1.21 Time Geography

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1.21.1 Time in Geographical Research

Traditional geographical research usually explores where, and to a large extent why, events and phenomena occur, and the notion of space is at the core of what we consider as the discipline of geography. Seldom (if not never) do geographers shed light on the notion of time, considering when and for how long those events and phenomena take place. Temporal issues are taken into consideration to examine the change of subjects or phenomena of interest in time. Nevertheless, even if time functions as a significant factor in the process, the traditional approach is to explore through a "snapshot model" where several static snapshots of the subjects or phenomena of interest are captured so as to study the temporal trends and/or mechanisms behind such trends (An and Brown, 2008; An et al., 2015; Armstrong, 1988). The objective of this review is to examine how time has been and/or can be involved in time geography, and more broadly, in geographical research, what research methods have been employed and what other methods are promising for this purpose. We conclude this review with future directions of time geography.

1.21.2 The Notion of Time

The classic dichotomy of space is between absolute space and relative space (Cresswell, 2013; Dainton, 2001; Hinckfuss, 1974). The former usually utilizes the longitude and latitude (or x and y coordinates, sometimes with the z coordinate or the elevation) defined in a certain geographical coordinate system, while the later locate an anchor/origin in the geographical space as a reference, and all other locations are defined as the relative relief from the origin. Similar to the above dichotomy, time can also be defined accordingly, with the absolute time represented by exact reading in a watch (e.g., second, minute, hour, date, month, and year), and relative time defined as the length of time prior to or has elapsed from a specific spot in the temporal domain.

1.21.3 Geographical Research Methods Involving Time

The related literature suggests that time can play three roles in geographical research. First, time can be considered as specific spot or interval in the temporal domain, which is the core issue of interest. Example research questions can be "When will things occur and for how long?" The second role of time is to be considered as a constraint, in which time may have a dominant effect on the occurrence of events. Research questions of this purpose can be "Given a certain amount of time, what will happen? Where can I go? And what can I do?" In the last scenario, time acts as the explanatory factor of events and phenomena. Most space–time geographical research involves time in this way, from pattern revelation and prediction, to time-series analysis of spatial objects. Example questions can be "How will the extent of a phenomenon change through time?" or "How will the object(s) of interest be located at certain times?"

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Before exploring potential research methods that consider temporal issues, it is beneficial to mention the different data types involved in time geography or generic geographical research (An et al., 2015). The first category of data is the individual movement data. The individuals of interest can be animals, people, vehicles, etc. that move across the geographical space. This kind of data records information considering the movement of the corresponding individuals, for instance time and position through the moving trajectory. The second kind of data is the so-called spatial panel data, which is usually consisted of georeferenced cross-sectional units at multiple times. Immobile pixels, parcels, polygons, or data collection sites are good examples. Beside the abovementioned two major types of data, another unique category is the so-called event or transaction data, which are usually nominal, indicating whether an event or phenomenon occurs at a certain time and location. In the next several paragraphs, we introduce some typical conceptual frameworks and/or methods that incorporate time in geographical research. All methods mentioned in this review will incorporate some or all of these data types.

1.21.3.1 Classical Time Geography

Classical time geography essentially deals with individual movements over space and time. Accordingly, its methods often incorporate individual movement data, and time usually acts as constraints to each individual's schedule. The sentinel article in time geography, "What about people in the regional science?" (Hagerstrand, 1970), has laid the foundation for classical time geography. Several key concepts are illustrated here with delicate details. We present these concepts with the help of hypothetical situations.

Consider this scenario of one person: after finishing that day's work, she leaves her office at 5 pm. She decides to be home no later than 6 pm. And she wants to stop by a grocery store and purchase some food materials for dinner. It takes her about 15 minutes to get to the store, and about half-hour to do the shopping. Finally she gets home on time. Within this scenario, there are three places, or *anchors*, involved in the space domain: work place, grocery store, and home. The time span is from 5 to 6 pm. The movement of the person and the time arrangement can be easily depicted as a *space–time path* (**Fig. 1**).

Sometimes the schedule of this person can be very flexible. But in this scenario, there are some constraints that shape or at least affect her schedule. First, since the work time does not end till 5 pm, theoretically she is not supposed to leave before that. This kind of constraint is referred to as *authority constraints*, within which a person must obey rules, and events are under control of a given individual, group, or organization with authority. For example, you can only visit a museum during its open hours, and you are not allowed to light a cigarette in smoke-free areas.

