Spatial Dynamics and Space-Time Data Analysis

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Abstract

This chapter provides an overview of spatial dynamics in the field of regional science. After defining the context of spatial dynamics and the alternative conceptualizations of space and time, the chapter surveys the various areas of substantive interest where spatial dynamics come to the fore. A second focus is on the methodological and technical issues surrounding the methods of space-time data analysis. Here the emphasis is on exploratory methods for space-time data focusing on the evolution of spatial patterns as well as the identification of temporal dynamics that cluster in space.

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69.1 Introduction

All human activity happens somewhere in space and time. As a consequence, spatial dynamics and space-time data analysis are of interest across a wide array of cognizant fields. Regional science is no exception as the consideration of the spatial and temporal domains in the theoretical and empirical analysis of socioeconomic phenomena is now a central theme in the discipline.

There are a number of forces that have given rise to this prominence. The first is technological in nature and reflects the increasing availability of longitudinal spatial data sets which have been made possible by the rise in geospatial technologies such as Global Positioning Services (GPS), network sensors, and areal photography.

The second development is theoretical in nature and reflects a shift in the focus of substantive theory from an initial view of independent agents operating in a spaceless world to one where geographical space becomes a key dimension of the underlying theory. The rise of spatial economics and the new economic geography are emblematic of this phase, which perhaps was prematurely labeled as "space: the final frontier" (Krugman 1998).

More recently, however, the frontier has been expanded by the recognition that in order to posit causal relationships, both the "where" question and the "when" question need to be addressed (Cressie and Wikle 2011). In this sense space-time is seen as the next frontier. Similarly, Goodchild (2008) sees spatiotemporal concerns as one of the key challenges facing the development of future GIS research. As regional science has increasingly adopted methods from geographical information science, it too faces these newly emerging challenges.

This chapter provides an overview of spatial dynamics in the field of regional science. After defining the context of spatial dynamics and the alternative conceptualizations of space and time, the chapter surveys the various areas of substantive interest where spatial dynamics come to the fore. A second focus is on the methodological and technical issues surrounding the methods of space-time data analysis. Here the emphasis is on exploratory methods for space-time data focusing on the evolution of spatial patterns as well as the identification of temporal dynamics that cluster in space.

69.2 Spatial Dynamics in Regional Science

To situate the discussion, it is important to first consider the different ways that space and time, as well as spatial dynamics, have been conceptualized in practice. Both space and time have been viewed in a variety of ways, which makes the consideration of space-time even more complex.

From a geographical perspective, two different conceptualizations of space have been used: the object and field views. In the former, the world is seen as populated by discrete homogeneous units such as factories, homes, roads, lakes, and rivers that are located using some form of geographical coordinate system. Often these are represented using a vector data model that relies on points, lines, and polygons.

Alternatively, in a field-based ontology, the focus is on the spatial variation in some phenomenon (such as temperature, risk exposure, or elevation) across space that can conceptually be observed at any location and is thus spatially continuous. For fields, a raster data model is adopted where pixels, grid cells, or voxels are used to exhaust space. Conventionally, the object view has been dominant in regional science given the focus on macro-spatial economic, demographic, and social phenomena.

In a similar way time has been treated as both discrete and continuous in regional science. By and large the former perspective is more commonly encountered, and this is in large part due to practical considerations related to the way data series are recorded. At the same time, work on continuous-time models has remained largely theoretical with emphases on understanding the dynamic trajectories following from various forms of growth and interaction specifications.

Consideration of the discrete versus continuous categorization of space and time gives rise to a four-way classification. By far the most commonly employed classification in regional science is the discrete-space, discrete-time classification, where, for example, space is organized as areal units (states, provinces, counties) and time is measured on an monthly, quarterly, annual, or decadal frequency. Although this is the dominant approach, exceptions can be found. The work by Arbia and Paelinck (2003) on regional convergence is an example of a discrete-space, continuous-time approach. Conversely, in Duranton and Overman (2008) the focus is on the distribution of individual firms over a continuous space but in discrete time. Finally, the theoretical work of Fujita et al. (2001) specifies models for optimizing agents in continuous time and continuous space.

The intersection of space-time provides a mechanism to move beyond the traditional cross-sectional focus that has long dominated empirical work in regional science. The estimation of econometric relationships using cross-sectional data rests on the assumption that the underlying process has reached a state of equilibrium. At the same time, however, many of the phenomena of interest to regional science are often viewed from an adjustment or disequilibrium perspective. Methodologically, the latter requires space-time data in order for empirical investigation to be possible.

Along with the discrete versus continuous view of space and time, existing work in regional science can also be characterized according to the relative dominance of one of these dimensions. For example, work in spatial econometrics and exploratory spatial data analysis has been predominately concerned with the analysis of spatially referenced data at one point in time. Here the spatial dimension is central, while the temporal dimension is ignored or radically reduced to $t = 1$. These could be referred to as large n, extremely small t type studies. In contrast, there are studies of single regions where the emphasis is on the dynamic behavior of the individual regional economic or demographic system as in the case of early work on single-region macroeconometric models (Bolton 1985). These are extremely small $n = 1$, large t-type studies where the time series dimension is exploited to parameterize models for a small number of regions.

