The Spatial Analysis of Gentrification: Formalizing Geography in Models of a Multidimensional Urban Process

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This chapter examines predominant and emerging approaches for conducting spatial analyses of gentrification; It begins with a brief review of relevant theoretical literature to describe why spatial analyses require formalizing gentrification studies in ways that unavoidably simplify a complex social, economic, political, and geographic process. It proceeds to make the case that, while there are many ways to define and quantify "gentrification," spatial structure remains a fundamental presence in both the theoretical underpinnings and empirical findings throughout. Following, it provides an overview of contemporary strategies for modeling the phenomenon, drawn from across the social sciences, and describes the assumptions and intentions of each modeling framework, the questions each is designed to answer, and the tradeoffs each approach embodies. The chapter concludes with a discussion of the promising avenues offered by new data sources and urban computation, as well as the potential pitfalls they offer for ethics and inference alike.

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INTRODUCTION

> "One by one, many of the working class quarters of London have been invaded by the middle classes—upper and lower. Shabby, modest mews and cottages—two rooms up and two down—have been taken over, when their leases have expired, and have become elegant expensive residences... Once this process of 'gentrification' starts in a district, it goes on rapidly until all or most of the original working class occupiers are displaced, and the whole social character of the district is changed. There is very little left of the poorer enclaves of Hampstead and Chelsea: in those boroughs, the upper-middle class takeover was consolidated some time ago. The invasion has since spread to Islington, Paddington, North Kensington—even to the 'shady' parts of Notting Hill—to Battersea, and to several other districts, north and south of the river (The East End has so far been exempt). And this is an inevitable development, in the view of the demographic, economic, and political pressures to which London, and especially, Central London, has been subjected."
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> — Glass and Rodgers (1964, p. xviii)

Gentrification is among the most engaging topics in urban social science today. And understanding why this specific variety of neighborhood change has garnered so much scholarly attention over the last half-century is simple. Neighborhoods provide unique contextual environments for social interaction, and a wide variety of resources and amenities (or externalities) that contribute to human development over the life course. But aside from providing environments in which to work and live, increasingly, the "neighbourhood has become more than a source of security, the base of a supportive network, as it has long been; it has become a source of identity, a definition of who a person is and where she or he belongs in society" (Marcuse 1993, p. 361).

Urban space has social meaning, and gentrification carries with it the threat of *displacement*, and the notion that one's home, the space that helps define her identity may be taken from her. With such a precious commodity as identity at stake, it is no surprise that gentrification scholarship has generated a vast literature over the past 50 years; neighborhood change is a visceral process that can transform the built environment, the demographic composition of a geographic area, and the cultural amenities it provides. Although gentrification is a topic of scholarship more than five decades old, spatially-explicit quantitative analyses of gentrification remain relatively rare, even today. Further, despite the subject's popularity, quantitative techniques for analyzing the process of gentrification are many and varied, often tracing lineage to a particular disciplinary perspective or modeling framework.

The goal of this chapter is to offer practical advice to researchers using spatial analysis to study the process of gentrification. While the topic has roughly 50 years of history in the literature, the *spatial analysis* of gentrification remains a novel frontier. As such, the chapter first examines briefly the historical development of gentrification as a theoretical construct and neighborhood change as social process, using this discussion as a vehicle for introducing the challenge of formalizing and quantifying gentrification in spatial models. Following, the chapter moves to a discussion of contemporary and emerging strategies for modeling gentrification. Each strategy is fundamentally different in its logic underlying drivers of change, the data required to estimate the model, and the parameters that define the envelope of 'gentrification'. The chapter makes no relative value assessment of the different approaches, but lays bare the unavoidable and unresolved challenges facing researchers adopting each of them. These challenges stem from the fact that there is no shared definition of the term gentrification, but that ambiguity manifests in different ways across the various quantitative frameworks.

The chapter illustrates these issues to make clear that, despite continuous methodological innovation, the spatial analysis of gentrification remains a daunting task and confronting the challenges raised in the chapter is a burgeoning frontier for urban scholars. The purpose of this chapter is threefold: first, to enumerate and elucidate lingering and longstanding conceptual issues in the spatial analysis of gentrification; second, to provide an overview of dominant frameworks for modeling gentrification, identifying how each framework intersects with the issues raised via the first goal; and third, to articulate how each framework incorporates formal notions of spatial relationships and the ways that emerging techniques could help overcome lingering empirical hurdles. Through these goals, the chapter offers practical advice for applied researchers studying gentrification, providing guidance not only for addressing the field's most pressing issues, but also for selecting an appropriate method for their research question at hand.