The second category of constraints, *capability constraints*, is related to that particular person's "biological construction and/or the tools he can command" (Hagerstrand, 1970). In our precedent scenario, it takes the person 15 minutes to commute from her work place to the grocery store. She can either walk on her own, which wastes no time, or take the bus, which costs her waiting for several minutes, but travels faster. Either way, she cannot get to the store in less than 15 minutes.

The third family of constraints, *coupling constraints*, occurs when one person has to join another person, entity, or tool to accomplish a goal. For example, she decides to work out after dinner, and she contacts her friend, who would not be available until 8 pm. Unless she wants to go to the gymnasium alone, she has to schedule for 8 pm or later.

Considering that same person, on the other day, she decides to take her time after work, and to get home no later than 6:30 pm. With the 1.5-hour time budget, she has many choices to perform all kinds of activities in different places. And she can also decide how much time she wants to invest in those activities during the time interval. The *space–time prism* can determine the potential space and time that is available given her time budget (**Fig. 2**). A space–time prism can be considered as an aggregation of all possible space–time paths. The projected gray area in the geographical space is the potential path space, which is a collection of all possible places this person can visit, given the 1.5-hour time budget.

One problem with the classical time geography model is that it assumes an equal accessibility to all geographical units. In this conceptually simple model, travel velocity is usually constant, thus their Euclidean distance divided by the velocity gives the commuting time between any two locations. With this assumption, if the time budget is defined, the longest possible travel distance

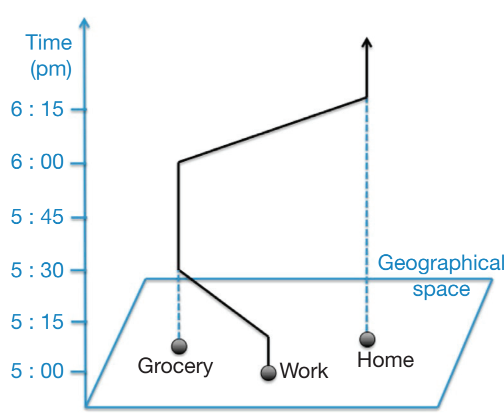

Fig. 1 Example of space–time path.

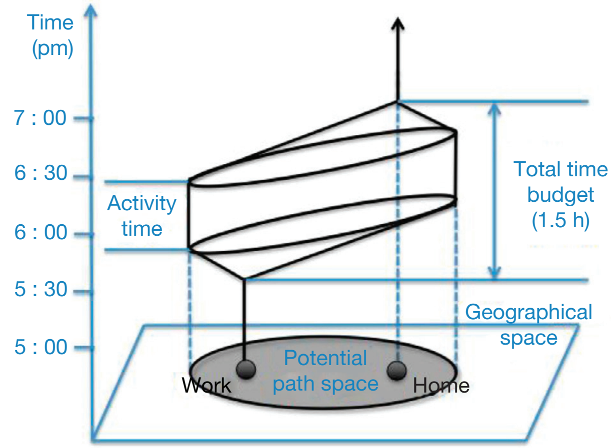

Fig. 2 Example of space–time prism.

(denote as D_{max}) will also be a constant. The calculation of potential path space (**Fig. 2**) will be a simple geometry problem: we are looking for points in the geographical space, where the sum of distances from this point to the two locations are no larger than D_{max}. The answer to this question will be an ellipse, and the two anchors are its focuses.

This can be a dangerous assumption to make, especially in developed areas, where the actual travel distance is defined by the route connecting the two locations, and the speed is decided by factors like traffic, transportation tool, etc. To make the geographical space more realistic in the original model, we can display the road networks and assign speed limits to the roads. Even more complicated road conditions, like one-way roads and whether allowing U turn or not, can also be introduced. With the help of modern GIS software like ArcGIS, we can conduct a network analysis and easily figure out the *potential path tree* (**Fig. 3**), which includes all potential paths that can be taken given the time budget.

