Spatiotemporal analysis

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Despite being central to the study of many disciplines, spatiotemporal analysis has not been defined in a unified way. This encyclopedia entry aims to bring together the different uses of, and methodologies for, conducting spatiotemporal analysis in order to provide a more centralized understanding of the topic. To achieve this, we define spatiotemporal analysis as "the depiction, representation, visualization and tracking of changing location in space and time of a certain phenomenon or event of interest, which are often (yet not necessarily) connected to seeking understanding about the mechanisms behind such data of spatial locations and temporal stamps" (An *et al*. 2015). Spatiotemporal analysis is also referred to as spatio-temporal analysis, space time (sometimes space–time) analysis, spatial temporal (sometimes spatial-temporal) analysis, and the like. Following an introduction of its historical, intellectual context, this entry investigates the range of disciplines that contribute to spatiotemporal analysis and the specific methods employed for conducting it. To conclude the entry, the future directions of spatiotemporal analysis are presented.

Intellectual context

From early civilizations to modern times, space and time have been the two fundamental domains under which people have characterized events and phenomena of interest around them. Space and time, both abstract and often invisible, are conceptualized in a variety of ways. Space can be understood as "absolute space," which can be characterized with a number of specific properties (Hinckfuss 1974). Under this view, space and time exist in their own right, which represents an object-independent framework. Space, along with time, is considered as a container within which all things or events of interest take place. Newton's analysis of space and time followed this line of conceptualization. To describe the laws of motion in regard to the trajectories of moving objects in space and time, he used the languages of mathematics (e.g., geometry and calculus). In his absolute framework, the objects move and change their properties in space and time, but the framework or the container itself remains unchanged (see Peuquet 2002).

In an alternative conceptualization of the so-called relative space proposed by Leibniz, space is created differently (Cresswell 2013). In contrast to a pre-existing container in the absolute space concept, relative space is conceptualized to represent relative locations among objects. Along this line, Minkowski extended the traditional three-dimension (x, y, and z) geometry to include time as a fourth dimension, which forms the basis of the united, relativistic space–time concept. The relative view of space continued in its development and culminated in Einstein's work on theory of relativity. Research in physics and mathematics, in particular, has enriched the conceptualizations of space–time at very large and very small scales, such as those in electronics, mechanics, and cosmology. At the human and landscape scale, conceptualizations of space–time analysis have been fertilized by the

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study of biology, ecology, hydrology, epidemiology, and geography (especially the subdisciplines of geographic information systems (GIS) and remote sensing).

Springing from the ideas of Kant and his fellow philosophers, earlier scholars largely held a dichotomous view of space and time, that is, that they are two separate key categories within which all activity occurs. Early geographers, such as Darwin, von Humboldt, and Ritter, focused their academic effort on depicting and understanding places, including their physical and human differences (Cresswell 2013). Under this view, space and time are not considered in tandem. For instance, regional geographer Hartshorne regarded that history aims to address changes in time, while geography addresses differences in space (Cresswell 2013). Early geographic models took a stance of either ignoring time or viewing it as a function of spatial variables such as distance or transportation costs (e.g., Von Thünen, Christaller; Cresswell 2013). Movement and transportation, which are concerned with time as much as space, can be "effectively studied in spatial terms" (Cresswell 2013). This means that movement is dictated by economics: supply and demand, least net effort, and travel costs (Cresswell 2013). Geographers, especially regional geographers, continued with this tradition until the so-called quantitative revolution in geography in the mid-twentieth century. The quantitative revolution has also witnessed the rise of spatial science within geography and the entry of geographers into the field of quantitative modeling. Since then spatiotemporal analysis has boomed in both quantity and quality (An *et al.* 2015), largely due to the advent of computers and advances in computing and analytical power.