More data rich studies arise when multiple regions and time periods are analyzed. Prominent examples of large n small t type studies would include most β-convergence studies where the growth rate over two points of time is analyzed for a large set of n regions (Rey and Le Gallo 2009). Further distinctions must be drawn between studies that involve multiregional versus interregional analysis. In the former multiple regions (i.e., $n > 1$) provide an increased sample size for model parameterization, but the regions themselves may not interact. By contrast, interregional models explicitly incorporate interactions between the regions. This provides for further differentiation between dynamic processes and spatial processes. A dynamic process is one that transitions over time, for example, in the study of regional business cycles, a focus on the characteristic of a particular region's cycle behavior. A spatial process is distinct from a temporal process in that the former does not act on a single location but involves interaction across different locations that transpire over time.

Spatial dynamics pertains to a dynamic process that is spatially dependent (Irwin 2010). Spatial dynamics are relevant to many areas of applied and theoretical regional science. A prominent substantive motivation for spatial dynamics is in the study of optimal currency areas (OCA). One of the key criteria for a group of economies to be a candidate for an OCA is that their business cycles display a high degree of co-movement or synchronization so that a single monetary policy could be effectively employed (Partridge and Rickman 2005). An additional example is the related literature that attempts to identify the leading-lagging relationships between pairs of regional economies using various Granger causality and vector autoregressive models (LeSage and Reed 1990).

A further distinction arises from a consideration of two related, but distinct, concepts: comparative statics versus spatial difference. In comparative statics, a system is compared at two, or more, points in time to identify shifts or changes in the state of the system in discrete time, such as movements of, or along, a supply or demand curve. In a geographical context, the analogy is one of spatial difference – that is, comparing the articulation of a process at two or more different locations, but at the same moment in time.

In practice the researcher is faced with the similar challenge of trying to make inferences about the process that may be responsible for the temporal change or spatial differences observed. Two broad strategies have been adopted here. The first relies on so-called pattern models which can be viewed as analogous to a reduced form model in that they focus on describing the evolution of patterns which reflect the operation of some underlying process. Alternatively process-based models are akin to a structural form in that model parameters are tied directly to behavioral units in the underlying substantive theory for the process under study. A key challenge to linking substantive theory to space-time patterns is that substantive theories are often not detailed enough to make this linkage.

Not only do the different conceptualizations result in different representations of phenomena in space and time, but they tend to be more prevalent in certain types of space-time domains and can also require different analytical and statistical methods as is explored below.

In addition to these different conceptual frameworks for understanding space-time data analysis, one can also approach the topic from the different space-time domains that appear in substantive studies. Goodchild (2008) has offered a taxonomy of space-time domains that considers five different areas of inquiry.

Tracking the movement of individuals within a city using GPS devices provides a new way to understand human activity patterns within an urban context. These can be seen as modern extensions of foundational work of Hägerstrand (1970) formalization of tracking individual activity spaces as space-time prisms. In the current implementation, the masses of data generated from real-time network sensors, RFID, GPS, and social media postings (i.e., Twitter) have generated an active literature developing interesting new ways to analyze such data, and these methods are driving new innovations in transportation planning.

The second domain for space-time analysis concerns change detection or so-called snapshots. Time series of remotely sensed images of urban areas (Yang et al. 2003) can be used to analyze changes in urban morphology as well as trends in rural–urban land-use conversion that are becoming increasingly important to the understanding of coupled human and natural systems. Formal modeling of the evolution of such spatial patterns has been a central concern in health and environmental applications (Abellan et al. 2008; Wikle and Cressie 2000).

Polygon coverage, the third space-time domain, focuses on changes in attribute values for areal units over time. As we return to below in Sect. 69.3, a rich set of methods has been suggested to characterize these space-time dynamics. An important challenge in the polygon coverage domain arises when the reporting units and boundaries as well as the attribute values change over time. We return to this challenge below.

The fourth space-time domain shifts the focus to the raster data model and employs cellular automata (CA) models in which a set of states for each raster cell are specified together with a set of rules that determine the state transitions through time. Emblematic of this line of inquiry is the work on urban development (Clarke et al. 2007). Closely related to CA models are agent-based models in which space is viewed as populated with discrete agents, which could be either geographical features or actors, that are embodied with rules governing their behavior.