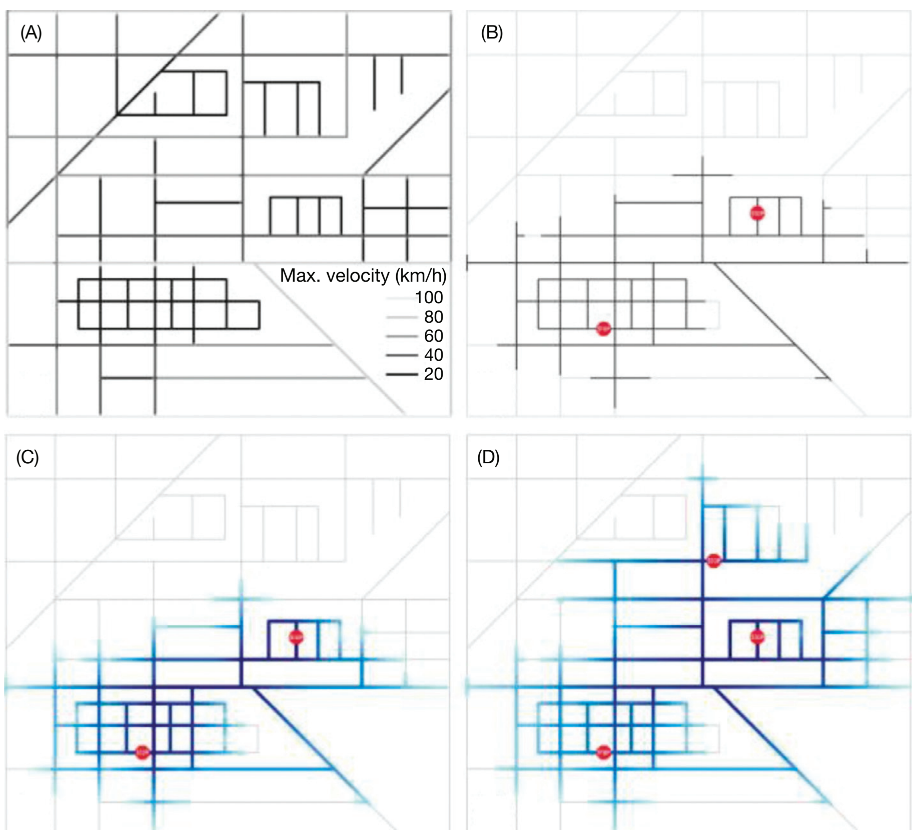

Fig. 3 Examples of a road network (A), potential path tree (B), the network-based TGDE for two (C) and three (D) anchors. The *red stop signs* are the anchors in the geographical space. *Darker blue networks* indicate higher probability of visiting. (C and D) From Downs, J. A. and Horner, M. W. (2012). Probabilistic potential path trees for visualizing and analyzing vehicle tracking data. *Journal of Transport Geography* **23**, 72–80.

Although theoretically the person can visit any part of the tree, in reality the probability of a particular part of the tree being visited may vary based on the nodes and topology of the road network. Utilizing vehicle-tracking data, Downs and Horner (2012) developed the network-based time-geographic density estimation (TGDE) to evaluate these probabilities. Network-based TGDE is adopted from the traditional kernel density estimation. It replaces the Euclidean distance of the original kernel in the decay function with a network-based travel time. The results of applying this function to the potential path tree are shown in **Fig. 3**. Panel (A) is a hypothetical road network, with maximum travel velocity assigned. Given two anchors in the network, panel (B) depicts the potential path tree, which entails the road network accessible by a vehicle given the time interval. Panel (C) applies the probabilistic TGDE to the potential path tree, in which *darker blue* roads are visited more likely than *lighter blue* ones. And panel (D) shows the results with a three-anchor case.

1.21.3.2 Space–Time Analysis

Traditional time-series analysis looks at the temporal changes of a certain phenomenon or a set of entities of interest without explicit consideration of the related spatial locations. Measurements are recorded at varying temporal intervals to capture the changes through time. Once we know the underlying temporal principle(s) or function(s), we can make predictions at a certain future time spot or interval. In this case, time is usually the only explanatory independent variable involved in this type of statistical analysis.

With some spatial factor(s) involved, space–time analysis examines, more often the case but not limited to, how the phenomenon or entities of interest are unfolded and evolve over time. Typical applications include the prediction of tidal heights and rainfall in the atmospheric and oceanic field, and generating terrestrial phenological metrics from remotely sensed satellite imagery.

1.21.3.2.1 Spatial panel data visualization and analysis

Spatial panel data largely refer to temporal sequences of snapshots, temporal sequences of polygon coverages, or time series of multidimensional data with locational data (An et al., 2015). We classify the related work into space–time pattern visualization and explanation/prediction for presentation convenience, though they are often intertwined with each other.

