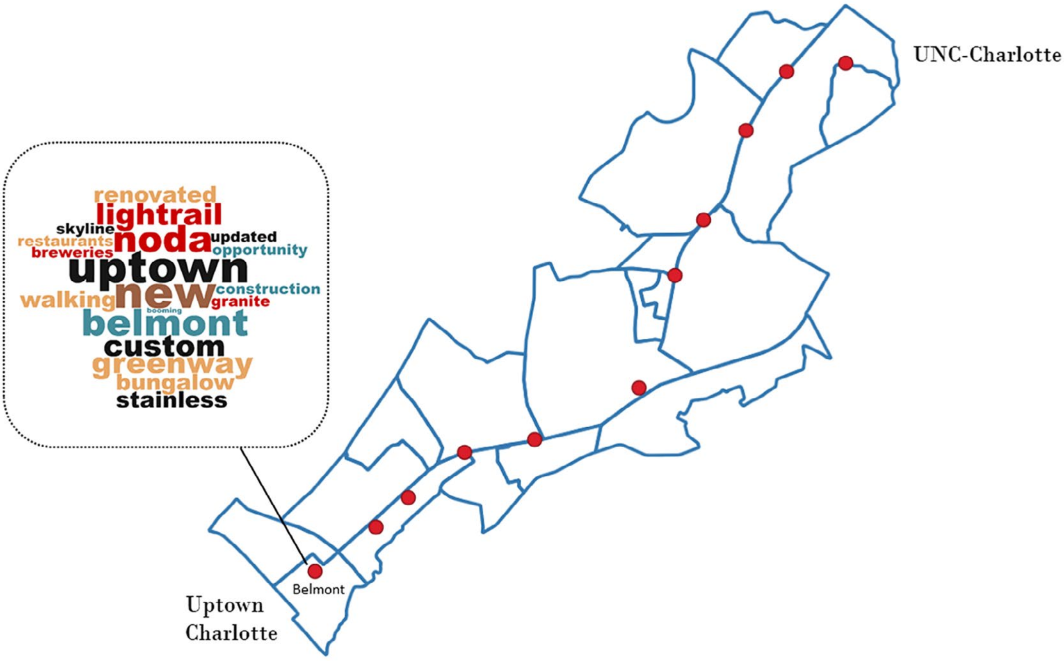

FIGURE 3 Wordcloud map of terms from property listings in a gentrifying neighborhood

are an active area of research that neighborhood dynamics research would benefit from engaging with (Hu, 2018; Ma et al., 2020; Martin & Schuurman, 2017).

Of course, new and emerging user-generated datasets have their pitfalls, which counter the timeliness and diversity of topics. Perhaps foremost are concerns regarding their representativeness, especially pertaining to user generation, social sensing, or more generally "Big Data."[1] Much has been written in the GIScience and information science literatures on some of the perils of working with these data (e.g., Boyd & Crawford, 2012; Liao et al., 2018), while the field of critical data studies has provided a framework for understanding and analytically engaging with them (Dalton, Taylor, & Thatcher, 2016). Dalton et al. (2016) suggest that "when we map Big Data we map the contours of capital, one intrinsically limited by the uneven contours of data as it plays out across space" (p. 6). This sentiment is illuminated quite clearly in Figure 4, where the intensity of running routes from the fitness app Strava is compared to the intensity of residential building renovation permits in Mecklenburg County, NC. The maps portray the same general spatial pattern, one which largely highlights the wealthiest and Whitest areas of the county, but the building renovations further emphasize areas of capital investment. The gaps in the Strava data largely represent areas of disinvestment. Similar patterns have been observed with other data sources, including Yelp (Folch, Spielman, & Manduca, 2018).

The implications of this for neighborhood dynamics research are twofold. First, predictive efforts that use such datasets are likely to miss changes that are unfolding in the data gaps, and second, our research agenda as a whole tends to be biased towards areas where investment is taking place, where we have data. Indeed, efforts to map, predict, and measure gentrification—a result of flows of both capital and people (Zuk, Bierbaum, Chapple, Gorska, & Loukaitou-Sideris, 2018)—far outweigh those tackling issues pertaining to disinvestment. It is easier to map and analyze where things are occurring, than where they are not.

