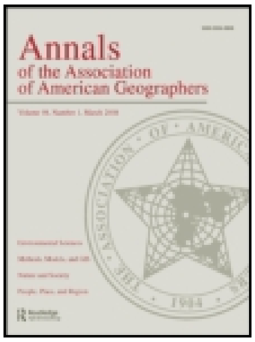

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Space–Time Analysis: Concepts, Quantitative Methods, and Future Directions

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Space–Time Analysis: Concepts, Quantitative Methods, and Future Directions

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Throughout most of human history, events and phenomena of interest have been characterized using space and time as their major characteristic dimensions, in either absolute or relative conceptualizations. Space–time analysis seeks to understand when and where (and sometimes why) things occur. In the context of several of the most recent and substantial advances in individual movement data analysis (time geography in particular) and spatial panel data analysis, we focus on quantitative space–time analytics. Based on more than 700 articles (from 1949 to 2013) we obtained through a key word search on the Web of Knowledge and through the authors' personal archives, this article provides a synthetic overview about the quantitative methodology for space–time analysis. Particularly, we highlight space–time pattern revelation (e.g., various clustering metrics, path comparison indexes, space–time tests), space–time statistical models (e.g., survival analysis, latent trajectory models), and simulation methods (e.g., cellular automaton, agent-based models) as well as their empirical applications in multiple disciplines. This article systematically presents the strengths and weaknesses of a set of prevalent methods used for space–time analysis and points to the major challenges, new opportunities, and future directions of space–time analysis. *Key Words: absolute versus relative space, review, simulation models, space–time analysis, statistical models.*

大部份人类历史所关注的事件与现象，透过运用空间和时间作为其主要的特徵面向，以绝对或相对的概念化进行描绘。时空分析企图理解何时、何地（有时是为何）事情会发生。在个体活动数据分析（特别是时间地理学）和空间面板数据分析的部分最晚近且实值进展的脉络中，我们聚焦量化时空分析。根据我们对知识网进行关键词搜索以及作者的个人档案资料所获得的七百篇以上的文章（自1949 年至2013 年），本文对时空分析的量化方法，提供了综合性的概要。我们特别凸显时空模式揭露（例如各种集群计量、路径比较指标、时空检定）、时空统计模型（例如存活分析、潜在轨迹模型），以及模拟方法（例如细胞自动机、以行动者为基础的模型），以及它们在多重领域的经验应用。本文系统性地呈现一组用来进行时空分析的盛行方法的优劣之处，并指出时空分析的主要的挑战、崭新的契机，以及未来的趋势。*关键词：绝对空间相对于相对空间，回顾，模拟模型，时空分析，统计模型。*

Durante la mayor parte de la historia humana, la caracterización de eventos y fenómenos interesantes se ha basado en el espacio y el tiempo como sus principales dimensiones, tanto en absolutas como relativas conceptualizaciones. El análisis espacio-tiempo busca comprender cuándo y dónde (y algunas veces por qué) ocurren las cosas. Dentro del contexto de varios de los más recientes y sustanciales avances en el análisis de datos del movimiento individual (geografía del tiempo en particular) y análisis de datos del panel espacial, nosotros nos enfocamos en la analítica cuantitativa del espacio-tiempo. Este artículo entrega una visión de conjunto sintética acerca de la metodología cuantitativa para el análisis del espacio-tiempo, a partir de más de 700 artículos (de 1949 a 2013) que obtuvimos por medio de una búsqueda con palabras clave en la *Web of Knowledge* [Web del Conocimiento] y en los archivos personales de los autores. En particular, destacamos el patrón de revelación del espacio-tiempo (e.g., varias medidas de agrupamiento, índices de comparación de rutas, pruebas de espacio-tiempo), modelos estadísticos de espacio-tiempo (e.g., análisis de supervivencia, modelos de trayectoria latente), y métodos de simulación (e.g., autómata celular, modelos basados en agente) lo mismo que sus aplicaciones empíricas en múltiples disciplinas. Este artículo presenta sistemáticamente las fortalezas y debilidades de un conjunto de métodos prevalentes usados para el análisis del espacio-tiempo y apunta a los principales retos, nuevas oportunidades y direcciones futuras del análisis espacio-tiempo. *Palabras clave: espacio absoluto vs. espacio relativo, modelos de simulación, análisis espacio-tiempo, modelos estadísticos.*

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Space and time are fundamental characteristics used to understand events and phenomena of interest, allowing people to make sense of the surrounding world (Cresswell 2013). Studied for millennia, space and time have often been described as the stage on which all these events and phenomena take place (Ashtekar 2006). From early civilizations to modern societies, humans have consistently viewed space and time as intimately linked and inseparable (Quespi 1994), which explains the notation *space–time* (Yuan, Nara, and Bothwell 2014). Various ontological frameworks for representing real-world entities over space and time, along with the associated epistemologies for addressing theoretical or practical issues in space–time analysis, have existed since antiquity and have become a hot research area in GIScience in the era of digital computers and big data (Kwan and Neutens 2014). In this context, the overarching goal of this article is to provide a synthetic understanding about the methodology for space–time analysis in the hope of advancing this important scientific field.

Space–time analysis, in general, seeks to answer questions of both when and where (as well as why to some extent) things occur, but the meanings of these words can vary greatly (Couclelis 1999). As Peuquet (2002) pointed out, space and time have twelve and twenty-nine separate definitions, respectively, in *Webster's New Twentieth Century Dictionary*. *When* can be defined as relative to another event (time between earthquakes), the time that it takes an event to occur (length of an earthquake), the time on the clock at which an earthquake occurs, or cyclicity related to repetition, sequentiality, or pattern over time of aftershocks (Van Fraassen 1970). *Space*[1] can be defined as the coordinates (e.g., in latitude and longitude and sometimes also in elevation) of an object or the distance[2] between objects (Van Fraassen 1970). These ambiguities have led to a rich literature on the nature of space and time in physics, psychology, cognitive science, and philosophy, seeking insights into whether space and time is a substance by itself or simply properties of some substance, whether the origin of space–time representation is constrained by objects, whether our ideas of space and time come from our perceptions and experiences of spatial or temporal relations, and so on (Janiak 2009; de Hevia et al. 2014; Yuan, Nara, and Bothwell 2014).

Various conceptualizations of space and time have arisen as a response to the fact that both are, in fact, invisible (Dainton 2001). Thinking of space as "absolute space" results in the concept of space having specific properties (Hinckfuss 1974). Space and time, in this view, are thought of as containers into which all other things occur (Dainton 2001). Newton's analysis of space and time used this conceptualization of absolute space, as he used the languages of mathematics (geometry and calculus) to describe laws of motion regarding the trajectories of moving objects in space and time. Here, space and time constitute an absolute framework through which the object moves, as the framework itself remains unchanged (Peuquet 2002).

Alternatively, the concept of relative space, proposed by Leibniz, grew as a response to Newtonian conceptions (Cresswell 2013). In relative space, space is created through the relationship between objects rather than being a preexisting container in which objects exist (Dainton 2001). In the nineteenth century, Minkowski developed the united, relativistic space–time concept, in which traditional three-dimensional geometry was extended to include time as a fourth dimension (Peuquet 2002). The relative view of space continued to be developed by scholars from many disciplines and culminated in Einstein's theory of relativity. Einstein emphasized the inseparability between space and time in his saying that "When forced to summarize the general theory of relativity in one sentence: Time and space and gravitation have no separate existence from matter" (Albert Einstein Site Online 2012). Conceptualizations of space–time have been developed at very large and very small scales in disciplines such as electronics, mechanics, and cosmology. At the human and landscape scales, space–time analysis has roots in and contributes to biology, ecology, hydrology, epidemiology, geography (especially the subdisciplines of geographic information systems [GIS] and remote sensing), and the like.

Space–Time Models in Geography

Space–time models in geography can be based on either the absolute or relative space time conception (Massey 1999). Studies using fixed coordinate systems to mark the changes in their variables (which include many of the models outlined here) employ an absolute representation, whereas studies using an object-oriented approach might be based on a relative representation (Raper and Livingstone 1995).

Geographic models of the physical environment have historically assumed a two-dimensional spatial structure of grid or vector, neglecting time as a key dimension of concern and the possibility of an integrated space–time conceptualization (Raper and Livingstone 1995). Early academic geography, as conducted by Darwin, von Humboldt, Ritter, and others, focused on places, including the physical and human differences between places. Until the mid-twentieth century, regional geographers continued with this tradition. Drawing on ideas of Kant and his fellow philosophers, regional geographers such as Hartshorne saw space and time as two key categories within which all activity occurs instead of viewing them as something to be considered in tandem. Hartshorne saw history as the discipline to address changes in time and geography as the discipline to address differences in space (Cresswell 2013).