We do not elaborate on software tools, especially those that are designed to perform spatial analysis alone, because of space limit as well as our equal emphasis on the ability to handle time variability. However, it is worth mentioning that software development is one of top priority areas for spatial panel data visualization and analysis. Several noncommercial packages such as STARS (Space–Time Analysis of Regional Systems, open source; to be mentioned later) and CrimeStat (freely distributed for educational or research purposes, but owned by Ned Levine and Associates) have strong capabilities for space–time clustering, diffusion, and interaction (Levine, 2004). Increasingly commercial GIS packages start to include a number of space–time metrics, tools, and techniques for pattern visualization and explanation/prediction purposes, such as visualizing events in three dimensions and performing space–time hot spot analysis in ArcGIS (ESRI, 2016). Also worthy of mention is the Spatial-Temporal Analysis of Moving Polygons (STAMP) program that is designed and implemented as an ArcGIS toolbar. This program can be used to generate graphs, calculate measures, and summarize space–time histories (Robertson et al., 2007).

For pattern visualization purpose, geovisualization has been long studied with a multitude of accomplishments. Excellent overviews by Dykes et al. (2005) and Nöllenburg (2007) are available for readers with interest in this topic. Pattern visualization has been focus of a range of studies or projects worth mentioning. The STARS package has been designed for exploratory analysis of spatial panel data (Rey and Janikas, 2006). Now STARS has evolved into PySal, which is a vector data oriented tool for spatial data analysis and geocomputation. In addition to visualizing spatial data over time, STARS allows for a set of geocomputational methods to calculate metrics such as global and local Moran's I. Along this line, the ArcGIS-based tool "Extended Time-Geographic Framework Tools" aims to generate aggregate-level metrics and visualization graphs (Shaw et al., 2008). The Spatio-Temporal Moving Average and Correlated Walk Analysis makes it possible to track the movement of the mean location of an event/feature, opening the door for predicting the location and timing of certain events or features (Levine, 2004). Similarly, developing space–time metrics (e.g., Anselin, 1995; Delmelle et al., 2014; Leibovici et al., 2014; Levine, 2004; Rey et al., 2005; Ye and Carroll, 2011), performing temporal query and dynamic navigation (e.g., Lee et al., 2014), and identifying spatiotemporal clusters (or hotspots) in a GIS environment represent recent progress in pattern detection and visualization.

In particular, recent years have witnessed development of probability density maps of space–time hotspots based on individual-level movement data (e.g., GPS measurements; Scheepens et al., 2014; Scholz and Lu, 2014). There are other studies that explore methods for determining correlation in both time and space, including space–time covariance structures (Guttorp et al., 1994) and spatial groupings in a GIS environment (Rouhani and Wackernagel, 1990). Readers with interest are referred to An et al. (2015).

1.21.3.2.2 Spatial panel data regression

Then we turn to explanation or prediction of space–time data. Panel regression models, largely available in the toolbox of space–time analysis, are regression models that make use of panel data. Such models are diverse for multipurposes, and here we list several major ones: space–time autoregressive models (without exogenous variables), multivariate space–time regression models (with exogenous variables), and other variants. Panel regression models are unique because of their consideration of (1) temporal autocorrelation (e.g., Elhorst, 2012); (2) spatial autocorrelation, and/or (3) both spatial and temporal autocorrelation (An et al., 2015). A large number of models have been developed by econometricians—e.g., fixed and random effects models—in the last decade or so (e.g., Elhorst, 2012; Lee and Yu, 2010). Readers with interest are referred to the excellent reviews by Lee and Yu (2010) and Elhorst (2012) about panel regression models, and by An et al. (2015) for overall space–time analysis.

There is a family of autoregressive models, in which the space–time processes are assumed to be stationary (or near stationary) in both space and time. Such models include space–time autoregressive, space–time moving average, space–time autoregressive moving average, and space–time autoregressive integrated moving average models. However, the spatial or temporal stationarity may or may not be true in many time-geographical applications, efforts have been invested to deal with potential nonstationarity (e.g., Cheng et al., 2011). Based on the geographically weighted regression framework, the geographically and temporally weighted autoregressive model developed by Wu et al. (2014) is a promising approach to handling both temporal nonstationarity and spatial autocorrelation simultaneously through creatively employing a linear combination of both spatial and temporal distances for all the space–time points in a spatiotemporal weights matrix.

Following An et al. (2015), we define multivariate space–time regression models to be panel regression models with exogenous (or independent) variables. These models often decompose the dependent variable of interest into some function of site-dependent, time-dependent, and/or site–time interaction terms (e.g., Assuncao et al., 2001; Lophaven et al., 2004; Natvig and Tvete, 2007). Alternatively, a latent space–time process can be assumed to generate the observed data, which are also subject to some random, unknown perturbation (Cheng et al., 2011). The latent space–time process can be determined by a set of site or time-related variables, which may be justified by the related theory or literature.