SPATIAL STRUCTURE AND SOCIAL BEHAVIOR

According to Glass, gentrification manifests through "demographic, economic, and political pressures," and the history of urban development sets the stage for these pressures to unfold. In some cases, the political influence is obvious, such as McCabe and Ellen (2016) who show that following the designation of a historic preservation zone in New York City, "the share of college-educated residents and the mean household income rise, and the poverty rate falls relative to surrounding census tracts". But in other cases, the rise of gentrification is attributable to longstanding patterns of urban land use and social partitioning of cities.

For this reason, in both popular culture and the scholarly literature–particularly In the American context–gentrification almost inevitably connotes racial tension. This is partly because some of the most prominent and universally-recognized symbols of gentrification today like Brooklyn, Harlem, and Washington D.C. have undergone dramatic racial turnover as their property values have risen, and partly because race and class are highly inter-correlated meaning "gentry" tend to be white. Further, because of discriminatory real estate lending practices such as redlining, combined with the historical legacy of white flight in large cities through the deindustrialization period, the inhabitants of older urban housing stock are typically people of color, most often black. Together these conditions create a deeply racialized concept of gentrification in which young white professionals displace long-established black families. Put differently, there are few low income, predominantly white neighborhoods remaining in most urban cores.

Together this history sets the stage for considering race as a critical variable in gentrification work, at least in the context of the USA. The structure of urban American housing markets is such that most downtowns, with the best access to jobs, desirable urban form, and architecturally nuanced housing stock are most often poor and predominantly minority. As those same locations become more attractive to wealthier white families, they are able to outbid minorities currently living in the area, leading to racial displacement and disruption of one of the few resources white patriarchy failed to strip of black Americans: community. Displacement, both demographic and cultural, is, therefore, an intertwined but distinct concept in the gentrification literature. Cultural displacement can occur even when there is no residential turnover or stark demographic change, severely complicating spatial analytical attempts to isolate and model the occurrence of gentrification.

Conceptual Models of Neighborhood Change

Conceptual models of neighborhood formation and neighborhood change are among the oldest and most studied constructs in urban social science. In a seminal overview of classical models of neighborhood change, Schwirian (1983) outlines three essential processes of neighborhood change he calls the invasion and succession model, the lifecycle model, and the gentrification/back to the city model. The invasion and succession model of neighborhood change, famously articulated by the Chicago School of urban sociology, borrows from ecology and the behavior of invasive plant and animal species (Park *et al.* 1925, Park 1936). Central to the concept of invasion/succession is that urban functional regions are characterized by multidimensional segregation, and that neighborhoods tend toward social homogeneity, internally. As such, periods of neighborhood integration are temporary, where one social group invades a neighboring territory and eventually supplanting other groups and becoming the majority. Assuming the invading group is the upper class, then arguably, the invasion/succession model is the exact dynamic described by Glass and Rodgers (1964) in the term's first use, where the "process of 'gentrification' starts in a district, it goes on until all or most of the original working-class occupiers are displaced, and the whole social character of the district is changed."

The lifecycle model posits that housing (re)development is a primary driver of neighborhood turnover, where an influx of new, higher income residents follows the (re)introduction of high-quality housing stock into formerly deteriorated areas. This model descends in large part from the tradition of the bid-rent and concentric zones theories described above, where redevelopment occurs in phases extending from the oldest housing stock in the center of the city, extending outward to the suburbs, before finally returning to the center in a cyclical process of decline and reinvestment.

The gentrification/back to the city model posits that there is a widespread return to classic ideals of urban living that include the cosmopolitan, transit friendly, and classic architectural environments provided by older urban centers. Much of Schwirian's insight remains true today, but it is useful to relax his taxonomy, and instead treat these different paradigms not as alternatives, but different components of a large, interactive system. A more holistic view is that these theoretical models of neighborhood change co-exist, and may each contribute to comprehensive neighborhood change collectively (Galster 2019).

Indeed, concurrent with the decline of preference for same-race neighborhoods (as predicted by the "back to the city" model) much of the housing stock in downtown urban areas is being redeveloped–partly due to its age (as predicted by the lifecycle model) and partly due to the change in the underlying hedonic housing demand function (i.e. changing preferences for same-race, same-income neighbors) that induces redevelopment. Falling preference for same-race neighbors also reshapes land value, apart from the housing stock, making central locations more attractive because of their shorter commutes and falling racial disincentive. Together, these trends are reshaping which neighborhoods are attractive to higher-income urban residents–and at different rates. Residents for whom the social composition of the neighborhood is least important (or is an attractive feature) serve as "pioneers," drawn to other neighborhood characteristics such as architectural character or more walkable urban amenities (Ehrenhalt 2012, Graif 2018). Thus, together, these processes instigate and comprise the neighborhood transformation called gentrification and no single process among them can describe gentrification in isolation.