The final space-time domain concerns events and transitions. The classic example is Minard's map in Fig. 69.1 depicting Napoleon's march and retreat on Russia. This visualization combines spatial and temporal dimensions along with the depiction of temperature and information on the size of Napoleon's army in a highly complex representation. Although to date it has not been done, there is no reason why such methods could not be applied to events in regional science, such as business cycles or interstate migration patterns. Currently the business cycles are studied at two spatial scales, with attention at one level on the individual business cycles of states and how those cycles may be correlated or synchronized with the cycles of other states, or how they may be related to the cycle at a higher

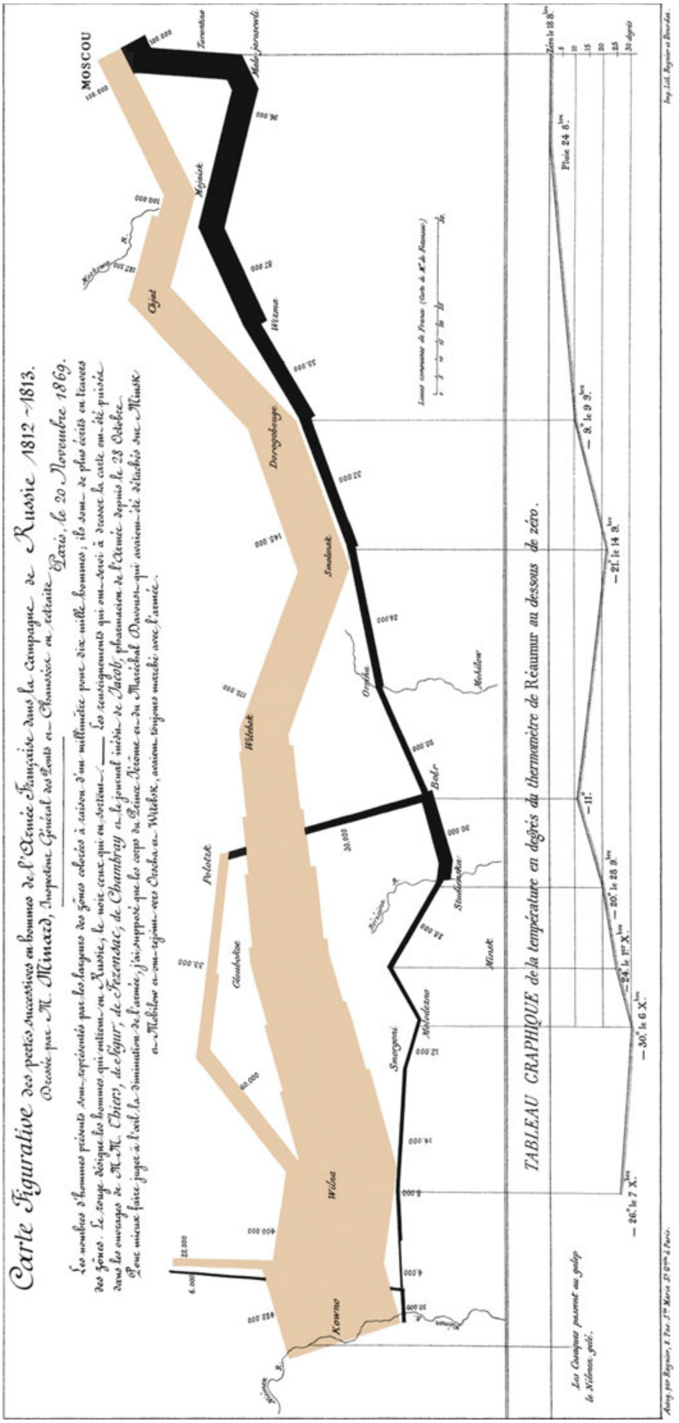

Fig. 69.1 Minard's map

spatial scale, say nation. The event framework provides the potential for integrating these seemingly distinct cycles into a unified cycle that may be articulated across space at different points and time.

The empirical analysis of each of these space-time domains relies on data that is organized in some space-time framework. Spatial data has conventionally been organized along the following taxonomy. Point data are used to represent the locations of individual events and the interest rests on the resulting spatial pattern of those locations together with any additional attribute data about the events – as is the case for marked point patterns used in the study of firm location and retail competition.

Geostatistical data arises when observations at fixed locations are obtained on some spatial phenomena that conceptually varies continuously over some spatial domain. Unlike point patterns, where the interest is on the pattern of the locations, in geostatistical data the focus is on the variation in the attribute across the fixed observation (or sample points), and models of this variation are used to develop predictions of the phenomena at target sites.

Arguably the most commonly encountered type of spatial data in regional science is lattice or areal unit data. Here space is viewed as partitioned into discrete areal units, and variables are measured for each of the units. The focus is on understanding the variation in the attribute across spatial units; however, unlike the case of geostatistical data, interpolation or spatial prediction is meaningless since the areal units exhaust the spatial domain.

Although these three types of spatial data form the core of the taxonomy in most spatial statistics texts, there are other types of spatial data that are commonly encountered in regional science research. Chief among these is network data which is prominent in many transportation studies. Network data are also encountered in various optimization models, and network concepts play a central role in defining spatial relationships between areal units in the analysis of lattice data. Networks are increasingly being used to model social interactions as in the growing literature on social networks with interest in embedding these social networks in geographic space.