The rise of spatial science within geography in the 1950s and 1960s signaled the entry of geographers into the era of quantitative revolution. Early models such as those by von Thünen and Christaller, however, largely ignored time or viewed it as a function of spatial variables such as distance or transportation costs. Movement and transportation, which are now concerned with time as much as space, were considered as being "effectively studied in spatial terms." This means that movement is dictated by economics: supply and demand, least net effort, and travel costs (Cresswell 2013). Time geography, an attempt to move away from the place-based aggregations and generalizations of early spatial science, arose to capture and model individual movement trajectories in both space and time (Hägerstraand 1970; Miller 2005). In formulating the research area, Hägerstraand (1970) noted that "we need to better understand what it means for a location to have not only space coordinates but also time coordinates" (9–10). At every point in space where a person exists, that person also exists at a particular point in time, which underlies the space–time cube representation[3] (Hägerstraand 1970).

Despite widespread recognition of a united space–time structure, many disciplines, in practice, have exclusively focused on adequate characterization of one at the expense of the other. Geographic space–time models often use GIS in their representation of space, and to some extent, time in a granular (contrary to continuous) space–time format (Couclelis 2010). Traditionally, GIS has represented space well using the snapshot GIS data model (Armstrong 1988) but has done a comparatively poor job at representing time (Peuquet and Duan 1995). Usually, a spatially and temporally continuous world is represented as a sequence of limited snapshots in time, and various frameworks (including data models) are presented to better track and query behaviors and interactions of discrete objects (Peuquet and Duan 1995; Yuan 1999; An and Brown 2008; Long and Nelson 2013; Yi et al. 2014).

Goals and Objectives of This Article

Given the long-standing tension between "scientific" and "humanistic" space–time conceptualizations (Travis 2014), this article focuses more on the scientific side of this concept. Even within the scientific domain, different disciplines—including but not limited to mathematics, philosophy, physics, biology, hydrology, epidemiology, electrical engineering, and geography—have developed distinct traditions of conceptualizing the relationships between space and time (Couclelis 1999). This literature review gives an overview of the breadth of space–time analysis research among numerous disciplines, before focusing on specific methodologies in geography.

There is no unanimous definition for space–time analysis, yet such analyses are used extensively across various disciplines. Here we offer a working definition: Space–time analysis is the representation (including mathematical, physical, or visual representation) of changing location in space and time of a certain phenomenon, object, process, or event of interest. The descriptive, explanatory, and predictive functions provided through space–time analysis generally seek understanding about the mechanisms behind such space–time data. Here an object could be both mobile (e.g., vehicles, persons) and immobile (e.g., land parcels, pixels) relative to the perceiver. Under our overarching goal of providing a synthetic understanding about the methodology for space–time analysis, three specific objectives are to (1) assemble and review literature from a wide range of disciplines, (2) synthesize and present the status quo of the related space–time analysis methods in these disciplines, and (3) point out promising areas of research in the future. We hope this article will be helpful to researchers in a breadth of disciplines or areas, particularly for those big data miners seeking understanding in various real (e.g., geographical systems, human–environment systems) or virtual systems (e.g., online tweet-based networks). We believe that our methodological focus will be a timely and meaningful contribution to GIScience in an era when "the availability of multi-temporal geographic data has outpaced the development of spatial-temporal analysis methods" (Robertson et al. 2007, 208).

Methods

With the preceding goal and objectives in mind, we have conducted the following three-step procedure, which aims to search articles related to space–time analysis. With the articles thus collected, we review them with a focus on the methods under which space–time analysis is conducted. Particularly, we are interested in how space and time are represented and how potential mechanisms are derived through analytical or simulation work on the corresponding space–time data.

As a first step, we performed an online search based on Web of Knowledge. We used a combination of "space time analysis" OR "space time model" OR "space time modeling" OR "spatial temporal analysis" OR "spatial temporal model" OR "spatial temporal modeling" OR "spatiotemporal analysis" OR "spatiotemporal model" OR "spatiotemporal modeling." Note that a dash between two words does not produce any differences in search outcomes—for example, spatiotemporal is considered identical to spatio-temporal. Some terms, although relevant, are excluded in the search because they are either deemed too peripheral or derivative (e.g., chronemics, sequential, timing, proxemics, movement, and motion) or not representative of the dual nature of space–time analysis (e.g., spatial analysis, spatial modeling, temporal analysis, and time series). As a huge number of papers are returned if topic is used, we limited our keyword-based search to title only.[4] To ensure that the words are shown in the title exactly as we have listed (e.g., *space time model* rather than *space ... time ... model*), we used quotation marks for each key word phrase, thereby excluding those bearing little relevance and limiting the number of returns.

In the second step, we reviewed and classified the articles assembled in Step 1 by putting a year stamp on each of them and classifying them into their corresponding disciplines based on their abstracts and key words. We then aggregated these papers from their disciplines into a broader category of social sciences, life sciences, formal sciences, physical sciences, earth sciences, and medical sciences. The term *formal sciences* is used to represent disciplines concerned with formal systems, such as logic, mathematics, statistics, theoretical computer science, information theory, game theory, systems theory, decision theory, and portions of linguistics.

Complementary to the search through Web of Knowledge, we then assembled articles and book chapters that have been either included in the authors' personal archives or recommended by the four anonymous reviewers of this article. Particularly we include a number of presentations or articles from (1) the 2010 Space Time Modeling and Analysis Workshop sponsored by ESRI, the largest GIS software company in the world (February 22–23 2010, Redlands); (2) the *Annals of the Association of American Geographers* (AAG) forum in 2013 that is based on the Space–Time Integration Symposium in Geography and GIScience at the 2011 AAG annual meeting (13–15 April 2011, Seattle); and (3) a recent special issue of the *International Journal of Geographical Information Science* (IJGIS) on space–time research in GIScience. The reason for so doing is that the search in the first step could be quite restrictive, and many related articles do not use the specified terms (e.g., *spatial temporal model*) in their titles.

Results

Descriptive Statistics

Our search based on the three-step procedure returned a total of 700 articles as of 17 April 2014. There are some interesting patterns associated with these papers. First, the forty years from 1949 to 1989 witnessed a slow linear increase in the number of publications, and then from 1990 the number rose rapidly at an exponential rate with some yearly fluctuations (Figure 1). To show that this exponential increase is not likely due to a similar increase pattern in the number of potential publication outlets, we also show the search results for "theory of relativity" and "urban geography" under the same parameters (key word within quotation marks and as title) on the same engine. It is clear that publications on these two other key words do not show a similar increase pattern as our results for space–time analysis. Then we claim that this trend of exponential rise would more likely reflect the increasing popularity of space–time analysis over the last two decades.

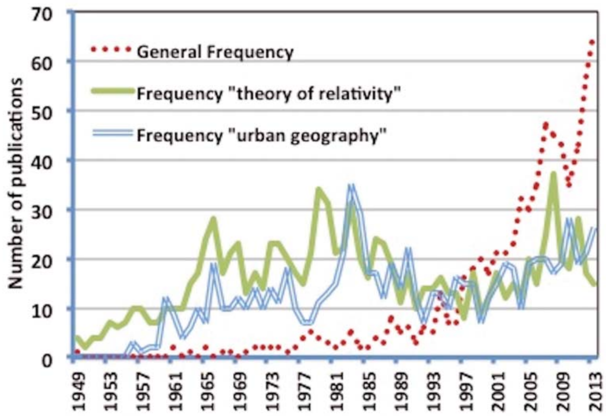

Figure 1. Number of papers with "space–time analysis" and alike in title from 1949 to 2013. (Color figure available online.)

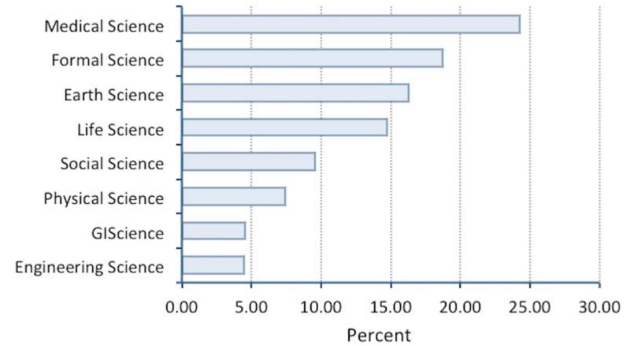

Figure 2. Bar chart of space–time analysis papers in different disciplines. (Color figure available online.)