Addressing research needs for the data gaps requires some creative solutions and alternative ways of thinking about the processes that give rise to spatial distributions of poverty and affluence (Shelton, 2018). Shelton's (in press) work on vacant housing is one such example. Rather than stopping at maps illustrating the spatial

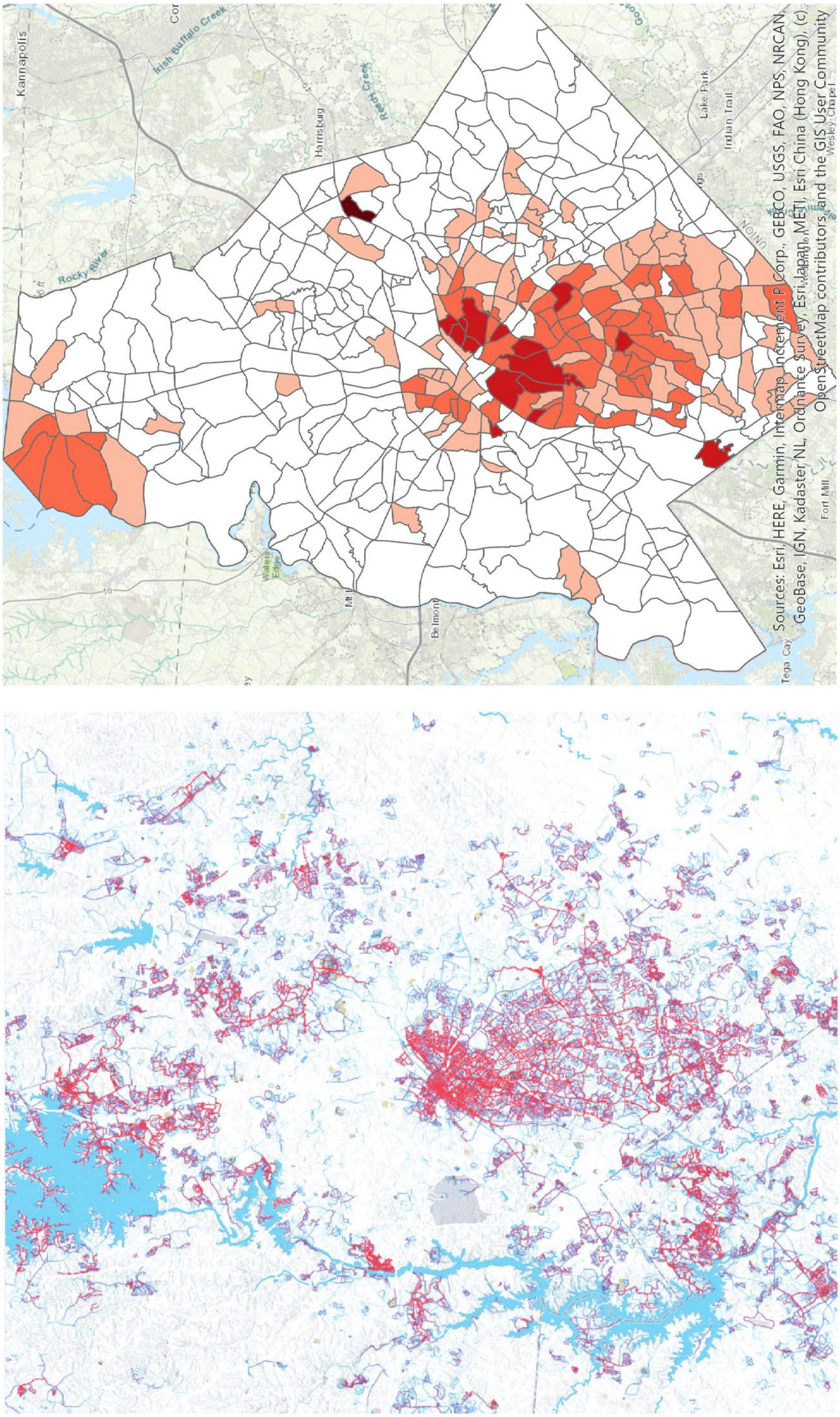

FIGURE 4 Strava heatmap versus density of residential building renovation permits in Mecklenburg County, NC