While each of these descends from a distinct body of social theory, be it social ecology, political economy, or capital expenditures, each nonetheless specifies a process by which *new* residents come to inhabit certain portions of a city, often feeding the process itself and a recurrent feedback loop. Further, regardless of whether it is made explicit in the early social science texts, what is central to all of these theoretical models of change is the concept of *spatial spillover*. Neighborhood change does not happen in leapfrogging or checkerboard patterns, but tends to start from an initial seed and move outward according to the connectivity and adjacency that link neighborhoods together.

Gentrification is a Spatial Process

The sections above make clear that gentrification is a multifaceted process connected to social dynamics, property markets, and urban geography–and that each of these facets may change independently or in concert with (or be triggered by) others. Thus, the concept of gentrification that emerges from classic social theory can be described as follows; there is an initial partitioning of urban space characterized by multidimensional segregation, followed by a period of integration, and another of re-segregation. The dimensions of segregation may include race or class, both, or others. Original residents may move out (sometimes forcibly by housing market pressure). The changing demographic makeup happens in tandem with rising housing market conditions, evidenced by increasing prices and the improvement of existing housing stock.

The sequence and timing of these changes is neither universal nor fully understood. Sometimes commercial investments and infrastructure revitalization kick start downtown housing markets and wealthy residents move in. Other times, artists take up residence in a cute neighborhood that gains the reputation for being cool; real estate inflates as wealthier residents bid up housing prices to trade cash for identity points. Regardless of which process preempted the other, gentrification occurs when there is a noticeable difference in the neighborhood structure–either through some interpretation of the demographic and socioeconomic data or through the common experience of sights, sounds, amenities, and interactions. Although the theories and disciplinary perspectives motivating gentrification research are many and varied, the literature nonetheless appears to reach some consensus on the notion that gentrification, like much in the urban studies, is subject to the first law of geography[1],

> "Are these patterns spatial? They are certainly reflected in space, and their spatial characteristics strongly influence their substance. But they are not rigid spatial patterns, in the old sense in which Burgess and Parks tried to describe city structure. And their spatial pattern varies widely from city to city, country to country"
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> — Marcuse (1993)

The *pattern* of gentrification is not always easily predictable from the classical models and early theories of spatial structure. Nevertheless, the *process* of gentrification is inherently spatial [2]. On one hand, this introduces complexity, as it's clear that models of gentrification require formal specification of spatial relationships. On the other hand, despite the definitional disagreements, one thing common to nearly all concepts of gentrification is the notion of spatial spillover.

SPATIALLY-EXPLICIT MODELS OF GENTRIFICATION

What emerges from this terse review of work from among the field's classic literature is that *definitions* of gentrification are many and diverse; though experts agree on common threads and concepts, very few have posited a strict, operationalizable definition applicable to a wide variety of circumstances and regional contexts. Absent such a definition, *modeling* gentrification, naturally, remains a sincere challenge. The remainder of this chapter assumes the position that gentrification results from a complex interplay of race, class, and housing market conditions, although the relative importance of these concepts are dependent on local and regional context. Even with this broad and rather abstract definition, however, critical questions remain. Among them, can *any* neighborhood gentrify?

In Glass's definition that opens the chapter, she describes the invasion of working class neighborhoods by the middle class. The political, economic, and demographic processes that lead to class transformation in neighborhoods are hard enough to model, but often overlooked are the additional questions about the definitions of other social constructs in the gentrification system: What are the boundaries of the working and middle classes? Or, what defines a working class neighborhood such that it is *eligible* to gentrify? And at what point does it exceed that threshold and become gentrified? Does a black working class neighborhood become gentrified if it transitions into a white working class neighborhood? Is the invasion of lower middle class neighborhoods by the upper-middle class a different process from gentrification? If so, do we learn anything about "proper" gentrification by observing neighborhood class transitions just off the margins of gentrification? Far from the margins?

[1] Tobler (1970)'s first law of geography states that everything is related to everything else, but near things are more related than distant things

[2] In large part, the difference in gentrification described by Marcuse (1993) in this passage is reflective of the difference in urban spatial structure between the two cities, rather than the difference in the appearance of *gentrification* per se.

"If one wants to better understand, predict and even alter changes in urban neighborhoods, one thus must be exceedingly careful in operationally specifying the exact dynamic in question, and must recognize that such a specification may, in itself, influence the outcome of the analysis."