These 700 papers are scattered among a range of disciplines. Studies in many areas such as epidemiology (e.g., Assuñçao, Reis, and Oliveira 2001), meteorology (e.g., Sansó and Guenni 1999), climatology (e.g., Nail, Hughes-Oliver, and Monahan 2011), and transportation (e.g., Kamarianakis and Prastacos 2005) focus on predicting space–time patterns of certain units or phenomena of interest with a disciplinary theoretical or empirical background. If we aggregate all of the related disciplines to the eight categories shown in Figure 2, then the top three scientific categories that contribute to space–time analysis are medical sciences (24 percent), formal sciences (19 percent), and earth sciences (16 percent).[5] If we delve into individual disciplines, then mathematics and statistics (ninety-seven entries, same hereafter), epidemiology (eighty-one), neurosciences (seventy-eight), biology (fifty-four), ecology (forty-four), urban studies (thirty-one), hydrology (thirty), and physics (twenty-nine) make the biggest contribution to the publications (data not shown). Among these publications, mathematicians or statisticians develop formulations (e.g., Bayesian models) to express space–time dynamics in mathematical or statistical terms and to create theoretical and applied frameworks for analysis and decision making under ambiguity. Conceptual and mathematical models are developed to represent, explain, or predict phenomena (e.g., high-energy scattering, Hadron–Nucleus collision at high energy) in the physics world.

The word cloud of all the papers (Figure 3) shows the high-frequency words that are used in the corresponding abstracts. It is expected that terms like *data*, *study*, and *patterns* are displayed as high-frequency words. More interesting to us would be those midfrequency words that show either the methods being used (e.g., Bayesian and [time] series), areas of study (e.g., rainfall, health, malaria, and disease), or data characteristics (e.g., correlation and cluster). All of these word-cloud findings corroborate our previous findings

Figure 3. Word cloud of words in abstracts of all searched papers (words of higher frequency are displayed in larger font either horizontally or vertically), where the words *space*, *time*, *analysis*, *model*, *modeling*, *spatial*, *temporal*, *spatiotemporal*, *using*, and *used* are excluded from the word cloud.

Table 1. Space–time analysis: Spatial units and data type

Space–time data type		Space–time analysis unit	
Subcategory 1	Subcategory 2	Individual objects	Cross-sectional units
Tracking data	Regular tracking data	✓	
	Event and transaction data[a]	✓	
Spatial panel data	Regular spatial panel data		✓
	Event and transaction data[b]		✓

[a]The data are about who enabled or participated in the event(s) or transaction(s) in what place(s) and at what time(s).
[b]The data are about some aggregated attributes of these events or transactions at various spatial units.

about what disciplines, by what methods, are contributing more to space–time analysis.

Before we review methods or conceptual models that can be used to perform space–time analysis with a focus on geographical and environmental studies, we classify units of space–time analysis into the following two broad categories and link them with the three major data types (Table 1):

1. Individual objects that are often mobile (relative to an observer; e.g., a space–time modeler). Examples include animals, people, vehicles, boats, aircrafts, or groups of these objects. When tracking objects over time, the resultant data are the so-called tracking (Goodchild 2013) or movement data (Long and Nelson 2013).
2. Cross-sectional units that are georeferenced and often immobile. Such units could consist of three subtypes of (1) pixels or cells (could be simplified to points), (2) parcels or polygons (e.g., vegetation communities, households, villages, or towns that are sometimes subject to changes in shape, size, or boundary), and (3) data collection (e.g., experiment or observation) sites (sometimes within a network) with spatial stamps. When collecting data of these three subtypes, we largely obtain the so-called temporal sequences of snapshots, temporal sequences of polygon coverages, and multidimensional data, respectively (Goodchild 2013). Here we use the term *spatial panel data* to indicate data of this type (Table 1) or "data containing time series observations of a number of spatial units" (Elhorst 2010, 377). Depending on the researcher's interest and objectives, sometimes tracking data can be "downgraded" to spatial panel data through, for example, aggregating object-level data at discrete times (or time intervals) and spatial locations to time sequences of cross-sectional measurements.

One special type of data is event or transaction data, where the variable of interest is often nominal (e.g., yes or no event at a certain time and location). For instance, when tracking individual people about their house or apartment purchase actions, we are only interested in the place (e.g., x and y coordinates or ZIP code of the purchased house) and the time related to the transaction rather than places and times of all their activities over a certain time span. Then depending on whether we are interested in individual objects (i.e., the ones who have enabled or participated in the event(s) or transaction(s) at a time and place) or the density, location, or timing of these events or transactions, we can classify such data into tracking data or spatial panel data, respectively (Table 1). Accordingly, we classify space data analysis models or methods into two categories of individual movement data analysis and spatial panel data analysis, which are largely (with exceptions) engaged in analysis of tracking data and spatial panel data, respectively (Table 2). Next we review space–time analysis models or methods based on this classification.

Individual Movement Data Analysis

Here we consider individual movement data analysis as a relatively new framework for space–time analysis, which represents a paradigm shift from the traditional place-based aggregations without explicit time consideration. The most noteworthy achievement along this line might be the time geography research, which originally focused on tracking human movements on an individual basis through creating space–time life paths (a path is an ordered sequence of fixes collected at regular or irregular time intervals), where a horizontal plane is employed to stand for positions in traditional geographical space and a perpendicular direction is used for times (Hägerstraand 1970). Space–time life paths are used to create space–time prisms, showing the potential range of movement

Table 2. Space–time analysis: Data type and methods

	Space time analysis		Data type		
	Purposes	Exemplar methods	Tracking data	Spatial panel data	Transaction / Event data
Individual movement data analysis	Pattern revelation	Time geography[a]	✓		
		Path description, comparison, accessibility[a]	✓		
		Space–time point pattern	✓		
		Spatial association of movement vectors	✓		
		Others	✓		
	Space–time statistical models	Probabilistic time geography	✓		✓
		Survival analysis models[b]	✓		✓
		Others	✓		
	Process-based simulation	Agent-based models[c]	✓		✓
		Others (e.g., Markov models)	✓		
Spatial panel data analysis	Pattern revelation	Multiple space–time metrics		✓	
		Multiple space–time tests		✓	
		Others		✓	
	Space–time statistical models	Panel regression models		✓	
		S-T autoregressive models & variants		✓	
		S-T weighted regression models		✓	
		Latent trajectory /multilevel models[c]		✓	
		Survival analysis models[c]		✓	✓
		Others (e.g., hybrid models)		✓	
	Process-based simulation	Agent-based models		✓	✓
		Cellular automaton		✓	
		Spatial Markov models		✓	
		Others		✓	

[a]We do not provide detail due to decent coverage in Long and Nelson (2013) and space limitations.
[b]Proposed by the authors of this article (nonexistent or rare in space–time analysis literature but available in other fields).
[c]Existing, but not common in individual movement data analysis literature (popular in other fields).

within an individual's world when accounting for various constraints on movement due to biological, physical, and physiological necessities and public and personal decision making (Hägerstraand 1970). Next we break the methods and models into three categories: pattern revelation, space–time statistics, and process-based simulation. As Long and Nelson (2013) made a very comprehensive overview on time geography methods and models, especially on those for pattern revelation, we only provide a brief review here and refer readers interested in more details to the article.

Pattern Revelation

Inspired by the time geography framework, individual movement data analysis aims at revealing movement patterns, via robust statistics and visualization methods, of any individual moving objects (e.g., animals, vehicles). In recent years, the amount of individual, georeferenced human or nonhuman activity data required to construct models of individual movement has increased greatly due to rapid improvements in geospatial information technology (Kwan 2004; Kwan and Neutens 2014). In conjunction with the wealth of new data, the ability to capture, represent, explore, and analyze large space–time trajectory data continues to improve (Miller 2005). These methods and models include the development of path descriptors, path similarity indexes, pattern and cluster methods, dynamics of individuals within a group, spatial field methods (generalizing movement data to cell-based densities), and spatial range methods (polygonal representation of movement area). The usefulness of these methods cannot be overestimated. For instance, comparisons between space–time paths can be conducted through the use of path similarity indexes including Hausdorff distance and Frechet distance, the dynamic time warping algorithm, the multi-objective optimization evolutionary algorithm

(MOEA), and the longest common sequence algorithm (Chen et al. 2011; Long and Nelson 2013; Kwan, Xiao, and Ding 2014). Other methods allow for grouping together individuals who have similar space–time paths or activity density surface (Kwan 1999; Chen et al. 2011), quantitatively modeling movement probabilities that incorporate object kinetics (Long, Nelson, and Nathoo 2014), and creating probabilistic space–time prisms depicting an individual agent's daily movement (Downs et al. 2014). For details about these quantitative methods, see Long and Nelson (2013).