Multivariate space–time regression models may ensue a large number of parameters, which present a daunting task for data collection and limits the usefulness (generality) of such models. In such instances, modelers often choose a (much) smaller number of parameters, assuming they follow some statistical distribution(s). Such parameters can be estimated using the Bayesian space–time approach. For instance, modelers often represent the dependent variable of interest at site i and time t as a function (f) of location, time, and (sometimes) a set of covariates (e.g., Assuncao et al., 2001; Furrer et al., 2007; Natvig and Tvete, 2007). Prior knowledge about the phenomena or events of interest is employed in the process of estimating the associated parameters. The Bayesian approach, though very useful, suffers from its high complexity and high computational intensity (Biggeri and Martuzzi, 2003). Some assumptions (e.g., certain parametric functions between the dependent variable and time and other independent variables) may be questionable and lack of clear guidelines, which warrants and more research. Similar challenges are also found in the process of choosing appropriate a priori conditional distribution and posterior distribution.

If the phenomenon or process of interest is too complex, researchers often consider decomposing it into several hierarchical processes or components. This sort of pursuit largely represents the hierarchical Bayesian approach of space–time analysis. Nail et al. (2011) present an example of this type of approach, where they decompose the ozone level at a certain site and time into two components: one is the local emissions and the other is regional transport. The local ozone level within a parcel of air is explained by a function of the amounts of NOx and volatile organic compounds (VOCs), the composition of VOCs, and the maximum daily temperature at the same time interval. At the regional level, the transported ozone level is a function of the weighted average of ozone observations at the previous time step.

Hitherto our focus has been on mainstream multivariate space–time regression models. Below we turn to several nontraditional methods or models due to their high analytical power for spatial panel data analysis. These methods, if employed appropriately, will very likely complement the abovementioned panel regression models.

1.21.3.3 Survival Analysis

Adopted from social science and public health, survival analysis (also called event history analysis) incorporates time as the core research objective by examining the occurrence and timing of events or phenomenon (An and Brown, 2008; An et al., 2011). The data being incorporated can be individual movement data, spatial panel data, or transaction data (An et al., 2015).

There are two basic concepts considering survival analysis. One is the hazard rate, which is the instantaneous risk that an event occurs at a certain time, given the individual survives to a time point of interest. The change of hazard rate through time is expressed through the hazard function. The other important concept is the survival probability, which is the probability that the individual will survive to a certain time of interest.

Hazard rate can be usually related to a suite of explanatory variables that are time dependent (changing through time, like age) or time independent (constant through time, like gender). Thus hazard rate can fluctuate as time elapses. The survival probability will be one minus the integral of hazard function, thus survival function is always monotonic and survival probabilities are either decreasing or constant.

Survival analysis tracks the history of individuals (people, machines, animals, etc.) until the event of interest comes up. So by its very nature, survival analysis deals with identifiable entities or objects (An and Brown, 2008; An et al., 2011). Survival analysis is relevant because it predicts or explains (at least partially) at what time (or time interval) a certain event or phenomenon may occur, which simultaneously examines the surrounding environment through looking into the values of the time-dependent and/or time-independent variables. Equally (if not more) importantly, survival analysis allows the use of censored timing data, in which knowledge only exists about the earliest time, the latest time, or time interval that an event may have happened. This handles more elegantly the time imprecision problem that besets many geographical data (such as the spatial panel data mentioned above) and the subsequent data analysis (An and Brown, 2008).

Traditional survival analysis models are often applied in social and medical sciences to handle change of status (e.g., marriage, divorce or end of marriage, child bearing, and death of patients), but seldom exposed to geographic research with very few exceptions (Coomes et al., 2000; Irwin and Bockstael, 2002; Vance and Geoghegan, 2002). An and Brown (2008) and An et al. (2011) extend traditional survival analysis to the geographic and land change arena innovatively, in which they treat land parcels as units of analysis, and explore what variables may help explain a certain land unit's survival (remain as is) or change of status (i.e., change in land use type).