— Galster and Peacock (1986)

The answers to all these questions are foundational to the proper specification of a gentrification model, but no single spatial analysis strategy addresses each of them satisfactorily. As the quote from Galster and Peacock above describes, the inability to properly define the critical elements in the gentrification equation suggests that much of our contemporary knowledge about the phenomenon is partially self-determined. As such, there remains an important need to be explicit about the challenges remaining in quantitative gentrification scholarship so that the field can continue to define collectively the required albeit missing elements. In the following sections, the chapter describes common ways that scholars have addressed these issues of definitional complexity, threshold delineation, and relative context in spatial analyses—most often by addressing some and ignoring others entirely.

The modeling frameworks discussed below are organized into a loose taxonomy that includes regression models, transition models, and simulation models. Although there is strong rationale for describing these as distinct frameworks, it remains important to be clear that the taxonomy is stylistic; although "transition models" are commonly estimated using a Markov chain framework, similar models can also be constructed via discrete regression, or they could be used to seed agent-based simulation models. Hence, the discussion below focuses on the assumptions underlying each framework and the research questions each approach is suited to address rather than the idiosyncrasies of model specification or mathematical details of estimation.

Linear Models with Sociospatial Indicators

The workhorse of the social sciences is the linear regression model and gentrification research is no outlier. Regression models are widely used and easy to understand–but they also require specific and well-defined dependent and independent variables. Regression-based approaches to gentrification scholarship take the perspective that gentrification can be modeled as a linear combination of observable variables. Implicitly, this perspective assumes that gentrification can be codified as a single or small combination of variables[3] The premise of these models is that certain kinds of people or development or market conditions are attracted by certain urban characteristics. By analyzing the relationships between these parties, analysts hope to uncover some policy levers that help influence the distribution of people, capital, and resources.

As described above, however, this can be a difficult convention to adopt, since "what seems to be a single dynamic of neighborhood transformation—gentrification—instead comprises multiple processes... there is more to neighborhood dynamics than growth, decline, and stability; and more to neighborhood reinvestment than incumbent upgrading and, gentrification" (Beauregard 1990). Given that reality, modelers are forced to choose a single, well-defined, indicator of neighborhood

[3] Using a combination of variables requires the further specification of a measurement model, such as principal components analysis or factor analysis, where covariation among several variables is viewed as originating from a single source. Models of this variety require additional assumptions, and are often better adopting a structural equation modeling approach.

change and remain vigorously loyal to that definition for the study at hand. Doing otherwise would require exploring too many potential models and interpretations. Precisely how gentrification (or other types of neighborhood change) is *operationalized* as such a variable can take widely different forms and has an important influence on the results (Galster and Peacock 1986, Barton 2016). In general, linear models of gentrification proceed by setting the gentrification as a dependent variable and using various urban characteristics as predictors. The continuous and discrete forms of gentrification in these equations present different challenges and each is discussed below.

Gentrification as a Continuous Outcome

When gentrification is modeled as a continuous outcome in a regression model, it often assumes a purely economic form, for example by defining gentrification as the increase in neighborhood income level. Although income is a common measure, a large body of work uses home prices rather than incomes as the measure of economic status. Scholarship adopting this framework uses, for example, (a series of) hedonic models examining how housing prices have changed in a particular neighborhood (Brueckner 1977, Lin 2002, Guerrieri *et al.* 2013, Immergluck and Balan 2018), or how housing prices and incomes have risen in concert (Brueckner and Rosenthal 2009). Elsewhere, scholars have argued that social class is a more relevant construct than income, using variables such as educational attainment to measure the influx of urban gentry (Freeman 2005), or that a more composite variable should be used (Ley 1986, Yonto and Thill 2020), e.g. defining gentrification as "the process in which neighborhoods with low SES experience increased investment and an influx of new residents of higher SES" (Hwang and Lin 2016).

Still other scholars focus on racial turnover (Freeman and Cai 2015, Ellis *et al.* 2017), redevelopment (Helms 2003, Markley 2017), urban densification, or householder age (Moos 2016), but nonetheless focus on a single element of complex neighborhood change. Some authors opt instead to use certain variables like race as predictors, (e.g. Hwang and Sampson (2014) and Timberlake and Johns-Wolfe (2017) who use racial indicators to predict changes in SES), but this approach raises questions of simultaneity and identifiability: what if the underlying social process of neighborhood selection is influencing the observed results in both race and class dimensions?. In this case the regression assumptions are violated and the coefficient associated with race is misidentified.