Some specific research efforts have focused on development and evaluation of space–time measures or algorithms that are "sensitive to person-specific situations and gender-role constraints" (e.g., Kwan 1998, 211), assessment of the similarity among individual activity patterns using the sequence alignment method that was originally developed to analyze DNA sequences (Shoval and Isaacson 2007; Kwan, Xiao, and Ding 2014), and exploration and visualization of large space–time trajectory data sets in the GIS software environment for both human (e.g., Kwan 2004) and nonhuman agents (e.g., Baer and Butler 2000; Downs et al. 2014). In parallel with such efforts, individual movement data analysis also aims at better understanding individual people's activity-travel scheduling behavior subject to space–time prisms (e.g., Liao, Rasouli, and Timmermans 2014) as well as revealing how individual accessibility constraints might factor into personal or social decision making (e.g., Neutens et al. 2008). Analytical and visualization methods have arisen that allow the generalization of a limited number of typical space–time trajectories within a large data set (Shaw, Yu, and Bombom 2008). A further analysis of such data allows the geo-computation of real-world accessibility measures by investigating the maximum travel distance due to multiple constraints on individuals in a particular study area (Lenntorp 1976; Kwan 2004). The ArcGIS-oriented package named "Extended Time-Geographic Framework Tools," developed by Shaw and associates, aims at "representing and modeling both physical and virtual activities as well as the interactions between them." This tool is able to visualize and explore spatiotemporal changes among individuals in large data sets (Shaw, Yu, and Bombom 2008).

To seek understanding about grouped individual movements, the two most prominent research areas include space–time statistics that aim to reveal both space–time point patterns and spatial association of movement vectors. First, considering that movements are composed of points with spatial and temporal coordinates, spatial point pattern analysis can be extended to space–time point patterns. Knox (1964) furnished a popular significance test for space–time clustering of point events, whose test statistic is the sum of both spatial and temporal neighbors. Mantel (1967) provided another popular test that is calculated as sum of multiplications of spatial and temporal distances among point events. Fundamentally, these tests evaluate whether or not point events are significantly different from a complete random process in space–time. Kulldorff (2001) developed a space–time cluster method extending the spatial scan test. Whereas the first two statistics are global statistics, the space–time scan test can detect local clusters using a space–time moving window that is cylindrically shaped. Significance tests for local clustering methods are often achieved with space–time permutation (Kulldorff et al. 2005) or bootstrap techniques (Kim and O'Kelly 2008).

Second, spatial association of movement vectors is used to explore pattern of space–time movements. Orellana and Wachowicz (2011) investigated "movement suspensions" (e.g., slow speed movement vectors) in pedestrian movement patterns. They analyzed vector segments of movement paths extending local Moran's *I* for vectors rather than paths themselves. They found that movement suspensions can be detected with local Moran's *I* and are associated with places where attractions are located. It is shown that a vector-based approach can provide useful insights to investigate activity patterns in space–time (X. Liu, Yan, and Chow 2015). Spatial association of vectors has not drawn much attention, however, except for a few studies (e.g., Y. Liu, Tong, and Liu 2014).

As Long and Nelson (2013) pointed out, space–time statistics for individual movements have not been much developed and not even clearly defined. Statistical aspects currently appear in path similarity indexes and pattern cluster methods as well as the probabilistic time geography, but they generally do not involve a statistical significance test. Obviously, space–time analysis for individual movements requires development of inferential statistics, which remains challenging.

Space–Time Statistical Models

Models of this type refer to the ones that could contribute to explaining or predicting certain space–time measures or patterns of moving objects. A current research frontier in individual movement data analysis is the so-called probabilistic time geography, which has arisen due to the understanding that although points within a space–time prism are accessible, not all points have an equal probability of being visited (Winter and Yin 2011; Downs and Horner 2012; Song and Miller 2014). A number of methods have been developed to compute these probabilities or space–time fields (contours), including the use of kernel density estimation to create density surfaces characterizing a moving object's spatial distribution over a fixed time interval (or space–time discs), random walk or correlated random walk methods that are used with discrete space and time intervals, Brownian bridges used for continuous space and time, and voxel-based geocomputational approaches (Downs 2010; Downs et al. 2014; Song and Miller 2014). Future research might revolve around integrating time geography and statistical density estimation to allow better portrayal of movement over a long time period for objects and phenomenon at various spatial scales (Downs 2010; Downs and Horner 2012).

It becomes very challenging, however, to predict relatively precise locations of a certain object over time using regular regression-based statistical models. If a modeler is interested in the timing of a certain event (e.g., transaction) and this timing is correlated with locational information, then a method named survival analysis has a great potential to predict the space and time of the event of interest with relatively high precision levels.

Survival analysis is also termed *event history analysis*, which has been extensively used in public health, sociology, demography (e.g., divorce, marriage, and mortality—thus the name survival analysis), engineering, and epidemiology (Klein and Moeschberger 1997; An and Brown 2008). Only in recent decades have a few pioneer researchers extended this method to spatial panel data analysis, particularly for analysis of land use and land cover (An and Brown 2008). A critical concept in survival analysis, the hazard function, offers unique opportunities for space–time analysis of a certain event such as land change or individual transaction. The hazard of a certain event is the instantaneous risk that this change will occur at a time of interest if the individual is able to survive to that time point. The hazard can be understood as an intrinsic property of any individual object or spatial unit (e.g., land unit), often defined based on empirical timing of events and some theoretical assumptions. Hazard is related to, but conceptually different from, probability. For instance, hazards might go up and down, whereas survival probabilities are always nonincreasing over time. Given individual movement data, calculating hazards for all relevant objects is based on the timing of each event, which switches the time dimension from a discrete time view in traditional space–time analysis to a continuous view, which is particularly useful in modeling transactions or events of individual objects with precise time stamps (Table 2).

When regressing the hazard of a certain event (often defined as a function of the time of event) related to a mobile object against a number of independent variables, survival analysis takes into account temporally changing values of some variables (named time-dependent variables; a key strength of survival analysis), where a modeler can use some explicit (e.g., x and y coordinates) or implicit (e.g., distances to known features) locational data as (part of) the independent variables. This is how space and time are connected in survival analysis of individual movement data.

At the same time, survival analysis allows varying precisions of time measurements for the event of interest: If events are known to occur earlier or later than a certain time, or within a certain time interval (termed as left-, right-, and interval-censored time, respectively; An and Brown 2008); survival analysis has algorithms to account for such data with varying temporal precision levels. Survival analysis has to make assumptions, however, about the hazards of the objects or spatial units under investigation (e.g., the well-known proportional hazard assumption in the Cox model; see Klein and Moeschberger 1997), which are sometimes beyond empirical tests. Also, survival analysis is designed for analysis of qualitative changes (events). If no event data are available, this method does not apply.

Most individual movement data-based models involve small spatial scale and short time intervals, whereas movements over larger distances and larger timescales are not well characterized by this type of continuous tracking and modeling approach (Meentemeyer 1989). This limitation might become more relaxed, however, with technological advances and decreasing costs of employing these technologies. Although the time geographic approach is able to characterize both time and space continuously,[6] it is weak in its ability to address movements at multiple spatial and temporal scales. Furthermore, it has been repeatedly shown that "time is a fundamental dimension that shapes people's access to and use of urban (and many other) opportunities" because they have many space–time constraints and temporal rhythms of activities; ignoring or downplaying this time dimension might lead to misleading or wrong conclusions (Kwan 2013, 1082). As pointed out by Long and Nelson (2013), however, "the first and foremost challenge" in handling movement data is "how to effectively characterize time" because unlike some spatial data sets (e.g., land use and land cover data), "objects move in both space and time and [spatial dimension and temporal dimension] cannot be explicitly linked" (306) using the existing GIS data formats. The challenge in individual movement data analysis also comes from the need for methods that are able to consider movement as "a function of the environment" and "are able to quantify interactions between individuals and with environmental variables" (Long and Nelson 2013, 311, 312). All of these challenges point to the need for employing the process-based simulation approach, which is described next.

Process-Based Simulation

Process-based simulation models focus on local-level processes and interactions that might give rise to emerging space–time patterns at aggregate levels. Among many models of this type, we review agent-based models (ABMs) that could have a great potential to address many space–time analysis challenges. Readers interested in other methods or models of this type (e.g., spatial Markov models) are referred to related literature (e.g., Patterson et al. 2009; National Research Council 2014).

ABMs, or individual-based models in ecological literature, are a bottom-up methodology that has the capability to perform space–time analysis. Based on the object-oriented programming (OOP) paradigm in computer science, ABMs group operations and data into modular units called objects (agents), which are conceptually equivalent to objects in individual movement data analysis. All objects are placed onto a structured network (Apple Computer 2000), which in geographical or human–environmental studies would often incorporate GIS space (e.g., cellular or vector) and other data layers. In some theoretical space–time explorations, the structured network could be a two-dimensional grid (e.g., the torus in Bala and Sorger 2001). The temporal dimension is enabled through an internal "clock" in the corresponding ABM: For each "tick," the time moves one step forward and all agents and objects can act or change certain attributes accordingly. The rules and a certain "schedule" that are programmed in the model control the sequential unfolding of agent activities over space and time. With a certain degree of self-awareness, intelligence, and knowledge of other agents and the environment (space), agents are often enabled to learn from (or exert impact on) other agents or the environment, adjust their own actions, and produce emergent outcomes (Parker et al. 2003; An et al. 2005).