Spatiotemporal analysis, as defined earlier, seeks to answer questions of both "when" and "where" (and, to some extent, "why" at the time or location) things occur. However, people use the words "when" and "where" in a variety of different ways (Couclelis 1999). The word "when" can be used in a relative sense (e.g., one event happens between two storms), or in an absolute sense that refers to time span (e.g., time duration of a storm) or clock time (e.g., at which time point a storm occurs). Similarly, space can be defined and used in varying ways. These ambiguities have led to a rich literature of the nature of space and time in physics and philosophy. In addition to the absolute/relative classification, Yuan, Nara, and Bothwell (2013) bring in another dichotomous classification of realism versus idealism, which refers to whether space–time, objects, or events are mind-independent (realism) or mind-dependent (idealism). The uniting principle underlying these conceptualizations and classifications is that space–time representation lays a foundation for subsequent spatiotemporal analysis methods as well as the corresponding results (see Yuan, Nara, and Bothwell 2014 for examples of this principle). Spatiotemporal analysis must recognize the intimate link between space and time, implying that changes of a phenomenon or object over either space or time would often inherently include a change in the other. This endorses the importance of putting space and time together to perform spatiotemporal (in contrast to spatial or temporal) analysis, and helps explain the exponential increase in number of publications related to spatiotemporal analysis since the late 1940s (An *et al.* 2015).

Spatiotemporal analysis in geography

The absolute or relative conceptions of space–time structure can be found in spatiotemporal models in geography (Massey 1999). In an absolute representation, researchers use fixed coordinate systems to represent the study site and events of interest, mark the changes in the associated variables, and explain or predict the pattern of change over time. Traditional geographic models represent the physical environment of interest in a two-dimensional space of grid or vector, without specific representation of time as a key dimension of concern. Largely ignoring time, such models are essentially spatial models. As time has moved on, the possibility of a space–time conceptualization has been explored by geographers. Early spatiotemporal analysis in geographic models often resorts to a GIS. Traditional GIS have elegantly represented space, but not so time (Peuquet and Duan 1995). The mainstream space–time representation in traditional GIS is through the snapshot model, where a spatiotemporally continuous world is shown at limited snapshots in time (Peuquet and Duan 1995). To address some difficulties faced by the snapshot model, the event-based spatiotemporal data model (ESTDM) by Peuquet and Duan (1995) allows organization of space–time data by time. Other data models, including the space–time composites model, the spatiotemporal object model, and the three-domain model, offer different tradeoffs between representing both space and time (An and Brown 2008).

On the other hand, a relatively new, object-oriented approach is arising in the geographic modeling and analysis arena. This approach leans more toward the relative representation of space and time. Under this approach, features on the earth's surface (e.g., land parcels, people, households) are conceptualized and represented as objects that are relatively independent entities, which may change their locational and nonlocational attributes over time – some of them may even have a certain level of intelligence and autonomy, make decisions, and/or adapt to the changing environment or the changes made by other entities (see the section for agent-based models below).

Spatiotemporal analysis techniques

This section sets out to give an overview of spatiotemporal analysis methods that have been used in geography, environmental sciences, and related disciplines. Each method will have a brief discussion of how it represents time and space, what type of data is required, what type of output it may yield, and whether it is primarily focused on prediction or explanation. These methods have been selected because they share several important features: they allow representation, visualization, or quantification of a system over space and through time in a dynamic way; they help in identifying mechanisms for observed changes in spatial patterns over time; and/or they can predict changes in temporal patterns by analyzing spatial data over time steps.

Time geography

Unlike early spatial science with focus on place-based aggregations and generalizations, time geography has arisen attempting to integrate individual trajectories of human movements in both space and time (Hägerstraand 1970). As a pioneer, Hägerstraand (1970) emphasized the need "to have not only space coordinates but also time coordinates" because people exist both in a specific space and at a particular point in time. In his seminal work on space–time life paths, a horizontal plane represents position in space and a perpendicular axis represents time. Space–time prisms, often derived from space–time life paths, are a powerful tool to show movement patterns within an individual's world, which are subject to physical and physiological constraints and also conform to public and personal decision-making (Hägerstraand 1970).