Space-time data opens up a number of important ways to address fundamental problems that confront researchers working in either a cross-sectional or time series framework. In spatial analysis there has long been tension between so-called complete spatial heterogeneity where each location can be seen as unique, and more general lawlike constructions that apply in all locations. From a data analysis perspective, the former is a nonstarter since insufficient degrees of freedom are available – in a sense the number of parameters grows with the number of areas under consideration since each place is unique and requires its own parameter values. Enforcing spatial homogeneity is one way to reduce the parameter space and make inference tractable. This comes at a cost of course of imposing uniformity on the processes over space.

With space-time data there is more flexibility in the types of specifications that could be considered. In cases where a long enough time series is available, the formally intractable problem of allowing each place to have its own model as it were can now be relaxed. Indeed, certain models adopted in practice actually require long time series for their use, as in the case of the Hildreth Prescott filter used to study regional business cycle behavior. Use of the HP filter with shorter series is known to introduce distortions (Partridge and Rickman 2005).

While the temporal dimension allows for a relaxation of the spatial homogeneity assumption, treatment of spatial dependence in a dynamic context must also be considered. Rather curiously, most approaches that consider spatial dynamics assume that the form of the interaction process is stable over time. In other words the strength of the spatial dependence is often held constant. For example, work on the identification of leading and lagging regions employs Granger causality type frameworks that exhaust the temporal dimensions to estimate the nature of the dynamic relationships between each pair of economies. The identified temporal lags are then assumed to hold over the entire time series.

While this approach does allow for spatial variation in the degree of spatial dependence (since each pair of economies can have distinct lead-lag relationships), it comes at a cost of assuming the spatial dynamics are temporally invariant. Such an assumption may be overly restrictive, since research in the area of regional income convergence (Rey and Le Gallo 2009) and business cycles (Partridge and Rickman 2005) is suggesting that the strength of spatial interaction in regional macro-series is often not constant over time.

Research that is extending these different types of spatial data supports and the associated analytical methods to include a temporal dimension is only at very embryonic stage of development. Most of the work on developing analytical methods for space-time data in regional science has focused on areal unit or polygon data and has adopted exploratory focus. An overview of the key directions in this regard is provided in the remainder of the chapter.

69.3 Exploratory Space-Time Data Analysis

Methods for exploratory space-time data analysis for lattice data can be organized in a number of ways. The first is to make a distinction between those that have their origins as cross-sectional methods that have been extended to incorporate a temporal dimension. Alongside of these are methods that were originally temporal exploratory data analysis (EDA) methods that were modified to incorporate space. The former group of methods can be viewed as studying the evolution of spatial patterns in time, while the latter switches the perspective to put temporal dynamics into space. In other words, the first group of methods views the spatial dimension from a temporal perspective, while in the latter the spatial signature of dynamic patterns becomes the focus.

To distinguish between these two sets of methods in what follows the acronym, ETSDA is used for the approaches that have their origins in the temporal domain but have been extended to incorporate space, while ESTDA is used for the originally spatial methods that have been extended to incorporate time. Although the perspectives are distinct across these two groups, in both cases there are methods that are numerical and sometimes coupled with novel visualization methods which are also discussed.

69.3.1 ETSDA Methods

A main branch of the ETSDA literature begins with discrete Markov chains. A Markov chain is a particular type of dynamic stochastic process $\{X(t)|t \in T\}$ that satisfies the following condition. For any $t_0 < t_1 < \ldots < t_n$,

$$\begin{aligned} &P[X(t_n) = x_n|X(t_{n-1}) = x_{n-1}, X(t_{n-2}) = x_{n-2}, \ldots, X(t_0) = x_o] \\ &\qquad = P[X(t) = x_n|X(t_{n-1}) = x_{n-1}] \end{aligned} \tag{69.1}$$

This condition implies that the conditional distribution function of $X(t_n)$ only depends on $X(t_{n-1})$. In other words, given the present state of the process, the future state of the process is independent of the past.

A discrete-state Markov process is one in which the random variable X takes on one of n unique values. Such a Markov process is known as a Markov chain in which case Eq. (69.1) takes the following form:

$$P[X_k = j|X_{k-1} = i, X_{k-2} = n, \ldots, X_0 = m] = P[X_k = j|X_{k-1} = i] = p_{i,j,k} \tag{69.2}$$

where $p_{i,j,k}$ is the state transition probability reflecting the conditional probability that the process will be in state j at time k given that it is in state i at time $k-1$. For a time homogeneous Markov chain, the transition probabilities are time invariant, which implies the following:

$$P[X_k = j|X_{k-1} = i, X_{k-2} = n, \ldots, X_0 = m] = P[X_k = j|X_{k-1} = i] = p_{i,j} \tag{69.3}$$

These transition probabilities satisfy the following conditions:

1. $0 \le p_{i,j} \le 1$
2. $\sum_j p_{i,j} = 1, \forall i, i = 1, 2, \ldots, n.$

Given the n states, the transition probability matrix is

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,n} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n,1} & p_{n,2} & \cdots & p_{n,n} \end{bmatrix} \tag{69.4}$$

Estimation of the transition probabilities can be based on maximum likelihood assuming time homogeneity:

$$\hat{p}_{i,j} = \frac{v_{i,j}}{\Sigma_j v_{i,j}} \tag{69.5}$$

where $v_{i,j}$ is the number of observed chain transitions from state i to state j.