In a study that aims to understand spatial stratification of human capital (education level) in a society, each family is put in a cell of two-dimensional torus (Bala and Sorger 2001). Agents of various generations (representing time) born into a family will reside in the corresponding cell/family or cell. A certain agent's human capital is dependent on his or her own previous human capital, his or her decision to work or to obtain further education, and the spillover effect of human capital in his or her neighborhood. The authors found that as time goes on, families (cells) with high human capital continue to accumulate more and serve as "nuclei" for nearby families to raise their human capital even when the simulation starts from a random spatial distribution of human capital among families. In this example, the absolute spacing (e.g., whether the family of interest is in the corner or near the edge) is not or less important; its relative space (the neighborhood the family belongs to) would play an essential role in determining its future human capital accumulation. On the other hand, the ABM by Torrens (2014) has objects and agents with a high level of detailed data (e.g., buildings with subsurfaces, foundations, façades; human agents with skeleton nodes) and resolutions (e.g., millimeters in space and fractions of a second in time). At this level, the space is absolute, which is important for simulating collision and evacuation behavior under earthquakes. At higher levels such as street-scale wayfinding, it is the relative space (e.g., corners of two streets, relative location between buildings) rather than absolute space (exact coordinates on the street) that helps agents to make movement decisions.

We also point out the potential usefulness of ABMs toward understanding accessibility of urban facilities and services. Suppose that under an ABM framework, a modeler has data of interest for a certain community regarding individual people, the spatially heterogeneous and temporally variant environment, interactions between agents, and interactions between agents and the environment over a time span of varying granularity. Using an ABM, the modeler could locate the people (agents), the parks (objects), and roads (objects) on a two-dimensional digital environment. Then he or she could assign attributes, including movement constraints or possibilities, to these agents and objects, such as age, race, work hours, and disability to people; road congestion hours to roads; and park hours to parks. Then according to domain knowledge, he or she can assign rules to the ABM, which might guide how agents interact with one another and with the environment. Once the simulation starts, the agents might stay or move over space along time ("tick"), often interacting with other agents (e.g., if you go to the park, I go) or the environment (e.g., checking park hours or road congestion). This corresponds to "the sequential unfolding of their activities over time" (Kwan 2013, 1082), which represents how ABMs integrate space and time in the "flow perspective" (Dijst 2013, 1060). With individual movement data collected from the simulation, a variety of time geography (or more broadly individual movement data analysis) methods or metrics can be used, such as space–time paths, space–time prisms, or time-geography density estimation (Downs 2010) for various purposes.

Clearly, ABMs have the capability to incorporate "interactions between individuals and with environmental variables" (Long and Nelson 2013, 312), to avoid potential "erroneous conclusions when time is ignored" (Kwan 2013, 1082), and to include various levels of temporal granularity—for example, traffic congestion at a road segment might last ten minutes, and a certain park might be open ten hours a day (Laube and Purves 2011). Therefore, ABMs have the potential to become a major tool in "analyzing the complex relationships among human space–time trajectories, racial segregation, environmental exposure, and accessibility" (Kwan 2013, 1083).[7] Although they have many other strengths, such as the capability to represent feedback and heterogeneity, the potential to encapsulate high-resolution spatial and temporal detail (Torrens 2014), and the power to include human decision making (Parker et al. 2003; An 2012), ABMs have several known weaknesses in relation to space–time analysis. ABMs could be very data demanding and sometimes too complex without offering much additional insight. It is also difficult to verify such models when path dependence, multifinality, and equifinality exist (National Research Council 2014).

Spatial Panel Data Analysis

A wide variety of space–time analysis studies result from the application of analytical and statistical techniques that are applicable to spatial panel data. We classify and review the methods and models for spatial panel data analysis also in three categories: pattern revelation, space–time statistical models, and process-based simulation (Table 2).

Pattern Revelation

One important research line is space–time analysis of exploratory nature, which attempts to detect, quantify, visualize, and link trends in both space and time using novel methods. The Space–Time Analysis of Regional Systems (STARS) package allows for exploratory analysis of spatial panel data (Rey and Janikas 2006). In addition to offering a platform to qualitatively view spatial data over time, STARS offers geocomputational methods that allow for space–time analysis, including global and local Moran's *I*, measures of inequality (the Gini coefficient), and Markov techniques (Rey and Janikas 2006). Temporal query and dynamic navigation in a GIS environment represents another useful line of research that shows great promise (e.g., C. Lee, Devillers, and Hoeber 2014). The ArcGIS-oriented package "Extended Time-Geographic Framework Tools" mentioned earlier is also able to generate aggregate-level metrics and visualization graphs (Shaw, Yu, and Bombom 2008).

Another research area in this category includes attempts at identifying spatiotemporal clusters or hotspots. The Barton and David test can be used to find if spatial patterns of events vary by temporal cluster, whereas the Knox test is used to identify space–time clusters by finding if events in one space–time window differ from the expected amount given the total number of cases and range of time of these events. The Mantel Index finds correlation between distance and time intervals (Levine 2004). Another method is to develop models or measures of how temporal rates or risk factors vary over geographic space. Various dimensions of clustering, including the frequency, duration, and intensity of events, can be assessed using local indicators of spatial autocorrelation (LISA; Anselin 1995), various entropy-based indexes (Leibovici et al. 2014), or space–time kernel density (Delmelle et al. 2014). Complementary to such indexes, probability density maps of space–time hotspots based on large quantities of individual-level movement data (e.g., Global Positioning System [GPS] measurements; Scheepens, van de Wetering, and van Wijk 2014; Scholz and Lu 2014) provide unique knowledge about activity patterns. Along this research frontier, other threads of effort also advance space–time analysis, such as the work on visualizing and analyzing regional economic inequality over time (e.g., Ye and Carroll 2011), development of LISA time paths (Rey, Janikas, and Smirnov 2005), and exploring space–time covariance structures (Guttorp, Meiring, and Sampson 1994). In a related study, spatial groupings are observed for a number of temporal scales to tease out climatic variations from seasonal fluctuations (Rouhani and Wackernagel 1990). In addition to finding clusters, assessing changes in individual feature locations in a GIS environment can have analytical utility. The spatio-temporal moving average and correlated walk analysis enables tracking of the movement of the mean location of an event or feature and allows prediction of the location and time of a similar event or feature in the future (Levine 2004).

We do not elaborate on software tools that mainly focus on spatial analysis because of space limits as well as our equal emphasis on the ability to handle time variability. It is worth mentioning, however, that software development is one of the top priority areas for space–time analysis. In addition to several noncommercial packages such as STARS (open source) mentioned earlier and Crimestat (freely distributed for educational or research purposes but owned by Ned Levine and Associates), which has tests for space–time clustering, diffusion, and interaction (Levine 2004), a number of space–time statistical techniques in this general category are included in commercial GIS. Similar to the space–time paths of time geography, ArcGIS allows the visualization of events in three dimensions, with the time of an event being displayed vertically (ESRI 2013). In addition, space–time hotspot analysis (LISA; Getis-Ord Gi*) can be conducted by defining a spatial weights matrix based on time (ESRI 2013). The Spatial-Temporal Analysis of Moving Polygons (STAMP) program, implemented as an ArcGIS toolbar, can generate graphs and measures (e.g., size and direction of moving polygons) and summarize space–time histories (Robertson et al. 2007). Also, the field of geovisualization has a close connection with space–time analysis, but we do not include it in this article due to space limits. For a nice overview, interested readers can refer to Dykes, MacEachren, and Kraak (2005) and Nöllenburg (2007).

Space–Time Statistical Models

To find out the mechanisms behind spatial panel data or make predictions, space–time analysts or modelers often use panel regression models. The term *panel regression models* refers to any regression models that make use of panel data, which include space–time autoregressive models (often with no exogenous variables), multivariate space–time regression models (with exogenous variables), and a number of variants (Table 2). One prominent feature that distinguishes panel regression models from standard regression models lies in their consideration of (1) temporal autocorrelation (i.e., "serial dependence" in spatial econometrics; see Elhorst 2012), (2) spatial autocorrelation, or (3) both spatial and temporal autocorrelation. Econometricians have made a substantial contribution to panel regression models (e.g., fixed and random effects models) in the last couple of decades or so (e.g., L. Lee and Yu 2010; Elhorst 2012). Both the so-called static (not allowing time lag terms as explanatory variables) and dynamic (allowing both space and time lag terms) spatial panel data models are of particular importance to space–time analysis. We hasten to stress that the reviews by L. Lee and Yu (2010) and Elhorst (2012) about panel regression models are comprehensive and updated, and readers interested in more detail (e.g., the specification of seven types of dynamic spatial panel data models) are referred to these articles. Next we bring forth several prominent issues that pertain to space–time analysis in geographic and environmental applications.