1.21.3.4 Spatial Latent Trajectory Models

Similar to traditional time-series analysis, latent trajectory models (LTMs) look at the changes for a specific object or phenomenon of interest through time. Unlike traditional regression models that fit relationships based on all data points, LTMs fit a quantitative trajectory for the repeated measurements of each study unit over time. The assumption is that the change over time can be described by a suite of parameters (e.g., intercept and slope), and these parameters can be explained (predicted in many instances) by a set of site-specific independent variables. The underlying assumption is that temporal changes of all subjects (units) follow a certain latent trajectory, and observed data are derived from such latent trajectory under some (spatially or temporally local) perturbations or deviations. In practice, the trajectory could be linear, quadratic, exponential, cosine or sine (for periodical phenomena such as seasonal change of canopy cover of deciduous forests), and the like.

Traditional LTMs are often applied in social and public health sciences to handle longitudinal data such as test scores of students over time and drug use behavior (Guo and Hipps, 2004). Combined with a spatial term that accounts for neighboring effects (Tiefelsdorf and Griffith, 2007), LTMs can be used to interpret temporal trends in spatial panel data, such as the intensity of online keyword search for "climate change" across the United States (An et al., 2016a) and the space–time change of body mass index (a measure of obesity) in four Ghanaian regions (Crook et al., 2016).

1.21.3.5 Spatial Markov Chains Models

Traditional Markov chain models aim to predict the status of an object (or a set of objects) or phenomenon at future times. There are several statuses the object(s) or the phenomenon of interest can be subject to, and the probability of changing from one status to another is derived from analyzing empirical observations. The principle is relatively simple: between adjacent time intervals, the changing probability between particular status pairs is constant.

Spatial Markov chain models address the change of spatial units, such as land cover/use change at different times. This method applies the traditional "snapshot" data model and examines the temporal trends of change. What distinguishes spatial Markov chain models from regular ones is the consideration of spatial dependence (e.g., through spatial lag or spatial weights matrix; Anselin, 2003) among nearby units. Despite many strengths of spatial Markov chain models (particularly it offers a simple methodology for exploring spatiotemporal changes), a number of drawbacks are also noteworthy, such as the questionable assumption of stationarity. For more detail, see An and Brown (2008), Iacono et al. (2012), and An et al. (2015).

1.21.3.6 Cellular Automaton

As a simulation tool, cellular automaton (CA) represents the real geographic space by laying out a two-dimensional plane that is populated with cells. At the beginning phase, some cells are turned on, which can represent the presence of some features or phenomena, while others are off. Certain predefined rules, usually neighborhood based, will guide the changes of the cell's status as time moves on. A simple example of the rule can be that if more than two of the focal cell's eight neighbors are on, and the cell was off at the previous stage, it will be turned on. And sometimes more complicated rules can be applied to represent more complex landscape changes. Several example CA applications (Clarke et al., 1997; He et al., 2005; Messina and Walsh, 2001) can be found in the literature.

Similar with most traditional geographic research methods, CA handles time through a "snapshot model". Changes through time are captured by snapshots during the modeling process. Patterns revealed in each snapshot and the differences among snapshots are analyzed. Here time functions as an additional dimension other than the two or three dimensions that defines the geographical space. Time itself is not the interest of research, and the researchers are more interested how objects and phenomena of interest evolve over time.

1.21.3.7 Agent-Based Simulation

Traditional simulation methods, like CA mentioned above, apply a top-down modeling scheme. As a major, powerful tool in complexity science and in studying many human or nonhuman systems, agent-based models (ABMs or agent-based modeling) have been widely developed and employed in various domains such as ecology, epidemiology, geography, land use, political science, and sociology (An et al., 2015). The use of ABMs has increased rapidly among various scientific communities over the last two decades. According to a Web of Knowledge survey, the number of articles reporting the development or use of ABMs has been steadily increasing in an exponential rate since the 1990s, ranging across such research fields as ecology, human-environment science, land system science, and sociology (An et al., 2016b).

In a typical ABM, action (behavior) rules are predefined and the subjects or phenomena evolve according to those rules. Usually these rules are static and not subject to change as time moves on. Nevertheless, the real-world situation may be more complex. Rules can change, and there can be interactions among different subjects that may reinforce or weaken (even cancel) this change. Agent-based simulation, or ABM, is a promising tool to handle this kind of complicated interactions.