Markov chains have played a central role in the literature on regional income convergence, following the pioneering work by Quah (1993). The typical approach is to discretize the distribution of per capita incomes or gross regional product measured over n regions into k classes in each time period, giving the discrete distribution π_t. Next, transition probabilities across each of the these k classes of this distribution are formalized in a $k \times k$ matrix of transition probabilities:

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,k} \end{bmatrix} \tag{69.6}$$

where $p_{i,j}$ is the probability of an economy moving from class i of the distribution at time t into class j in period $t + 1$. Two key assumptions are often relied upon in regional convergence applications of Markov chains. The first is that temporal homogeneity holds

$$P_t = P_{t+1} = \ldots = P_{T-1} = P_T \tag{69.7}$$

The second assumption is that the chain is first order:

$$P(X_t = j | X_{n-1} = k, \ldots, X_0 = l) = P(X_t = j | X_{n-1} = k) \tag{69.8}$$

This means that the only relevant information is the state of the chain in the preceding period – the state of the chain from more distant periods has no effect on future dynamics.

These two assumptions allow a mapping of the distribution between any pair of periods:

$$\pi'_{t+1} = \pi'_t P \tag{69.9}$$

or, more generally,

$$\pi'_{t+b} = \pi'_t P^b \tag{69.10}$$

A final assumption that is also sometimes made is that the chain is irreducible. Formally, for each pair of states there is some length of time $v_{i,j}$ where

$$\pi_{i,j}^{v_{i,j}} > 0 \; \forall \; i, j \tag{69.11}$$

meaning that movements between any pair (i, j) of states in the distribution are possible over some time horizon.

Homogeneity and irreducibility combined implies that the chain will have a steady-state distribution π_* where

$$\pi'_* = \pi'_* P \tag{69.12}$$

with

$$\Pi_* = P^{v}_{v\to\infty} \tag{69.13}$$

The rows of the matrix Π_* will be identical and represent the long-run or ergodic income distribution π_*.

In the convergence literature this framework has been used to study a number of issues, including the time required to achieve convergence, the extent of polarization, and the degree of intradistributional mobility (Rey and Le Gallo 2009). In addition to regional convergence, Markov chains have seen application in the area of city-size distributions (Black and Henderson 2003). It should also be noted that approaches such as the stochastic kernel which is the continuous equivalent of the transition probability matrix that overcomes some of the inherent shortcomings of a discrete-space setup have been suggested (Fischer and Stumpner 2008).

The classic Markov framework applied above has been extended to incorporate a spatial dimension in a number of ways. The first is through regional conditioning (Quah 1993) in which the distribution of neighbor-relative incomes is mapped into the distribution of nation-relative incomes, with the former obtained by normalizing incomes relative to the average of those of a region's geographical neighbors:

$$yr_{i,t} = \frac{y_{i,t}}{\sum_j^n w_{i,j} y_{j,t}} \tag{69.14}$$

where $y_{i,t}$ is income in region i in time period t and $w_{i,j}$ is an element of a row-standardized spatial weights matrix expressing the neighbor relation between each pair of economies. The national-relative distribution is defined using

$$yn_{i,t} = \frac{y_{i,t}}{1/n \sum_j^n y_{j,t}} \tag{69.15}$$

The regional conditioning allows for an analysis of the degree of spatial clustering in the regional income distribution since the two discrete relative distributions (69.14) and (69.15) should be independent if incomes were randomly distributed in space. This would be reflected in a diagonally dominant transition matrix that maps Eq. (69.14) into Eq. (69.15).

Spatial Markov: Regional conditioning, however, considers spatial autocorrelation at one point in time, so in a sense it is not a dynamic Markov chain. Rey (2001) extended the classic dynamic Markov chain to include a spatial component through the concept of a *spatial Markov chain*. Defining Markov chains conditioned on different classes of the spatial lag (defined using the denominator of Eq. (69.14)) allows for an assessment of the role of spatial context in shaping the transitional dynamics. A growing body of research reveals contextual effects of a spatial nature as transition probabilities show clear dependence on the relative incomes of neighboring economies (Bosker 2009; Hammond 2004; Le Gallo 2004).

Spatial Rank Dynamics: A second subclass of ETSDA methods departs from the use of various bivariate correlation methods to explore dynamics. Borrowing from work on map comparisons where different types of correlation methods are applied to two contemporaneous map patterns (Lloyd and Steinke 1977), it was a short step to apply the same framework for maps from two different time periods (rather than for different variables at the same point in time).