Thus, while there are a variety of approaches for modeling gentrification as a continuous outcome in a regression model, this approach also requires fixation on certain variables rather than capturing the full spectrum of neighborhood change. Even when composite indicators such as SES are used to operationalize gentrification, regression models cannot also account simultaneously for real estate and racial change as dependent variables as well. In some cases, authors argue these processes are ancillary to the social phenomenon of gentrification, for example Timberlake and Johns-Wolfe (2017) contend "other indicators commonly used to identify gentrified neighborhoods are epiphenomenal to change in population SES. Hence, we do not measure, for example, the presence of boutique stores, art galleries, or cafés, or even changes in housing value because we believe these to be outcomes or manifestations of underlying population change."

In addition to issues regarding the conceptual specification of a regression model, the data necessary to truly identify gentrification or displacement are rarely, if ever, available for study. Census data can only facilitate analyses of whether the income of a spatial unit has risen on average–so it remains impossible to determine whether incomes have risen because new residents have moved-in, or if the incomes of existing residents have risen in place.

Spatial relationships in gentrification regression models are typically incorporated either through notions of Location Theory and spatial effects through independent variables such as distance to the nearest park, proximity to the CBD or, more recently, by incorporating formal spatial econometric specifications. While still rare, examples like Bardaka *et al.* (2018) show the causal effect of transit induced gentrification using a spatial econometric model.

A less obvious implication of this framework is that when regression models of gentrification use data from the entire study region to estimate the relationship between neighborhood drivers and neighborhood change, the X variables represent marginal change in *all* neighborhoods. In practical terms this means that a rich neighborhood that got richer contributes just as much to the coefficients as a working class neighborhood that became middle class. Put differently, unless data are filtered beforehand, regression models typically isolate the relationship between neighborhood upgrading and certain inputs. If all neighborhood upgrading can be considered gentrification, then this is moot; if not, this is a crucial element to consider when adopting a model.

Gentrification as a Discrete Outcome

When gentrification is treated as a discrete outcome, spatial models thereof carry their own set of challenges. First, as with above, modeling gentrification requires a specific definition thereof, which in the discrete case takes a binary form (most often)–i.e.areas are either "gentrified' or they are not. Defining this binary criteria can be based on a threshold for some variable (race? Class? Housing prices?) or by another process such as polling the local public or using another model. Regardless, a continuing issue in the current research is how those thresholds should be chosen, and authors have offered many approaches.

A notable example is given by Owens (2012), who uses factor analysis to define a measure of SES, then defines "relevant" neighborhood change as those neighborhoods that experienced at least a ten percent increase in SES between successive decades[4]. Another prominent example is given by Landis (2016) uses the "double decile difference" or "3-D" method that "define SNSEC as a two or more decile changes in the median household income level of a census tract over an extended period of time". This is a useful definition because it is easy to operationalize, but it is also wanting, since two deciles is an arbitrarily-chosen threshold with no sound theoretical justification. According to Landis, the 3-D method "avoids over interpreting small changes in household incomes as indicative of more substantial neighborhood-level change. And, by using deciles (which are calculated separately for each metropolitan area and year) to compare neighborhood income levels at earlier and later points in time, it avoids the problem of having to determine precisely how much household income change constitutes substantial change."

But this explanation confuses precision with relativity; although the *value* of a two decile change is relative to a given metro, "two deciles" is nonetheless a precise quantity. Further, in sparsely populated and/or urbanizing areas, a two decile change can be caused by a small absolute change in

[4]Gentrification represents only one type of relevant neighborhood change in Owens's typology

measured variables. Put differently, the 3-D method will quickly identify a rural tract whose median income increased from $30,000 to %36,000 as having gentrified. Such a change could have been triggered by a very small change in resident population (or none at all) and likely fails to meet the conceptual definition of gentrification. Finally, a tract anywhere in the income distribution can experience a two decile change, so wealthy neighborhoods that got richer contribute to the model's notion of gentrification. To skirt these issues, analysts may wish to follow Timberlake and Johns-Wolfe (2017) who first create a composite SES variable using factor analysis, then define a neighborhood as "eligible to gentrify" if it is in the lower three quintiles of SES, and a neighborhood as "gentrified" if its SES score increases by at least twenty percent over the study period.

Another prominent example is given by Chapple (2009) who identify gentrification as "a central city neighborhood with housing price appreciation above the regional average, increase in educational attainment above the regional average, and household income at or below the 40th percentile of regional household income (roughly 80% of median income, a standard definition of low- income) in the starting year (as the process begins)" [p. 2]. As with the above, this definition of gentrification is both reasonable and convenient, but carries subjective nuance. Usefully, it expands the definition of gentrification to include demographic change, though it excludes race as a relevant criterion and defines gentrification to be possible only in downtown areas. On their face, these are all reasonable decisions, but it may also be important to consider certain factors as drivers of gentrification rather than definitional criteria. For instance, it may be more likely that downtowns will gentrify, given the legacy of spatial structure discussed above, but a growing literature also documents gentrification in the suburbs (Lung-Amam *et al.* 2019). As such, one could consider proximity to central cities as a predictor variable rather than a criterion.