Similar with CA, ABM can first set up the geographical space as a plane populated with two-dimensional cells, or three-dimensional space with cubic units. Agents can be in all forms ranging from an individual, a household, an organization or institution, or even some abstract entities. ABM applies a "bottom-up" scheme, which can account for the interactions among different agents and between agents and the environment. The agents are designed to be "intelligent" to adjust their behavior according to feedbacks from the environment and other agents. All these features contribute to the power of ABMs: their capabilities to represent heterogeneity, nonlinearity, feedback, and individual-level activity and decision making. Furthermore, ABM has demonstrated to be very useful in integrating data and models across multiple disciplines and scales (An, 2012; An et al., 2015).

1.21.4 Conclusion and Discussion

Even with an intellectual origin from many other disciplines for a long time, the dichotomy of space and time still besets geographers. There is no doubt that contemporary advances in technology such as GIS, GPS, and remote sensing have brought up a growing number of opportunities (challenges at the same time). In this review, we conclude that time can play three roles in geographical research: time as the interest of research, as a constraint, or as an attribute domain of the data. Most traditional geographic research incorporates time as a data attribute by applying a "snapshot" model. These methods tend to emphasis the spatial aspects of the problem while not paying enough attention to the temporal aspects.

1.21.4.1 Tight Integration of Space and Time

Probably due to the abovementioned difficulties in integrating space and time, few studies treat time as the core research issue, for example, investigating the timing and endurance of events or phenomena. It poses considerate challenges to reveal processes or phenomena with fast changing paces, especially when the sampling intervals are long and the temporal resolution of the data is low. One methodological opportunity is the ABM framework, which has a high potential to elegantly address many of the aforementioned challenges.

The classical time geography methods and their later developments are good for dealing with questions where time acts as constraints. And for more complex situations with multilayer interactions and feedbacks, simulation tools like ABM are very useful for dealing with this nonlinearity. Assume a time geographer (city planner) aims to deploy some urban facilities and services such as overpass bridges. Under an ABM framework, the planner collects data regarding: (1) demographic data—gender, education, race, age, and work hours; (2) the spatially heterogeneous environment data: road network, home address, and local people's preference, availability and capability of conducting certain actions, for example, going to work at certain time(s); also data can be gathered about the timing and location of traffic congestion on a daily or hourly basis; and (3) interactions between agents and the environment over a time span of varying granularity, for example, one person with work hours from 8 am to 4 pm may decide to take a certain highway or local roads.

Using an ABM, the planer may locate commuters (agents), work and home addresses, roads, and intersections (objects) on a two-dimensional digital environment. Then (s)he may assign attributes to these agents and objects, such as age, race, work hours, and preference to commuters, etc. Then according to domain or survey knowledge or artificial intelligence, (s)he may assign rules to these agents, which could be in the "if…then…(with a certain probability)" or "if…then…; else if…then…" format. Then the simulation begins with all such data and rules included: the agents stay or move over space along time, often interacting with other agents or the environment (e.g., stop at a red light or traffic congestion). Such simulation may ultimately provide information about what areas may be subject to traffic congestion at what time and for how long, answering many "what-if" questions: what if a new road is added near a certain "bottleneck" place? What would happen if more time of green light is allowed at one direction of an intersection?

The ABM-based simulation mimics "the sequential unfolding" of agent activities over time (Kwan, 2013, p. 1082), showing how ABM may integrate space and time more in the so-called "flow perspective" (Dijst, 2013, p. 1060). Additionally, an ABM may generate a large amount of individual movement data that can be subject to many classical time geography methods or metrics, such as space–time paths, space–time prisms, or TGDE(Downs, 2010). In the context of the above ABM, we can examine whether path bundling may exist and contribute to traffic congestion at the corresponding road or intersection.

Clearly this is a typical time geography/accessibility problem, involving movement constraints or possibilities such as people's work hours, road network, and geographic locations of homes and work addresses. More interestingly, ABMs are able to simulate "interactions between individuals and with environmental variables" (Long and Nelson, 2013, p. 312). It is self-evident that planners are likely to make erroneous conclusions if time is ignored or looked at a too coarse resolution. As illustrated above, ABM has the potential to become a major tool in representing, explaining, and predicting individual movements and interactions with one another and with the environment, shedding important insights into the space–time patterns and the mechanisms behind such patterns.

1.21.4.2 Span and Granularity of Time

Current geography, GIScience in particular, has been powerful in terms of handling spatial heterogeneity. In spite of considerable efforts, geographers still fall short of the capability to handle temporal variability (e.g., An, 2012; An and Brown, 2008; Long and

Nelson, 2013; Peuquet and Duan, 1995; Yi et al., 2014; Yuan, 1999). The advent of and advances in several modern technologies (e.g., GIS, GPS, and remote sensing) have substantially empowered time geographical research. However, choosing the time span and temporal granularity of data is still largely driven by data availability, the convenience of data collection, or even personal preferences with little consideration of the related theory or knowledge about the process(es) of interest. Questions should be directed toward the validity of time span or temporal granularity in data collection or analysis.