Interestingly the methods used are classical, or spatial, correlation methods. More specifically, a traditional rank correlation statistic is applied:

$$\tau_{t,t-1} = \frac{C_{t,t-1} - D_{t,t-1}}{n(n-1)/2} \tag{69.16}$$

where $C_{t,t-1}$ is the number of concordant pairs of observations and $D_{t,t-1}$ is the number of discordant pairs between time periods $t-1$ and t. A pair of regions i, j is concordant if

$$(r_{i,t} - r_{j,t})(r_{i,t-1} - r_{j,t-1}) > 0 \tag{69.17}$$

where $r_{i,t}$ is the rank of region i in period t. If the sign of the rank difference product is negative, the pair of regions is discordant. A close inspection of this statistic reveals that the only position that matters here is the relative location of each area in the rank distribution. The geographical location of the observation is ignored.

Rey (2004) has suggested an extension of this traditional rank correlation measure to incorporate a spatial dimension. Using a spatial concordance decomposition,

$$\tau_{t,t-1} = \frac{CG_{t,t-1} + CN_{t,t-1} - DG_{t,t-1} - DN_{t,t-1}}{n(n-1)/2} \tag{69.18}$$

where the number of contiguous pairs is separated into those involving geographical neighbors (G) and those that are not neighbors (N):

$$C_{t,t-1} = CG_{t,t-1} + CN_{t,t-1} \tag{69.19}$$

and the same decomposition is used for the discordant pairs. This can be viewed in a number of ways. First, the contributions of the two types of pairs to the spatial level of concordance or discordance can be evaluated. Alternatively, the degree of rank concordance for the two sets of pairs of regions can be contrasted, by noting:

$$\tau_{t,t-1} = \omega_G \tau_{G,t,t-1} + \omega_N \tau_{N,t,t-1} \tag{69.20}$$

where ω_G is the share of all pairs that involve geographic neighbors and

$$\tau_{G,t,t-1} = \frac{CG_{t,t-1} - DG_{t,t-1}}{\omega_G n(n-1)/2} \tag{69.21}$$

This provides insight as to the role of spatial dependence in the overall degree of temporal rank concordance. By contrasting the degree of rank correlation for neighboring pairs of regions with that of geographically separated pairs, the degree to which distributional mixing is spatially clustered can now be estimated.

69.3.2 ESTDA Methods

For ESTDA methods the point of departure is a method that was originally developed for cross-sectional analysis. Typically this takes the form of a method designed to detect spatial autocorrelation, either as a global or local form. From here, a dynamic component is added to enable the analysis of spatial dynamics. A common strategy is the repeated application of Moran's I to a temporal sequence of measurements on a variable for regions. Moran's I in period t is given as

$$I_t = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} z_{i,t} w_{i,j} z_{j,t}}{\sum_{i=1}^{n} z_{i,t}^2} \tag{69.22}$$

where $S_0 = \sum_{i=1} \sum_{j=1} w_{i,j}$ and $z_{i,t} = y_{i,t} - \bar{y}_{i,t}$, and $w_{i,j}$ is as defined in Eq. (69.14). Examples of this approach can be found in the convergence literature where a common finding has been that time series of global Moran's I values for per capita income/product display significant positive spatial autocorrelation over time but also the strength of that spatial clustering exhibited substantial temporal variation (Rey and Le Gallo 2009).

The same comparative static design has also been used to explore how local measures of spatial autocorrelation change over time. In a cross-sectional setting, local measures provide indications of departures of the overall pattern of global spatial dependence or allow for the detection of spatial outliers, hot spots and/or cold spots (Anselin 1995). In a similar vein, when extended to a space-time setting, this provides a useful complement to the comparative static analysis of global spatial autocorrelation dynamics. The focus remains on the relative stability of local spatial association patterns through time which is enabled through a comparison of a series of snapshots. The situation is more complex in the local case as now there are n values in each snapshot and there evolution over time increases the analytical demands relative to the global case in which only a single indicator is studied from a dynamic perspective.

Space-Time LISA: Closely related to the comparative static analysis of the LISA statistics is the bivariate LISA. The bivariate LISA modifies the original indicator by shifting the time period for either the variable or the spatial lag of the variable. Two possibilities exist. The first consists of a temporal lag of the spatial lag:

$$L_{i,t} = z_{i,t} \sum_{j=1}^{n} w_{i,j} z_{j,t-k} \tag{69.23}$$

which relates the value at focal unit i in period t to that observed in its geographical neighborhood k periods previously. In the second form the shift is applied to the variate:

$$L_{i,t} = z_{i,t-k} \sum_{j=1}^{n} w_{i,j} z_{j,t} \tag{69.24}$$

The two forms lend themselves to different types of questions about local spatial dynamics that relate to the form and direction of the space-time spillover or diffusion. In the first form, if positive local space-time associate was indicated, this would be consistent with inward diffusion from the surrounding units into the core focal unit. By contrast, the temporal lag of the focal unit in the second form means that any positive association revealed would be consistent with diffusion originating from that unit and spreading outward to the neighbors.

The bivariate LISA moves the ESTDA methods from a comparative static view toward an explicit consideration of spatial dynamics in the sense that the dependence between a measurement at one location and point in time is being related to a different location at a different point in time. This is an important shift because it reduces the gap between the patterns being observed and the underlying dynamic process that may be responsible for that pattern.