A second major challenge in discrete models is the additional burden of including formal spatial terms in the regression equation. Only recently have such models been possible to estimate using modern consumer hardware because they require more intensive computational approaches to estimate their parameters (Smith and LeSage 2004), and they are more difficult to interpret (Lacombe and LeSage 2018). Empirical examples of spatial discrete linear models include LeSage *et al.* (2011), Marsh *et al.* (2000), Wang *et al.* (2015) Arima (2016), though none have yet been operationalized to study gentrification.

Transition & Sequencing Models

Transition models assume the perspective that a neighborhood's history is indicative of its future, and that the future is predictable from either short-term knowledge of the neighborhood's recent transitions, or more holistic depiction of the neighborhood's medium-term trajectory. Unlike the linear modeling approach, transition models do not attempt to explain the process of gentrification or describe which variables correlate with its presence. Instead, they focus on the antecedents of certain neighborhood transitions. Put differently, transition and sequence models identify short or long-term trajectories of neighborhood change by focusing on prediction and temporal pattern recognition rather than covariates that plausibly describe why neighborhood change occurs. Analytical strategies that adopt transition and sequence approaches today align closely with the Chicago School perspective in that neighborhoods are considered discrete containers and the process by which neighborhoods adopt and discard different discrete labels is conceived as social succession (Delmelle and Thill 2014, Delmelle 2019). The strict Chicago School interpretation is not required, however. Indeed, the earlier quote from Marcuse (1993) makes this case succinctly: we assume that neighborhoods tend toward a handful of prototypical compositions, but the physical layout need not follow the concentric rings pattern of early Chicago to nonetheless display tendencies of spatial succession.

The empirical strategy for constructing transition and sequence models is to collect neighborhood-level housing market and demographic characteristics (typically census data at the smallest geographic scale available) and use them to define a set of discrete neighborhood types or labels based on groups of neighborhoods that share similar characteristics. If analysts define gentrification as a change in a single variable, this discretization can be simple, such as quantization of median household income. If an analyst desires a more complex, multivariate definition of gentrification, then she could build a geodemographic typology as an intermediate data model (Singleton and Longley 2009, Singleton and Spielman 2014). Geodemographics leverage cluster analysis to assign neighborhoods into similar groups, then describe those groups according to the average or prevailing characteristics that distinguish each type. Examples of geodemographic labels include "soccer moms" or "heartland communities"[5], each of which is designed as shorthand to evoke a particular demographic mix. Once an analyst has identified k neighborhood types, neighborhood change is conceived as a transition between two types and models proceed by examining either short term (i.e. year-to-year or decade-to-decade) transitions between types (Delmelle 2016, 2017), or whole sequences in which a temporal series of neighborhood types is arranged in order and analyzed as a complete history, for example by using sequence analysis to find groups of neighborhoods who have experienced similar historical trajectories (Delmelle 2015, Dias and Silver 2019, Kang *et al.* 2020).

In the former, the universe of potential neighborhood change is represented by the $k \times k$ transition matrix, and gentrification analyses proceed by identifying which transitions in the matrix meet a conceptual definition of gentrification. On one hand, this offers a richer possibility of definitions used to define gentrification. Neighborhood racial turnover can be identified separately from housing stock upgrades, and transition models can help provide perspective on which pieces of the gentrification process (i.e. physical upgrading, racial turnover) unfold prior to others. A major downside, however, is that analysts are still required to make a series of subjective decisions, such as the appropriate level of k, the collection of variables chosen to encapsulate the gentrification process, the clustering algorithm used to identify neighborhood types, etc. While there are statistics and heuristics available to help guide some of these decisions (i.e. measures of cluster fit to help determine the optimal k), others are subject to many of the same subjectivity critiques of linear models described above.

In the latter, gentrification is identified similarly, by choosing which neighborhood types represent neighborhoods "eligible" to gentrify, choosing which types represent "gentrified" or "post-gentrified", and articulating the pathways that neighborhoods took prior to their gentrification transformation. Zeroing in on these pathways help identify neighborhoods whose current trajectories are similar to other neighborhoods that have already gentrified providing some forewarning into the process. The drawbacks of sequence-based approaches are that they do nothing to *explain* the process of gentrification or its antecedents, and that historical patterns may not necessarily be

[5] https://www.esri.com/en-us/arcgis/products/tapestry-segmentation/overview

the best predictors of gentrification in the future, particularly if the process is influenced by external political forces (to which these models are blind).