Analysis based on such preference- or convenience-driven data may not uncover the realistic patterns or mechanisms behind such patterns. The LTM approach, adapted from the social and health science fields, may help address these kinds of questions, especially those in the land use and land cover change domain. In the context of our introduction of LTMs earlier, we demonstrate how LTM may help us determine the appropriate time span and/or granularity.

Assume that a spatial LTM gives rise to a set of interesting temporal trajectories, characterized by insignificant time-related coefficients. What do such insignificant coefficients mean? Among many possible reasons, one possibility could be that our time span is too short or data are collected at a too coarse granularity of time. We might further explore whether the phenomena of interest may have temporal patterns (e.g., periodicity). If so, we should adapt our data collection scheme so as to accommodate such type of complexity.

1.21.4.3 Imprecision of Time Measurement

In many research applications, coarse granularity of time is unavoidable in data collection due to technological, financial, administrative, or labor limitations. When studying discrete or qualitative events at individual or aggregate levels, survival analysis models can make data collected at a coarse granularity more useful. This advantage lies in survival analysis' capability in handling censored data (see the section for survival analysis), which deserves more attention from time geographers or modelers.

One intriguing feature of survival analysis is that we could record data about event (e.g., transaction) time, x and y coordinates, and the environment as continuous (or at a very fine granularity if discrete) attributes of the objects under consideration. When an event or transaction happens at time t or a time interval (t, $t+\Delta t$), we can link the event with the data of the very object, of other objects, and/or of the environment also at time t (or earlier times such as $t-1$) through a set of time-dependent variables. Survival analysis models deserve more effort and attention in time geography, especially in dealing with events and transactions data that are very much time variant.

1.21.5 Future Directions

Our review and discussion may point to a few future directions in time geography. First, the current loose space–time integration is still a challenge in time geography and other related disciplines, and we should continue to invest time and efforts in this exciting, yet challenging research frontier. ABM is a very promising methodological framework to handle individual movement data, spatial panel data, and event/transaction data. It would be ideal to develop ABM modules, platforms, or tools that are relatively easy to use (e.g., in combination with GIS), free (e.g., open source), and accessible (e.g., online available and well documented).

Second, time geography has come to a point, in which vigorous frameworks and theories are in dire need. Various disciplines, especially land change science, GIScience, and complexity science, may take lead in developing such frameworks and theories. Particularly, complexity science may play an important role because of its strengths in dealing with feedback, heterogeneity, time lag, path dependence, multifinality, and equifinality that are common in complex systems (An, 2012; Liu et al., 2007; National Research Council, 2014). Modeling human actions and behavior should be a very important research frontier in time geographic research, and there are a multitude of models or methods that time geographers can benefit from. For an overview of the related models, we recommend An (2012).

Third, time geographers should continue to move forward in the data-mining direction with input from multidisciplines even when we do not have enough domain knowledge, theory, and understanding toward our topic or phenomena of interest. This is particular important in this era of big data. The panel regression and simulation models reviewed in this article should contribute to this direction substantially. We have highlighted the usefulness and importance of several "nonmainstream" methods for time geographic research, such as LTMs, survival analysis models, and ABMs, expecting more advances in time geography resulting from the application of these methods.

Fourth and last, more efficient data models, robust metrics, along with powerful statistical- and simulation-based methods, should be developed to accommodate the need to handle space–time data, especially big space–time datasets. The traditional "snapshot" data model has the advantage of conceptual simplicity and ease of understanding, but suffers a lot from its low efficiency (e.g., the same data are stored at different times repeatedly). In developing space–time GIS or STGIS (Goodchild, 2013), it is a worthwhile investment if more time and efforts can be devoted to developing, testing, and employing more efficient data models in time geographic research, especially when dealing with individual movement and/or transaction data. Related to this need, more robust metrics, statistical- and simulation-based methods, and tools should continue to be developed and tested as we move toward better visualizing, explaining, or predicting space–time patterns.

We do not expect to give a completely objective (e.g., no personal preference or bias) review of all time geographic research. It is our hope that this article may synthesize what has been achieved in the subarea of time geography, pinpoint areas for further research, and stimulate more meaningful efforts in the future.

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