Worthy of mention is the rich set of autoregressive models, including space–time autoregressive (STAR), space–time moving average (STMA), space–time autoregressive moving average (STARMA), and space–time autoregressive integrated moving average (STARIMA) models. These models are fundamentally extensions of autoregressive moving average (ARMA) model for univariate time series to space–time domain (Cliff et al. 1975). These models often assume that the space–time processes can be considered as stationary (or near stationary) in both space and time. These STARMA models are frequently used for forecasting purposes (e.g., Cliff et al. 1975; Pfeifer and Bodily 1990). In an example for space–time prediction of traffic flow in a road network, measurements of traffic flow are taken at multiple time points at a number of measurement stations within a road network (Kamarianakis and Prastacos 2005). The authors show that each measurement at a certain site and time is modeled as a linear function of the three previous measurements at this site, a weighted average of the measurements taken from its first-order neighbors at the previous time, a weighted average of the measurements taken from its second-order neighbors at the previous time, the prediction error that was made at the previous time, and a random error.

Space–time analysis frequently uses panel regression models with exogenous variables (Table 2). To avoid creating models with a large number of parameters that overfit the data and thus lose generality, and due to data limitations (e.g., sparse data over space or time), these models often decompose the dependent variable of interest (or some transformation of it) into some function (e.g., linear combination) of site-dependent, time-dependent, or site–time interaction terms (e.g., Assuñçao, Reis, and Oliveira 2001; Lophaven, Carstensen, and Rootzén 2004; Natvig and Tvete 2007). In instances with high complexity or uncertainty as well as data collection difficulty (e.g., spare data over space or time), a latent space–time process can be assumed to underlie the observed data that are also subject to some random, unknown perturbation. Cheng, Wang, and Li (2011) proposed a hybrid model that uses an artificial neural network model to extract a global, generic trend and a statistical model to extract a local, stochastic trend in the "space–time series" temperature data collected from 137 Chinese meteorological stations.

Whereas space–time panel models are commonly estimated with maximum likelihood–based estimation methods (e.g., Baltagi 2005; Yu, de Jong, and Lee 2008), Bayesian approaches have also been used frequently in various areas including epidemiology (Assuñçao, Reis, and Oliveira 2001), climatology (Furrer et al. 2007), and natural disasters (Natvig and Tvete 2007). Using the Markov chain Monte Carlo approach, Bayesian methods allow flexible model specifications to reflect complex space–time processes. Worthy of mention is the hierarchical Bayesian approach in space–time analysis (Wikle, Berliner, and Cressie 1998). The phenomenon or process under investigation might be too complex, and decomposing it into several hierarchical processes or components should help conceptually and computationally. In modeling ozone level at a certain site and time, Nail, Hughes-Oliver, and Monahan (2011) decomposed the ozone level into two components of local emissions and regional transport, and each is modeled differently. The Bayesian approaches are often computationally intensive (Biggeri and Martuzzi 2003). It is critical to choose an appropriate a priori conditional distribution, and more research is needed in this regard.

Several relatively new methods to model spatial data have been extended to the space–time analysis context. Extended from the geographically weighted regression (GWR) framework, the geographically and temporally weighted autoregressive (GTWAR) model developed by Wu, Li, and Huang (2014) is a promising approach to handling both temporal nonstationarity and spatial autocorrelation simultaneously. The GTWAR model creatively forms a spatiotemporal distance (a linear combination of both spatial and temporal distances) for all of the space–time points and develops a spatiotemporal weights matrix that accounts for both spatial and temporal laggings. Then through a unique estimation technique, GTWAR can better fit the space–time data and subsequently generate better predictions. Another notable method is the eigenvector spatial filtering (ESF) technique that uses eigenvectors generated from a spatial weights matrix (Griffith 2003). Extending the ESF technique to a generalized linear mixed model (GLMM) structure, this method accounts for spatial structure with eigenvectors and temporal structure with random effects (Chun and Griffith 2011; Chun 2014).

Latent trajectory models. Another related set of methods are the so-called latent trajectory models (LTMs), which are also termed structural equation growth curve models or latent growth curve models (LGMs). LTMs are powerful in modeling longitudinal data, in which repeated measurements are observed for some outcome variable(s) over time (Guo and Hipp 2004). Conceptualized and expressed under the structural equation modeling (SEM) framework, LTMs are widely used in social and environmental sciences. Using patterns of change (not necessarily monotonous increase or decrease; see Bollen and Curran 2006, 108) in the response variable (y) as latent variables, LTM estimates complex causal relationships or plausible pathways among these change patterns and a set of independent variables (Preacher et al. 2008). LTMs are useful in space–time analysis because it is the trajectory of each spatial unit over time that is of primary interest. By exploring individual trajectories, space–time analysts could obtain firsthand insights into the temporal trend of the phenomenon of interest. When such trajectories are regressed against time, relevant time variants and covariates, we can obtain knowledge about what environmental, socioeconomic, and geographic factors could shape each trajectory in terms of the beginning points, changes in direction, or magnitude of change in such trajectories (An et al. forthcoming). The drawback of LTMs in space–time analysis is the assumption that the temporal change pattern, or time trajectory, of the response variable follows a predetermined mathematical function such as a linear or quadratic function of time, which in some instances might not be practical.

Multilevel models (MLMs) and LTMs are similar in many aspects, and sometimes they might give equivalent results. Therefore, we do not elaborate on MLMs but refer readers with interest in MLMs to Browne and Rasbash (2004), Subramanian (2010), and Goldstein (2011). They each lack some abilities of the other, however: For instance, traditional LTMs cannot accommodate more than two hierarchical levels as MLMs can, whereas MLMs do not allow model parameters to serve as predictors of other variables in the system (Preacher et al. 2008). It is possible to combine the strengths of both and develop multilevel latent trajectory models (M-LTMs), for space–time analysis as well as for more generic analysis of longitudinal, multilevel data. This method has rarely been used in space–time analysis to the best of our knowledge, with a small set of exceptions (e.g., Johnston, Jones, and Jen 2009; Elhorst 2012; An et al. forthcoming).

Worthy of mention is that the survival analysis models presented earlier can also be used in spatial panel data analysis. The difference is that when used in spatial panel data analysis, survival analysis aims to understand the change of state in cross sections rather than in individual objects dwelled on these cross sections. For brevity considerations, we skip this topic and refer readers to An and Brown (2008) and An et al. (2011).

Process-Based Simulations

Next we turn to a set of simulation models that can be employed in space–time analysis. These models focus more on relatively lower level processes that generate emergent space–time patterns (National Research Council 2014). Here we focus on spatial Markov chains and cellular automata (CA). ABMs, as reviewed earlier, are also applicable to spatial panel data analysis (Table 2), even though the modeler is more interested in using an ABM to predict or explain the observed spatial patterns (e.g., habitat or land use and cover at discrete times) rather than in time paths or movement patterns of individual agents. We skip ABM in this section for brevity, though, while pointing out some literature about using ABMs in this manner (Parker et al. 2003; An et al. 2005; Brown et al. 2005; Brown et al. 2008; An 2012; An et al. 2014).

Spatial Markov chains models. A traditional nonspatial Markov chain process is a process in which all cross sections under the system of interest belong to a number of states and can change states under some stationary transition probabilities. The state of a cross-section is a function of only its previous state and transition probability and, ultimately, the whole system converges to a steady state as the system of interest progresses over time stamps that correspond to calendar time intervals. Transition probabilities, compiled in matrix format, are obtained by assessing historic conversions between transition types. Markov models thus enable calculation of expected number of each transition event for the time elapsed before the subsequent time stamp. As an application in spatial context, spatial Markov chain models have individual cells/pixels or other spatial units (e.g., counties, states) as cross-sectional units, each with spatial coordinates corresponding to an area in space. What distinguishes them from regular nonspatial Markov chains is the consideration of spatial dependence (e.g., through spatial lag or spatial weights matrix; Anselin 2003) among nearby units. Markov chain models are able to represent changing temporal dynamics and spatial patterns of the phenomenon of interest such as land changes (National Research Council 2014) or regional income changes (Rey 2001; Le Gallo 2004).