Simulation Models

Simulation models are designed to study intricate and large-scale systems where many components interact with one another. They may include several models "stacked" on top of one another and whose predictions feed back into one another in successive time steps. In urban social science, simulation models typically represent individuals and households interacting (e.g. buying property, traveling to work, etc.) in a large spatial area like a metropolitan region. For this reason, simulation models are a natural fit in many ways for gentrification scholarship, because they can facilitate representation of multiple simultaneous components of the gentrification equation (e.g. the housing market, the [changing] location preferences of different groups of residents, or the policy effects of land-use designations). And indeed, this flexibility is why simulation models are used classically to represent complex processes like urban growth (Clarke *et al.* 1997, Maria de Almeida *et al.* 2003, Clarke *et al.* 2007, Clarke and Johnson 2020), or feedback between housing markets and transportation systems (Waddell 1998, 2002, Waddell and Ulfarsson 2004, Waddell *et al.* 2010). The premise of these models, which include Cellular Automata (CA), agent-based models (ABM) & microsimulation, is that pathways of neighborhood change such as gentrification are complex, bottom-up processes that often display properties like "emergence" and fractal self-similarity patterns, which can be difficult to predict at the system-level without modeling the interaction of the system's constituents (Batty 2005, 2013). "The bottom up approach represents the city as a potentially infinite collective of simple elementary units whose interactions define the dynamics of the urban system at large" (Benenson 1998). Depending on the operationalization of these models, bottom-up approaches can embody systems of persons, households, employers, or any combination thereof. Although grouped collectively under the simulation model banner, CA, ABM and microsimulations are distinct methodologies with different formulations and model structures.

Agent-Based & Cellular Automata Models

Agent based models define a set of rules for individual behavior, then construct a computational model with many agents who abide by those rules and interact with one another. Both the agents and the behavior rules in an ABM can be exceedingly simple but nonetheless demonstrate complex patterns that mimic human behavior. The classic example is given by Schelling (1971), whose simple model of residential segregation demonstrates that large urban areas can become deeply segregated even if individual households have only a small preference for same-race neighbors. The genius of Schelling (1971)'s model is its simplicity; the stylized model does not need perfect representation of human behavior to reveal stark patterns that emerge from social systems. Put differently, ABMs can provide unique insight into systemic patterns even if agents are conceptually simple and seeded by a small set of behaviors. A particular drawback of ABMs is that they can be difficult to program and calibrate, often requiring a considerable amount of computer science knowledge, although platforms like NetLogo and the increased educational emphasis on programming languages is helping to reduce this barrier. Agent-based models have been used to study social dynamics and neighborhood change in urban settings for decades, but are only now becoming more widespread and applied more specifically in gentrification research (Benenson *et al.* 2002, Benenson 2004, 2012, Jackson *et al.* 2008, Eckerd *et al.* 2019, Roy and Lees 2020, Tomasiello *et al.* 2020).

At a high level, cellular automata (CA) are a special case of an agent-based model where the agents are represented as cells on a two-dimensional lattice. In practice, this means the literature often uses "agent-based" when referring to models that simulate the actions of individual entities, such as a person or household, whereas "cellular automata" typically refers to models that simulate the actions of different parcels of land. In more complex models, this distinction becomes difficult to disentangle because a single model could include the interactions among both individual households and units of land. Simulations with both agent-based and cellular automaton components are often labeled multi agent systems (MAS), and, examples such as Torrens and Nara (2007), Sabri *et al.* (2012), and Liu and O'Sullivan (2016) articulate convincing examples that combine both approaches for studying gentrification.

Although they can be difficult to construct, ABMs and CAs have tremendous potential to offer insight in gentrification research. Because they are built from the bottom up, simulation models avoid many of the definitional complexities of models discussed in earlier sections, because there is no need to define precisely which variables and at which thresholds gentrification occurs. Instead, models are treated as experiments in social systems, and they can be used to test different hypotheses regarding the emergence of gentrification. A particularly useful example is Liu and O'Sullivan (2016), who construct a multi-agent system to test three distinct hypotheses regarding the emergence of gentrification and the supply and demand pressures underlying it. Other examples such as Tomasiello *et al.* (2020) show that ABMs can be useful for policy analysis in addition to hypothesis formulation and exploration. Finally, an important benefit of CA and ABM is that spatially-explicit constraints or considerations can be added to any level of the model with ease.