Recent years have witnessed rapid improvement in geospatial information technology, paving the way for quickly collecting individual, georeferenced human activity data in large amounts or over large spatial extents (Kwan 2004). In parallel with this increasing data availability, a number of models and techniques are being developed to capture, represent, and analyze such data, including the ones focusing on the exploration, visualization, and generalization of large space–time trajectory datasets in the GIS software environment (Kwan 2004). Such models and rich datasets have also opened new perspectives and opportunities in geocomputation; for example, real-world accessibility measures can be developed and obtained by calculating the maximum travel distance of individuals subject to multiple constraints (Kwan 2004; Lenntorp 1976). Among these models and techniques, statistical methods have played an essential role in time geography, allowing quantitative analysis and comparison of the space–time trajectories of different individuals or groups. The statistical methods allow calculation of a number of different measures, including the Hausdorff distance, Fréchet distance, dynamic time warping algorithm, and longest common sequence algorithm. Also worthy of mention in time geography is space–time path clustering analysis, which classifies individuals sharing similar space–time paths into groups.

There is no doubt that the time geographic approach is particularly important in space–time analysis because for individuals under investigation, both spatial coordinates and temporal coordinates are tracked down continuously and given equal weights in later data analysis. Nonetheless, it is a big challenge for time geographic researchers to address patterns and processes at multiple spatial and temporal scales. Currently, most activities captured in time geography research operate either at a small spatial scale or over short time periods, or both. Seldom have movements over larger distances and larger time scales, without sacrificing spatial or temporal resolution of data collection and analysis, been included and characterized well in this type of continuous tracking (Meentemeyer 1989).

Analysis of time series spatial data

One category of spatiotemporal analysis methodologies consists of analysis of time series spatial data using a number of spatial statistical and analytical techniques. Broadly, this category includes time-based descriptive statistics, statistics for clustering and dispersion, and establishment of correlations or causal relationships through regression analysis. Change through time is assessed either qualitatively or quantitatively, through the comparison of maps and graphs at different time steps, and by graphical output of statistical change over time. Below several increasingly recognized methods are introduced, which are powerful at analyzing time series spatial data and potentially unveil the mechanism behind such data – for nearly all these methods, spatiotemporal patterns are represented by the so-called snapshot data model, where space at one time is represented in a certain GIS layer (often raster unless otherwise specified), and time is represented at (and constrained by) the associated data collection frequency.

Exploratory space–time data analysis

This category of spatiotemporal analysis attempts to develop novel measures (including graphs) to show trends in both space and time. A number of space–time statistical techniques in this general category are included in commercial GIS. For instance, ArcGIS has enabled the visualization of events in three dimensions, with the time dimension being displayed vertically, which is conceptually similar to the space–time paths in time geography. The Crimestat software has tests for spatiotemporal clustering, diffusion, and interaction (Levine 2004). The Space–Time Analysis of Regional Systems (STARS) package is designed to perform exploratory analysis of spatial data with numerous time points (Rey and Janikas 2006). STARS offers several important functions, including qualitatively displaying spatial data patterns over time, and calculating descriptive statistics such as global and local Moran's I, and the Gini coefficient (Rey and Janikas 2006). Though spatial analytical and statistical software tools are not elaborated here, it is worth mentioning that software development is one of the rapidly improving areas for spatiotemporal analysis.

Identifying spatiotemporal clusters, for example epidemiologists identifying clusters of disease outbreaks, stands out as a very important type of applications. Many useful indices and/or tests have thus been developed for different purposes: (i) the Barton and David test, which aims to find if spatial patterns of events vary by temporal cluster; (ii) the Knox test, which focuses on finding whether events in one time–space window would differ from the expected amount in the same window given the total number and time range of all events; (iii) the Mantel Index, which helps find correlation between distance and time interval (Levine 2004); and (iv) many other indices, including frequency, duration, intensity of events, spatiotemporal covariance structures, and space–time hot spot indices (local indicators of spatial autocorrelation or LISA, bivariate LISA, Getis-Ord Gi*), which continue to be developed to assess the spatiotemporal patterns of the phenomenon or event of interest.