Spatial Markov chain models offer a logically simple methodology for exploring patterns of spatiotemporal changes, with a number of drawbacks (An and Brown 2008; Iacono et al. 2012). Primarily, the original assumption of stationarity (in time and space) might not hold true in many applications unless modifications are adopted (Brown, Pijanowski, and Duh 2000). Like other types of models assuming temporal stationarity, Markov models are appropriate within a relatively short time span and sometimes suffer from the problem in relation to annualizing the corresponding Markov matrix (Takada, Miyamoto, and Hasegawa 2010). In addition, traditional Markov models give no insight into causality or involved processes. In many studies, some of these drawbacks have been overcome through the integration of other simulation techniques, such as CA to spatially allocate transition areas (National Research Council 2014) and Monte Carlo simulation to calculate probabilities or parameter values in Bayesian models (e.g., Furrer et al. 2007).

Cellular Automaton Models. As mentioned erlier, Markov models allow change of cell status in a certain stochastic manner, and transition probabilities (often calculated from empirical time series data) are used to control the related changes. Transitions are largely independent of the surrounding neighborhood, however. This might limit the application of Markov models in a world with spatial dependence. CA models are able to model space–time patterns through representing the environment on a cellular basis and letting the cells update at each time step ("tick"). In updating cell state, the effects of spatial interactions on cell status transition are specifically considered: The future state of a cell is set as dependent on its current state and that of cells within a predefined neighborhood around the cell. An essential characteristic of CA models is to repeatedly calculate the related algorithms or heuristics and update and report the status of all cells at each time.

A number of empirical (Clarke, Hoppen, and Gaydos 1997; Messina and Walsh 2001; He et al. 2005) and theoretical (e.g., Conway game of life, Gardner 1970) applications of CA models are available in the literature. From a space–time analysis perspective, CA models are limited in a number of ways; for example, they lack capability to handle human decision making, and it is difficult to calibrate and incorporate rules that extend beyond the status of the cell under consideration and its neighboring cells. Such difficulties might be eased, however, as new CA calibration methods are developed, such as those based on genetic algorithms (Cao et al. 2014).

Other Related Topics

This article emphasizes space–time data, that is, data explicitly with both spatial and temporal stamps, as well as models with tight space–time coupling. For these reasons, we do not elaborate on traditional spatial data analysis measures (e.g., Moran's *I*, LISA) and models (e.g., logistic regression, artificial neural network). There exists a vast literature for this topic (e.g., Fischer and Getis 2010). This, however, by no means depreciates these essential models. On the contrary, many such "traditional" models can be adapted or extended to analyze space–time data. For instance, logistic regression is more oriented toward analyzing cross-sectional data (Wang et al. 2013). If the dependent variable is switched from original presence–absence (e.g., of agriculture) format at one time point to nominal trajectories over time (e.g., forest → forest → agriculture, forest → agriculture → agriculture, etc.; Mertens and Lambin 2000), or presence–absence data are grouped into predetermined time intervals (Doherty et al. 2014), logistic regression is also able to reveal some temporal variability of the process. See An and Brown (2008) for the drawbacks of this type of loose space–time coupling.

Also due to space limitations, we do not elaborate on several related issues. First, various model verification indexes and methods, including the ones for map comparison (Hagen 2003; Pontius, Peethambaram, and Castella 2011) and the variant–invariant method (Brown et al. 2005), are very useful in space–time analysis as they provide an approach to examining the closeness between predicted and observed outcomes. Second, a growing volume of literature about historical and narrative GIS (Nakaya 2013; Yuan, McIntosh, and DeLozier 2015) has not been included in our review due to our focus on quantitative methods. The contribution from this field might be substantial in space–time analysis, however. Third, the previously listed models or methods are by no means exclusive or nonoverlapping—in many instances, hybrid models are employed in understanding space–time dynamics of the system of interest. Fourth, some disciplinary space–time models, such as the diffusion models in the form of differential or difference equations that explain rainfall patterns (Polyak, North, and Valdes 1994), are not included in this article because such models represent specific physical processes and are not likely employed in space–time analysis in other disciplines.

Discussion

Human experience can only occur in, and through, movement over space and time—there is no absolute stationarity in human realities. Things happen one by one, and it is this sequence that might give rise to the sense of time (Núñez and Cooperrider 2013). Time exists, as Einstein illumined: "The only reason for time is so that everything doesn't happen at once." Analogously things happen here and there, and we would add, "The only reason for space is so that everything doesn't happen everywhere." Only when the nexus of time and space, and movements through such time and space, is understood can a better comprehension of the human condition and many of its true complexities become possible. Space–time analysis, especially time geography, helps us build this nexus.

Integration of Space and Time

Even with a long history and intellectual origin from many other disciplines, the dual nature or dichotomy of space and time still besets space–time analysis. With the advent of contemporary advanced technologies, a growing number of challenges and opportunities emerge. One big challenge is as the "real-time space-time integration" (Richardson 2013), which has become increasingly possible due to (1) the explosion of real-time space–time data using GPS- and GIS-enabled devices, (2) the advances in mobile computing techniques and facilities including geospatial cyber infrastructure, and (3) the development of tools to analyze, model, and visualize space–time data. One methodological frontier is the ABM framework, which has a substantive potential to elegantly address many of the aforementioned challenges. Within the ABM framework, each agent (object) can move to or stay at any accessible location at any time, providing huge opportunities for real-time space–time integration. The survival analysis approach, when regressing the survival time–based hazards against time-variant (including locational data) and time-invariant variables, is also potentially able to link space and time data at a relatively high precision level.

The usefulness of these models in integrating space and time, to a large degree, however, hinges on what space–time data are available in what format, which connects to the challenges related to space–time data models. The last two decades have witnessed development and application of many innovative data models, such as the event-based space–time data model (Peuquet 1994), the object-oriented data model (Frihida, Marceau, and Thériault 2002), the field vector–based approach (Bothwell and Yuan 2010), and the space–time data models for raster data (Zhao, Shaw, and Wang 2014). These existing space–time data models are often limited to specific situations such as data format and geometry type. Development of space–time data models with higher levels of flexibility and adaptability would advance space–time analysis and, more broadly, GIScience.

Span and Granularity of Time

Current geography (GIS in particular) has a powerful capacity to handle spatial heterogeneity, but temporal variability has not been well addressed (Peuquet and Duan 1995; Yuan 1999; An and Brown 2008; Long and Nelson 2013; Yi et al. 2014). It is laudable that remote sensing data have been increasingly employed in relevant space–time analysis studies (e.g., Yi et al. 2014). Nonetheless, choosing the time span and temporal granularity of data collection is largely driven by data availability or convenience of data collection rather than by domain knowledge, theory, or insight into the process(es) of interest. Seldom have researchers asked questions about the validity of time span or temporal granularity (e.g., from instantaneous to interval to episodal to global scale; Laube et al. 2007) regarding data collection or analysis. Throwing such data to conventional spatial panel data analysis may not reveal the related patterns or mechanisms behind the data, despite methodological developments to handle flexible temporal granularity such as continuous time modeling (Oud et al. 2012). One promising approach, especially for exploratory analysis or data mining, is to employ LTMs. If the temporal trajectories of all relevant cross-sectional units are random or chaotic or coefficients for some time parameters (e.g., time or time square) are insignificant, this might be a sign of inadequate time span or granularity that is too coarse and we should ask further questions: Is the time span too short such that any temporal trend cannot be captured by our spatial panel data? Is our data collection frequency (temporal resolution) too coarse such that some temporal patterns (e.g., periodicity) in the process of interest are overlooked?

In many data collection instances, coarse granularity of time is unavoidable due to technological (e.g., Landsat Thematic Mappers 4 and 5 had a sixteen-day revisit cycle), financial, administrative (e.g., every ten years for census data), or people power limitations. When studying discrete or qualitative events at individual or aggregate (cross-sectional) levels, survival analysis models have great advantages in making data of coarse granularity more useful. This advantage is based on the capability of survival analysis in handling censored data, which deserves more attention from space–time analysts or modelers. Survival analysis models are useful not only for spatial panel data but also for event or transaction data about individual objects (Table 2). Survival analysis, by its very nature, is a method dealing with identifiable and independent objects, whereas what is presented in An and Brown (2008) and An et al. (2011) is its modified version used in analyzing spatial panel data. One intriguing dimension of survival analysis is that we could record data about (survival) time, location (e.g., x and y coordinates), and the environment as continuous (or very fine granularity if discrete) attributes of the objects under consideration. When an event or transaction happens at time t, we can link the event with the data of the object itself, of other objects, and of the environment also at time t (or $t - 1$) through a set of time-dependent variables. Therefore survival analysis models deserve more effort in individual movement data analysis, especially in dealing with event and transaction data.