Microsimulation Models

Microsimulation models are similar to ABMs and CAs in their consumption of data and computational resources, but function in a slightly different fashion. "The defining feature of spatial microsimulation is that the 'environment' is defined in predominantly geographical terms: the individuals are allocated to small parcels of land which affect their characteristics and inferred behaviour" (Lovelace and Dumont 2016). A canonical example in modern urban analysis is the UrbanSim platform (Waddell 2000, Patterson and Bierlaire 2010) which is used in many operational contexts at metropolitan planning organizations to help model housing markets and transportation systems. Although there is variation in model implementation, an UrbanSim model generally consists of a study area populated by households and individuals. A hedonic price model simulates the affordability of different housing units, and a discrete choice model simulates the willingness of different households to move into different locations (McFadden 1978, Ben-Akiva *et al.* 1997, Ben-Akiva and Bowman 1998). As the simulation steps forward in time, these models are re-estimated according to interactions that occurred during the last time step (e.g. a different allocation of households places more strain on the transportation system resulting in traffic congestion, which feeds back into the hedonic price model and the utility of each home).

As a tool for modeling urban real estate markets, software like UrbanSim is arguably ideally suited for modeling gentrification patterns into the future, but there have been no published attempts to do so. Part of the reason likely stems from the difficulty of adequately modeling the segregation tendencies of different racial and income groups. Further, it can be difficult to incorporate critical features of the real estate market that help drive residential inequalities such as information asymmetry, marketing, and predatory lending practices. These difficulties aside, microsimulation remains an extremely promising frontier for gentrification research. In addition to data challenges, microsimulation models can also have difficulty incorporating formal spatial elements into their framework. For example, Lovelace and Dumont (2016) articulates main assumptions underlying all spatial microsimulation models:

1. The individual level microdata are representative of the study area.
2. The target variable is dependent on the constraint variables and their interactions in a way that is relatively constant over space and time.
3. The relationships between the constraint variables are not spatially dependent.
4. The input microdataset and constraints are sufficiently rich and detailed to reproduce the full diversity of individuals and areas in the study region.

Particularly notable is assumption three, which is often violated in practice. Recent work continues to address this critique, however, and demonstrates that spatially-explicit models can be incorporated into microsimulation frameworks like UrbanSim in both the hedonic estimation (Löchl and Axhausen 2010) and in the location choice estimation (Zhou *et al.* 2016).

CONCLUSION

This chapter makes the case that the spatial analysis of gentrification is hard work. While there are several modeling strategies available to scholars today, adopting any of them requires formalizing the concept of gentrification in ways that unavoidably simplify a complex social, economic, political, and geographic process. Together, each of the methods described above provide insight into a different part of the gentrification process. Linear modeling approaches are particularly useful for policy development since they excel at isolating individual relationships. The drawback is that they are reductive and focus on certain relationships at the exclusion of others. Transition and Sequence approaches are particularly useful for forecasting and exploring neighborhood stability since they excel at examining neighborhood histories. The drawback is that they are blind to factors external to each neighborhood's longitudinal history and have difficulty incorporating formal spatial terms. Simulation models are particularly useful for hypothesis generation and testing interactions among different systemic components. The drawback is that they are data voracious, are often difficult to interpret, and can generate unpredictable results based on malformed assumptions.

Regardless of the modeling framework chosen by an analyst, a number of challenging conceptual issues remain facing gentrification researchers. Chief among them is articulating a shared and precise definition of the term "gentrification." While commonly understood and nearly 70 years old, "gentrification" carries a variety of meanings that makes it difficult to quantify and model. Further definitional issues include the specification of eligibility (can any neighborhood gentrify? And if not, which can? And what variables define their eligibility?). A final piece of the conceptual puzzle is the relationship between gentrification and displacement, both physical and cultural. There is no scholarly consensus on whether gentrification without physical displacement can actually be captured with traditional data sources and whether cultural displacement itself constitutes gentrification in the whole.

Moving forward, the near future of gentrification scholarship has several promising avenues. The rise in both computational power and programming literacy in recent years promises important advances in methodological development, model complexity, and data consumption. The increasing diversity of computational scholars will also help shape gentrification research into the future, as computational models slowly move away from the exclusive domain of white male academics. New data sources also offer potential pathways forward, as data with higher temporal resolutions and those from novel sources increase in availability. Exponential growth in the variety and penetration of sensor devices in today's urban fabric mean that there are many more ways to collect information from passive devices (as opposed to large-scale surveys like the census). Urban sensor networks, data mining and crowdsourcing may all contribute in this regard, but each also carries an additional set of concerns related to representativeness, inclusion, and accessibility (O'Brien *et al.* 2015, Kontokosta *et al.* 2016, Bader *et al.* 2017).

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