In addition to finding clusters, assessing changes in individual feature's locations in a GIS environment is another application domain of spatiotemporal analysis. Worthy of mention is the Spatio-Temporal Moving Average and Correlated Walk Analysis by Levine (2004), which facilitates tracking of the mean location of a moving event/feature and thus helps prediction of its location in the future. All these methods conceptualize a spatially continuous world at limited snapshots in time (Peuquet and Duan 1995), and the snapshot GIS data model (often raster layers over multiple time points) underlies the corresponding data collection and analysis.

Spatial panel data analysis

Spatial panel data refer to time series observations of a number of spatial units over time (Elhorst 2010), and often raster layers over multiple time points are data input. Spatial panel data analysis consists of two types of models. The first type includes dynamical models that predict the dependent variable at a given time by its value at the prior time and a set of independent variables using the so-called difference equation models. Though conceptually such models are ideal for spatiotemporal analysis, they are considered less compelling and more complex and thus not commonly employed in literature. The second type is related to two kinds of multilevel models (MLMs), that is, fixed effects and random effects models, where the multi-time observations for each individual unit (e.g., land parcels) are lower-level (level-1) data, and the individual units are higher-level (level-2) data. This data structure is the same as that in multilevel models (see the section for MLMs below). The model for this type of panel data analysis is similar to an ordinary least squares (OLS) regression model in many aspects (Elhorst 2001; Petersen 2009).

What distinguishes the above spatial panel data analysis from regular OLS regression models is a spatial effect term that deals with the impact of neighboring spatial units on the unit of interest. Depending on how the space–time autocorrelation in data is to be addressed, researchers may use spatial lag models (when the dependent variable of interest is autocorrelated) or spatial error models (when residuals from OLS models are autocorrelated; Anselin, Le Gallo, and Jayet 2008; Elhorst 2010). Then essentially spatial panel data analysis has to extend the fixed (or random) effects models with a spatially lagged dependent variable or with a spatial error term. Therefore the challenges related to MLMs, for example the need for large and balanced samples and the inability to incorporate endogenous predictor variables, are also extant (see the section for MLMs below). Also, model estimation may be biased by the spatial dependence among observations, and this complication may need special attention, according to Anselin, Le Gallo, and Jayet (2008).

Markov chain modeling

This type of model aims to represent changing temporal dynamics and spatial patterns of spatial units (e.g., individual cells/pixels). With input being often raster layers over multiple (at least two) time points, Markov models often focus on predicting or projecting future spatiotemporal patterns (e.g., in terms of raster maps). All units have spatial coordinates, and their attributes can change over time. In a Markov process, the landscape type at a given location and certain time depends only on its previous type and a transition probability. Transition probabilities, often presented in a matrix form, are obtained through assessing historic conversions between transition types.

Markov chain models are logically simple and useful for exploring patterns of spatiotemporal changes within a relatively short time span. Nonetheless, they have a number of drawbacks that deserve attention of spatiotemporal modelers (An and Brown 2008). Primarily, the assumptions of spatial independence and stationarity (in time and space) may not hold true in many applications (NRC 2014). In addition, Markov models focus explicitly on prediction, and provide little insight into causality or low-level processes that generate the observed spatiotemporal patterns (NRC 2014). In many studies, Markov chain models are made more useful when they are integrated with other modeling or analysis techniques (see the section for cellular automaton).