Visualization and Space–Time GIS

Geographic research has a long tradition of using graphical representations for various purposes, including understanding spatial patterns of geographical phenomena, choosing an appropriate modeling method, and evaluating model performance. Space–time analysts, with no exception, have strived to effectively visualize space–time data. As an early example, the concepts of time geography are efficiently described with visualization tools including space–time cube, space–time prism, and space–time path (Hägerstraand 1970). Also, Tobler's (1970) effort to visualize the process of urban growth in the Detroit region with map animation furnishes another example.

The development of space–time visualization has heavily depended on GIS and geovisualization, which provide conceptual frameworks and practical tool sets to deal with space–time data. Geovisualization could provide guidelines on how the movement patterns of individuals should be effectively visualized and analyzed in time geographic research, and these guidelines are often implemented in a GIS environment (Kwan and Lee 2004; Ren and Kwan 2007). Especially, a three-dimensional GIS environment is widely used to explore space–time patterns such as space–time cube (Kraak and Koussoulakou 2005). Also, the space–time kernel density analysis extensively uses three-dimensional GIS in its data processing and output visualization (e.g., Delmelle et al. 2014). They also provide tools to track locations and states of event-based geographical phenomena, which can be coupled with GPS devices (e.g., Dodge, Laube, and Weibel 2012).

It has still been very challenging, however, to implement geovisualization in a GIS environment. According to Goodchild (2013), discussing the functions of "a space–time GIS (STGIS) that unifies the functions needed to capture, store, analyze, visualize, model, and archive space–time data" (1074), many essential tools for space–time analysis are not available in a GIS environment. Especially, process-based simulation tools including CA and ABM are still very limited. Also, dealing with tracking or individual movement data (e.g., GPS data) is largely isolated from main GIS modules. He concluded that STGIS is not likely to emerge in the near future. Nevertheless, GIScientists are making rapid progress in various areas, including dealing with a complex structure of space–time data (e.g., Yuan 1999), using different space–time units (e.g., Downs et al. 2014), and implementing more tools in a GIS environment (Rey and Janikas 2006; Shaw, Yu, and Bombom 2008). We expect that more effort will be devoted to development of STGIS, which might greatly advance space–time analysis.

Analyzing Big Data

It has been increasingly recognized that with rapid advances in modern information and other related technologies, data are coming from virtually everywhere: sensor-gathered land cover or climate patterns, cancer genome sequences, digital photos and videos, posts on social media, online transaction records, cellular phone GPS signals, and so on, at the magnitudes of terabytes (10^{12} bytes) or petabytes (10^{15} bytes). Such data are often characterized by four Vs: volume (large scale), velocity (streaming data over time), variety (different forms of data), and veracity (varying uncertainty in data) according to IBM. The advent of such "mountains of data" (Marx 2013), or big data, is revolutionizing data collection, storage, processing, transfer, visualization, analysis, and interpretation in many academic, industrial, and commercial ventures. Big challenges are also arising in many disciplines—with no exception in GIScience (e.g., Kwan and Neutens 2014)—such as close coupling between big data and tools (e.g., they should talk to one another), hardware and software sharing (e.g., Hadoop open source software framework), high-performance computing (e.g., cloud computing, parallel computing), software stability and longevity (e.g., some software tools crash too often), and developing big data protocols and standards (e.g., data can be shared and used by other people).

As mentioned earlier, GIScientists have started to consider or meet the challenges in big data (big space–

time data in particular), such as developing STGIS (Goodchild 2013) to better address the velocity dimension of big data and open source software packages (e.g., STARS; Rey and Janikas 2006) to enable software sharing. Nonetheless, it is worth pointing out that most of the methods, algorithms, and packages reviewed here are oriented toward regular data rather than big data—for example, they are often loaded or installed on a local computer and have seldom been exposed to cloud computing (for exceptions, see Tang and Wang 2009; Tang, Bennett, and Wang 2011) or subjected to meaningful tests on big space–time data in terms of theoretical validity, stability, efficiency, and applicability. On the other hand, big data (big space–time data in particular) could bring forth some advantages; for example, giving researchers more freedom to select a subset of data to avoid spatial autocorrelation without concerns about small sample size (An et al. forthcoming). Overall, big data do provide challenges, as well as opportunities, to GIScientists in terms of data science theories or frameworks, data models and standards, fast-computing techniques, and efficient methods, algorithms, or packages to extract information from data mining.

Conclusion

We present a comprehensive typology (Table 2), intending to synthesize the major data types as well as the methods appropriate for these data types in space–time analysis. We believe that this typology contributes to the continued advance of space–time analysis through, for example, stimulating exploration of other data models and types or methods and extending methods to nontraditional use domains. Under this typology, we hope to provide an overview of space–time analysis, especially about what methods are available, which are possible and promising, and what their strengths and caveats are, with a focus on those that are (potentially) useful in geographic and environmental applications. Such efforts could help space–time analysts or modelers, especially novice ones, to grapple with the complexities in space–time analysis, such as choosing the appropriate temporal or spatial scales and picking the most reasonable methods or tools.

According to this review, it is worthwhile pointing out a few future directions in space–time analysis. First, improved space–time integration will and should continue to be an exciting research frontier, and several promising methodological frameworks (including ABM and survival analysis), along with innovative data models, should receive adequate attention to handle both individual movement data and spatial panel data, especially in the era of big data. Effort should be made both within GIS through, for example, developing space–time GIS or STGIS (Goodchild 2013) and outside GIS given the difficulties of "representing the temporal domain within GIS" (Long and Nelson 2013, 312). Second, vigorous frameworks and theories for building a reasonable time dimension and directing space–time data collection and analysis are still in dire need. Various disciplines, such as sociology, political science, land change science, GIScience, psychology and behavior science, and complexity science, could take the lead in this direction and bring us closer to a "science of integration" (Goodchild 2013, 1073). Particularly, complexity science might play an important role because of its strengths in dealing with feedback, heterogeneity, time lag, path dependence, multifinality, and equifinality, which are common in complex systems (O'Sullivan 2004; J. Liu et al. 2007; An 2012; National Research Council 2014). For instance, when modeling human movement and mobility in an ABM, theories in psychology or behavior science should help developing rules about their path-taking or other decisions. Third, space–time analysis should contribute to increasingly recognized big data science in terms of providing visualization, analytical, and simulation tools. The panel regression and simulation models reviewed in this article should be very helpful in this regard. One contribution of this article is to "borrow" (from other disciplines) and propose several methods, including latent trajectory models and survival analysis models, for the arena of space–time analysis. Fourth and last, space–time models can be based on either absolute or relative conceptions of space–time[8] even though most of the space–time analyses, including the so-called process-based models like ABMs (except the cases in Bala and Sorger 2001; Torrens 2014), largely rely on the absolute conception of space and time. It is worth investing effort in developing models that work with relative space, time, or both or models that have both absolute and relative space–time representation. Such models can provide some relatively "fuzzy" solutions to questions of interest. In many instances, aiming to acquire precise space or time location might warrant unnecessary, huge amounts of time and effort, although such high precision is not very useful.

It is very difficult, if not impossible, though, to give a complete and objective (no personal preference or bias) list of all space–time analysis methods or models used in geographic, environmental, or other related research. It is our hope that this article might synthesize the major achievements in the space–time analysis arena, point out areas for future research, and stimulate interest and effort in this promising scientific field.

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Notes

1. We consider geographic space only in the context of this article. Other dimensions of space, such as information space in relation to channel capacity, entropy, and information gain (Shannon and Weaver 1964), are not considered.
2. The term *distance*, unless otherwise specified, refers to the Euclidean distance in this article, among many other alternatives such as the least cost path, Manhattan, and network distances.
3. Space–time cube can be also used in representing, mapping, and understanding the arts and humanities (e.g., Travis 2014).
4. For this set of key words, if "title" is chosen, 618 records are returned, representing 36 percent of the 1,723 records returned by choosing "topic."
5. As mentioned later in the Conclusion and Discussion, our search is based on Web of Knowledge alone and does not include all publications in the relevant disciplines. For instance, our search has found sixty-seven papers in social sciences; under the same search parameters, 102 papers published in scholarly peer-reviewed social science journals were returned, using the search engines of Communication and Mass Communication Complete (CMCC) and PsycINFO (Psychology).
6. Here the word *continuously* is not used in the strict mathematic sense but implies that people's movement can be potentially tracked in very fine spatial and temporal resolutions.
7. ABMs are also powerful in analyzing other nonhuman individual movement data. See Tang and Bennett (2010) for a nice review of agent-based modeling of animal movement.
8. In addition to the dichotomy of absolute versus relative space (or absolutism vs. relationalism), useful dimension for space–time data is the dichotomy of realism versus idealism, which refers to whether space–time or objects are mind-independent (e.g., physical objects) or mind-dependent (e.g., abstract constructs). See more detail in Yuan, Nara, and Bothwell (2014).

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