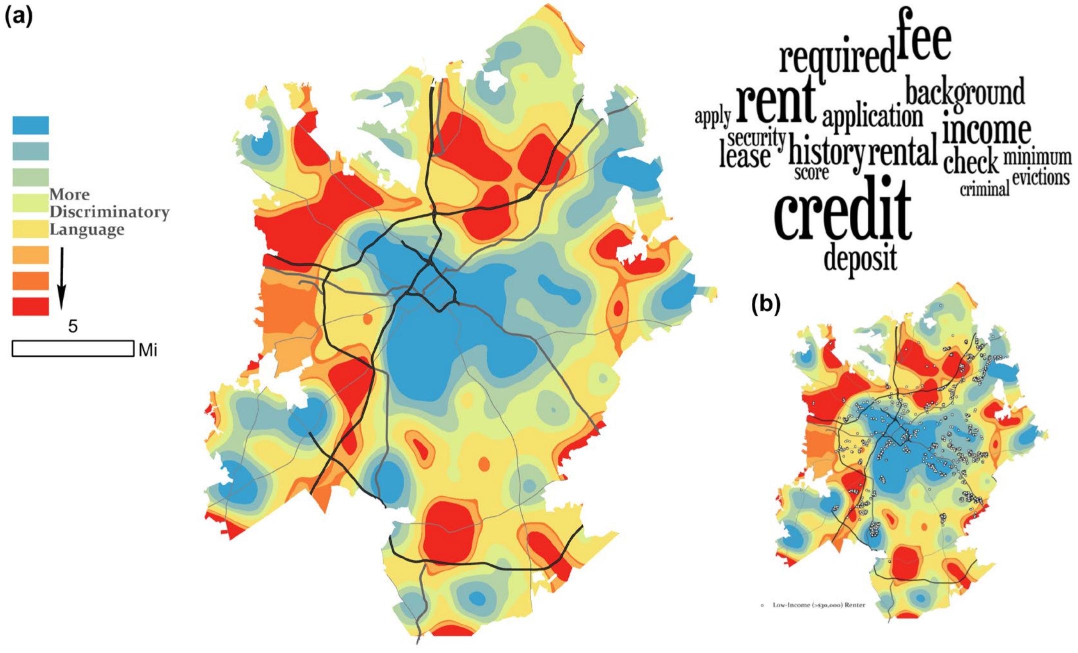

FIGURE 5 (a) Intensity of discriminatory language in rental advertisements in Charlotte, NC. (b) Location of new low-income renters overlaid

concentration of vacant housing in one area of a city and concluding that it was a problem unique to that area, he produced relational maps depicting the location of property owners dispersed throughout the United States, thus demonstrating the broader spatial context through which the observed pattern is linked. Research on mapping and modeling spatial patterns of evictions is another example that strives to highlight underlying processes that help shape outcomes observed from more traditional census data sources (Medina, Byrne, Brewer, & Nicolosi, 2020; Nelson, Gromis, Kuai, & Lens, 2021; Preston & Reina, 2021).

When thinking about the processes that lead to disinvestment, Smith, Caris, and Wyly (2001) hone in on discrimination and uneven development as two critical causal processes. Discrimination could be on behalf of multiple actors: realtors serving to steer prospective renters or homebuyers; lenders rejecting minority loan applications; landlords deciding whom to rent properties to; or developers constructing exclusionary amenities like golf courses that help reinforce segregation patterns, among others. Maps of race-based home mortgage denial rates (Smith et al., 2001) and subprime loans (Wyly, Moos, Hammel, & Kabahizi, 2009) using data from the annually updated Home Mortgage Disclosure Act (HMDA) represent one way of depicting that form of discrimination.

Another example, building on the property text examples discussed above, visualizes discriminatory terms used in rental advertisements. Figure 5a shows a map created by scraping a sample of Craigslist and Zillow rental advertisements in Charlotte, NC, searching listings for discriminatory or restrictive terms, and creating a kernel density surface weighted by the number of discriminatory terms (normalized by the total number of listings). The word cloud to the right of the map displays some of the commonly used restrictive language (minimum credit scores, background checks, minimum incomes, no prior evictions, etc.). This sort of map brings to light an invisible process that restricts location choices for some residents and therefore contributes to observed changes in neighborhood population composition. Figure 5b follows with an overlay of the spatial location of low-income renters in the city, obtained from Data Axel's database of recent movers (formerly Reference USA). At least visually, there appears to be some avoidance of residents in the areas of higher discrimination, but further confirmatory modeling would be needed to disentangle other confounding and explanatory factors. Nonetheless, this exploratory exercise provides an exposé on some of the more creative uses of non-traditional data sources that can bring to light underlying, invisible processes of change, especially those occurring in shadows of Big Data. These examples also use point-level or microgeographic data, and are therefore not constrained to census tract boundaries, an additional opportunity inherent in these newer data sources (Petrović et al., 2020).

4 | CONCLUDING THOUGHTS AND CHARTING A COURSE FORWARD

GIScience contributions to neighborhood dynamics research have flourished over the past decade as the field has advanced from the simple display of static time series maps in the form of small multiples to an embrace of innovative techniques for mapping and analyzing time-in-space changes. In this review, I have focused on data and, primarily, data-driven methodological innovations that have enabled processes of neighborhood change to be uncovered. Research that has been historically focused has sought to identify, classify, and map the predominant pathways of change across multiple attribute dimensions. While the use of SOMs, sequential alignment methods, and growth curve models has been an important innovation in this line of research, future research is needed to advance it beyond a descriptive exercise by linking explanatory variables with trajectories of change. Methods that better group neighborhood trajectories as a function of absolute, rather than relative, changes would be welcome contributions to the literature and better approaches to classifying attribute trajectories may be found by engaging with advancements in analyzing movement trajectories, an active area of GIScience research.