Bayesian spatiotemporal models

Bayesian statistical models have been adapted for use in spatiotemporal analysis. With input being often raster layers over multiple time points, Bayesian models often focus on predicting future spatiotemporal patterns (e.g., in terms of raster maps) or explaining observed patterns. In this type of model, a spatial dependent variable (with both spatial and temporal stamps) is described as a function of both time and a number of parameters (that are related to the specific site). According to prior knowledge (e.g., physical laws) about the phenomena or events of interest, a priori statistical distributions are used in order to impose constraints on a model that may have too many parameters, for example through a conditional autoregressive function. This results in a relatively small number of site-independent hyperparameters. Posterior distributions of site-specific parameters are used to update the parameters based on empirical spatiotemporal data, specifically by maximizing the probability of observing the empirical data through modifying parameter values. In determining these probabilities, researchers could use techniques such as the Markov Chain Monte Carlo method to generate samples for these posterior distributions. Weaknesses related to Bayesian spatiotemporal models include the fact that subjectivity might come into play when choosing either the posterior distribution or the a priori distribution, and also that modelers may have to assume some untested parametric distributions between space, time, the dependent variable, and the independent variables.

Survival analysis

Survival analysis is a methodology that successfully integrates both time and space in order to understand the contribution of different mechanisms to observed spatiotemporal patterns. While related to, and comparable to, more traditional static spatial analysis techniques such as logistic regression, it represents a more dynamic, integrated method for spatiotemporal analysis (An and Brown 2008; Wang *et al.* 2013). With input being raster or vector layers over multiple time points, survival analysis models are very useful for either prediction (e.g., in terms of raster maps) or explanation purposes. The technique has been adapted to land-change studies from a diverse range of earlier uses, including public health and demography (An and Brown 2008). While the name of the methodology is derived from investigations into mortality, it can easily describe the survival of a particular land unit, that is, not being changed to an unintended land use or land cover. Indeed, in recent years, a multitude of studies have used survival analysis to find drivers of land change (An and Brown 2008; Wang *et al.* 2013).

The hazard function is central to survival analysis. Based on theoretical assumptions or empirical event frequency and timing, the hazard function can be calculated as a measure of the risk that a change will occur at a given space and time point. Related to survival probabilities, the hazard function differs in its ability to either increase or decrease depending on the influence of explanatory variables over time. Survival analysis uses information at all of the time steps to calculate the hazards for each individual pixel over time. The hazard function is regressed against a set of predictor variables, including those time-dependent ones. Because it accounts for dynamic values of these variables at different time steps, a key strength of survival analysis is that it allows varying contributions of each time-dependent predictor variable to the hazard over time. Survival analysis is also suited to accounting for censored data: if an event happens outside of or in between time steps in a set of time series data, it can still be included in analysis and contribute to estimating the related model parameters.

Despite its strengths in incorporating time into statistical studies of change, survival analysis has a number of drawbacks. First, it is weak in handling continuous changes in a certain dependent variable because essentially it deals with events or qualitative changes that happen at specific time points. Second, and related to the first drawback, it depends on the use of subjective thresholds to specify whether change has occurred if the dependent variable is continuous. Percent of a land cover cannot be included in the corresponding dependent variable, which must be declared as one type or the other based on a cutoff value. Third, the hazards of different spatial units sometimes may require certain untestable assumptions to be made; for example, the hazards are constant within each period in the piecewise exponential model.

Multilevel models and latent trajectory models

Multilevel models (MLMs) and latent trajectory models (LTMs) are two types of relatively new models that contribute to spatiotemporal analysis. MLMs use data at multiple hierarchical levels, including individuals who are members of a group or neighborhood, in order to account for the clustering effect that may exist within individuals of the same higher-level grouping (Browne and Rasbash 2004). These clustering effects violate the assumption of independence in standard OLS, meaning that conclusions of statistical significance may be drawn incorrectly at the individual level. In various demonstrated case studies in health and education, significance of outcomes at the individual level were found to no longer be significant when clustering due to higher-level group membership, such as classrooms or hospitals, was accounted for. Functionally, MLM differs from OLS regression by allowing variability in both the intercept and the coefficients of the model. For each intercept or coefficient, there is one random term that is allowed to change from entity to entity, and/or a fixed term that describes the influence of the higher-level grouping on each individual within the same group.