Nowhere is this more apparent than in the distinction between apparent and true contagions. The former arises from a spatial pattern that could be consistent with a dynamic process such as the spread of an infectious disease through contact of individuals in close proximity to one another. A single map displaying spatial autocorrelation of disease incidence would be consistent with the operation of such a process. However, there are other processes that could also give rise to the same pattern – such as when the disease incidence may be driven by environmental factors (i.e., contaminated water supplies). Based on the single map, it is impossible to identify which is the operative process.

With maps from multiple time periods, however, the possibility to differentiate between true and apparent contagions now exists. The key signature difference would be for the map pattern to change over time in the case of true contagion reflecting the transmission over space, while the area of high incidence would remain spatially fixed in the case of apparent contagion – assuming the focal source was spatially immobile.

In the bivariate LISA, outward diffusion can be represented on a scatterplot where the x-axis has the rate in an initial period and the y-axis measures the spatial lag of the rate in the future period. For inward diffusion, the x-axis has the rate in the future period, while the y-axis depicts the spatial lag in the previous period. In other words, the spatial lag is shifted either backward (inward diffusion) or forward (outward diffusion) in time to depict different forms of spatial dynamics.

There are several complications in association with this interpretation of the bivariate LISA as an indicator of spatial dynamics. One difficulty is that these patterns are also consistent with spatial dependence that is not changing over time. For example, if there was positive spatial autocorrelation that was constant over time, then a bivariate correlation of a variable at time t and its spatial lag at time $t \pm k$ are likely to be positive. Because the correlation is positive for both the forward and backward time-shift of the spatial lag, the approach would yield indications of both false inward and outward contagions, when in fact the underlying spatial dependence has been constant over time.

Directional LISA: A number of extensions to the LISA in a dynamic context have recently been suggested as ways to address these issues. The first is directional LISA that explicitly considers the movement of the LISA statistic between a pair of periods (Rey et al. 2011). More specifically, two Moran scatterplots are compared: one for the initial period (Fig. 69.2a) and one for the end time period (Fig. 69.2b). Based on these, the movement vectors are extracted to form the directional Moran scatterplot (Fig. 69.2c). The movement vectors can be either origin or destination standardized, which then permits a visualization of the direction, magnitude, and any biases in the spatial dynamics between the two periods (Fig. 69.2d).

The characteristics of these movement vectors can be summarized using several new visualization or inferential tools. For the former, a rose diagram depicts the relative frequency of movement vectors providing insights as to the concentration and potential biases of movements observed over a period (Fig. 69.2e). Coupled with this is a computationally based approach to inference in which the extent of spatial dependence in the movement vectors is tested against a null hypothesis that an observation and its spatial lag move independently over the time period.

LISA Markov: Closely related to both the directional LISA and the original space-time bivariate LISA is the LISA Markov (Rey 2001). This extends the focus to consider a sequence of moves by the local statistics, not just one period as is the case for the directional LISA. This relies on the quadrants of the Moran scatterplot which are now used to define the states for a discrete Markov chain. The four quadrants are I (H,H), II (L,H), III (L,L), and IV (H,L) with the first position indicating whether the observations are above or below the mean, while the second does the same but for the spatial lag. These four states give rise to 16 types of transitions.

The 16 transition types offer a rich taxonomy for characterizing spatial dynamics. For example, the issue of outward and inward diffusion that was encountered in the discussion of the bivariate space-time LISA can now be associated with particular moves in this taxonomy. Outward diffusion would be reflected in transitions where the spatial lag increases in value over time and the core either declines or remains high: (H,L)–(H,H) or (H,L)–(L, H). The two cases allow for a differentiation between saturation diffusion, in the former, and displacement diffusion in the latter. For inward diffusion the relevant moves