With respect to novel forms of data and neighborhood predictive efforts, in this review I stressed the need to pursue a research agenda that highlights processes at play within the data gaps—the often-forgotten places of disinvestment, as so much of our research has followed the data and flows of capital, tracking the causes and consequences of gentrification. What novel or creative uses or sources of data can illuminate the invisible processes that give rise to observed outcomes later captured by census surveys? These points are increasingly important as data-driven approaches to research, especially as those aimed at prediction are biased towards the places where things are happening (i.e., capital investment and reinvestment). As researchers eager to capitalize on new data and methods, we need to be cognizant that as the urban socioeconomic landscape becomes increasingly unequal, in a data-driven world, the research landscape does not follow.

In thinking more critically about processes of neighborhood change and how GIScience can contribute to its understanding, if we wish to move this research forward in a more transformative sense, rather than with incremental improvements, it is worth thinking outside of the box on what this would entail. To date, many of the methodological advancements made in this line of research have borrowed techniques developed for other fields of study and applied them to examine sequences or trajectories of neighborhood change. But that practice has its limitations in that these techniques are conceptually and theoretically disjoint from how we understand processes of change to take place. In reality, processes of neighborhood change are the product of multiple actors and decisions operating on different spatial and temporal scales across an unequal urban landscape whose history cannot be ignored. An integrated analysis of change could consider these simultaneous processes—representing the actions of residents and developers, enabled or constrained by real-estate agents, social networks, and government regulations, for example. Some of this vision is in the spirit of recent work on multi-scalar processes of residential sorting and segregation using agent-based models or simulations (Ardestani, O'Sullivan, & Davis, 2018; Jackson et al., 2008; Olteanu, Randon-Furling, & Clark, 2019). However, advancements in GeoAI and deep learning neural networks that are more theoretically grounded than their earlier predecessors may also be a path forward (Gahegan, 2020).

The handling of both space and time within GIS with respect to neighborhood change studies has thus far been artificially rigid, aligning with the spatial and temporal resolution of readily available data sources. Micro data sources—both user-generated and increasingly high-resolution built environment data—offer an opportunity to move beyond the fixed spatial and temporal boundaries imposed by traditional aggregate statistics in such a way that neighborhood processes can be depicted as fuzzy and multi-scalar (Petrović et al., 2020; Poorthuis, 2018). Similar critiques of modeling physical processes in GIS were made more than two decades ago by Wilson and Burrough (1999), who made the case for fuzzy clustering and classification techniques. This remains one option forward for classification-based neighborhood research, while testing for the importance of multiple spatial and temporal scales of various explanatory variables is more feasible with machine learning methods that are not constrained by traditional parametric modeling assumptions.

Finally, as has been a source of longstanding tension in geography, understanding a process driven by the decisions and actions of humans cannot be fully understood by taking a solely quantitative perspective. Therefore, advancements in GIS that can seamlessly integrate qualitative data, facilitating a mixture of methods and data sources, are long overdue. Prior qualitative GIS neighborhood research has demonstrated how engagement with residents can provide critical insight into indicators that may be key for understanding processes of change and generate alternative hypotheses about causal mechanisms (Elwood & Leitner, 2003). Yet, these two modes of research largely continue to operate separately. Renewed interest in text analysis afforded by emerging datasets applied to neighborhoods may also spark ideas on how to integrate traditionally collected qualitative data in a way that brings to light additional factors in the change process and that can be linked with other quantitatively collected data.

To conclude, the prospects for GIScience contributions to neighborhood change research are brimming with opportunity: novel data sources and methods are increasing in quantity and sophistication. To fully take advantage of these developments in a way that can truly apprehend the processes of change, the next generation of research should strive to be intentional about developing methods that align with our theoretical understanding of the underlying processes and critically engage with all forms of data, paying attention to the gaps, the left-behind places, and the invisible processes at play. Finally, they should think beyond a neighborhood as a fixed spatial container that changes at neat temporal increments and recognize the multi-scalar and multi-temporal processes that simultaneously shape neighborhood outcomes.

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CONFLICT OF INTEREST

No conflicts of interest are declared.

DATA AVAILABILITY STATEMENT

No data are available (review article).

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ENDNOTE

[1] The challenges of working with these data sources are not restricted to representativeness. Other challenges with handling data uncertainty and error are also important limitations and areas in need of innovation (see Shi, Zhang, Zhou, & Zhang, 2018 for a review).

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