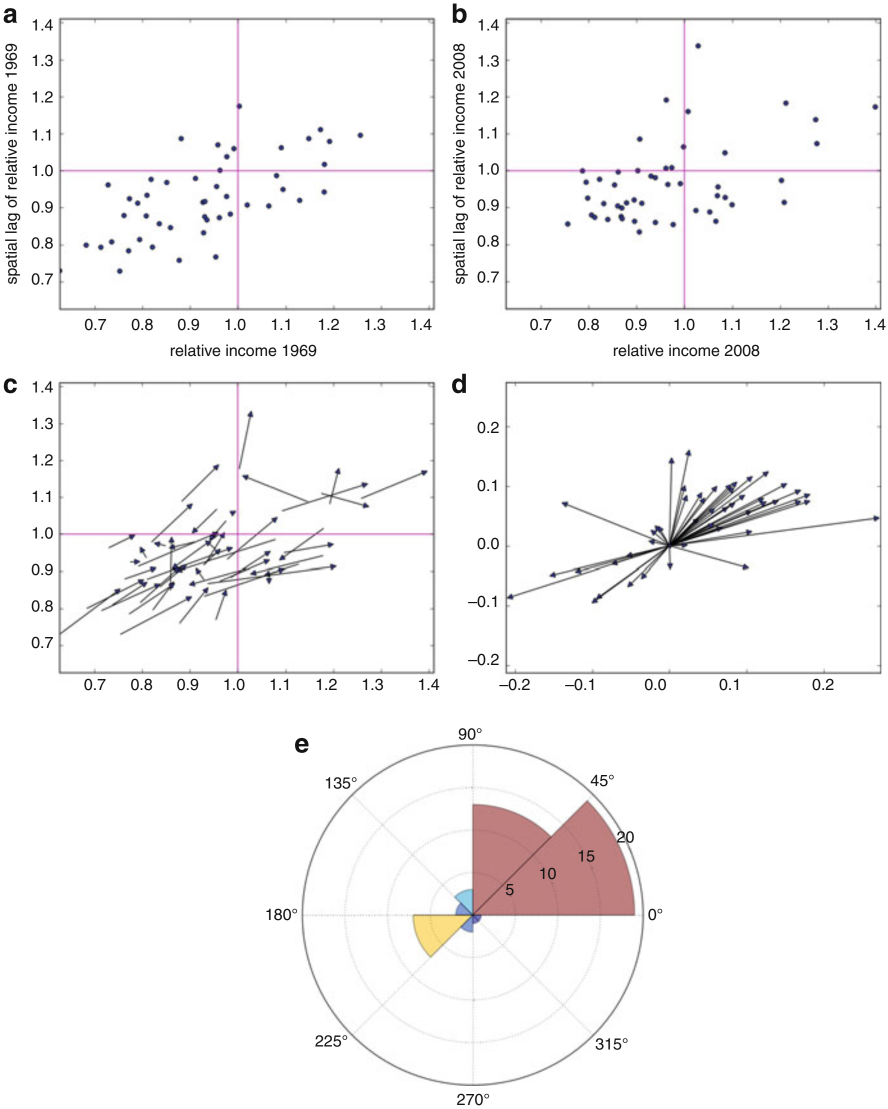

Fig. 69.2 Directional Moran scatter plots. (**a**) Moran scatter 1969. (**b**) Moran scatter 2008. (**c**) Unstandardized movement vectors. (**d**) Origin standardized movement vectors. (**e**) Rose diagram

would be (L,H)–(H,H) or (L,H)–(H,L); in either case the core increases over time, while the lag declines (displacement) or remains high (saturation).

Formal inference on these spatial dynamics has been suggested by Rey et al. (2012). The notion of a joint spatial Markov chain decomposes the spatial dynamics into two separate discrete chains, one for the original attribute and one for the spatial lag of this attribute. Each of these individual chains can occupy one of two states in a given period, either (H) or (L). Letting $P(Y)$ represent the transition probability matrix for the original attribute chain and $P(WY)$ the transition probability matrix for the spatial lag of this attribute, under a null of independence (or lack of spatial dynamics), we have

$$P(\widetilde{Y, WY}) = P(\widetilde{Y}) \otimes P(\widetilde{WY}) \tag{69.25}$$

where $\otimes$ is the Kronecker product operator.

The estimated joint transition probability matrix from Eq. (69.25) is then compared to the observed joint transition probability matrix, $P(\widehat{Y, WY})$, and a formal test of the equality of these two transition matrices can be based on large sample theory for discrete Markov chains. Rejection of the equality hypothesis means that the two chains are non-separable. In other words, the dynamic transitions of the attribute values at a given location are not independent of the transitions of the spatial lag of these values.

In addition to providing a global test of spatial dynamics, comparison of the two estimated joint transition probability matrices allows for an identification of what types of moves are over, or under, represented in the observed spatial transitions, relative to the case where the dynamics displayed spatial randomness.

69.4 Conclusion

Regional science has long considered spatial dynamics as an organizing framework from which to view different regional phenomena. Regional growth theory by definition would not exist without a space-time framing. The inverted-U pattern proposed by Williamson (1965) of regional inequality provides a specific example where the level of regional inequality is viewed through a dynamic lens. While regional growth is a process that operates over space and time, the inverted-U framework is largely a-spatial as the regions are simply observational units used to measure dispersion in incomes. The actual location of these regions and issues of spatial interactions have not given explicit empirical treatment in this framework. As Miller (2006) has argued in the context of other areas of regional science, the spatial and temporal dimensions underlying human activity cannot be meaningfully separated. By the same token, regional science cannot be separated from a space-time framework or a consideration of spatial dynamics.

With recent technical and methodological developments in the areas of space-time data analysis, the possibility now exists to extend the traditional framework to include a richer spatial dynamics component, one that allows for a tighter linkage between abstract theoretical constructs and their empirical implementation. There are also gains to be had from applying some of these new measures of space-time dynamics to summarize outcomes of other types of modeling frameworks. For example, more comprehensive summaries of the predictions from land-use change models become possible. Similarly, the growing use of agent-based models and cellular automata creates a need for efficient methods that can capture and summarize the spatial dynamics of these complex patterns generated from these frameworks.

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