MLMs are used in spatiotemporal analysis because of their ability to investigate time series spatial data by nesting multiple time measurements within each individual unit. In this case, time measurements would be the level-1 units, individual observations (which could be pixels) would be level-2 units, the neighborhood or other higher-level group would be level-3 units, and so on (Subramanian 2010). By structuring spatiotemporal analysis in this way, causal mechanisms that are operating at different levels over time can be revealed. Challenges in using the technique include the need for sufficiently large populations of higher-level groups in order to draw a sample of adequate size, as well as the related need for significant computing power to conduct analysis of such large datasets. In addition, MLM models do not allow endogeneity within the model, that is, they do not allow parameters of the model to function as predictors for other variables (Preacher *et al.* 2008).

LTMs are related to MLMs, and in some cases result in equivalent models for spatiotemporal analysis. This technique, however, is more explicitly aimed at analyzing longitudinal data in order to find the impact of time and a number of independent variables on a dependent variable (Guo and Hipp 2004). The input data of both LTMs and MLMs could be either vector or raster maps at multiple times, and both can be used to predict or explain spatiotemporal patterns. Using patterns of change (such as quadratic or linear, but not necessarily monotonous increase or decrease) in the response variable y as latent variables, LTMs are able to model change patterns in y as latent variables, and estimates complex causal relationships or plausible pathways among these change patterns and a set of independent variables (Preacher *et al.* 2008). Weaknesses of LTMs include the assumption that the dependent variable follows a mathematical function in time, when the reality may be more complex, and also the assumption that LTMs are limited in integrating hierarchical data in the way that MLMs do. By combining LTMs and MLMs into hybrid multilevel latent trajectory models, the strengths of both can be accentuated and the weaknesses minimized.

Spatiotemporal simulation techniques

The previous sections focus on statistical models that establish empirical relationships between drivers and outcomes in order to derive understanding about processes from observed patterns (NRC 2014). Another category of spatiotemporal models is that of simulation-based ones that focus more explicitly on the processes through which changes develop. These rule-based models, including cellular automaton (CA) and agent-based modeling (ABM), concentrate on how systems function, and how lower-level processes result in emerging higher-level patterns.

Cellular automaton

CA models portray the spatial variable of interest in a contiguous array of cells (or pixels), and the cells can change between a certain number of predetermined states (e.g., land-use and land-cover types) as time passes (Parker *et al.* 2003). CA rules and parameters are set on a time step basis such that each snapshot outcome represents the system's status at a certain step. CA models can be used for either prediction or explanation purposes. In these models, change is dictated by transition rules, under which the change of state of a certain cell of interest is often dependent on the state of neighboring cells. For instance, one rule might state that an undeveloped cell that has four developed cells in its neighborhood may remain in its undeveloped state due to "crowding.". Due to these simple rules, the states of all cells may change over each successive time step, resulting in a progression of new patterns. In empirical studies, change rules can become more complex. For example, one study assessing patterns of urban growth over time in the Bay Area of California formulated transition rules based on slope, roads, and amount of nearby development (Clarke, Hoppen, and Gaydos 1997).

CA models are often combined with other techniques such as Markov models, overviewed earlier. Markov analysis alone projects future change based on transition probabilities calculated from time series data. Integrating CA with Markov models allows neighborhood interactions to be integrated so that the amount of change between any two types is derived from a Markov process, while change locations are prioritized based on CA rules. Together, they better address spatial dependence while predicting changes over time. Despite their utility in projecting change and investigating emergence, CA models have a number of drawbacks. Specifically, they are weak in making links between real-world, human decision-making and conversion rules, and they have a poor ability to project over long time periods (due partly to an inability to include feedbacks that operate across spatial, temporal, or organizational scales; NRC 2014).

Agent-based models

Agent-based models (ABMs), also called multi-agent systems and individual-based models, focus on lower-level processes that generate larger-scale patterns (Parker *et al.* 2003). Unlike a CA model that only deals with fixed pixels, ABMs use agents that are allowed to move in time and space. Its input often includes (i) at least one layer of raster data, ArcGIS shapefile, or ASCII file (increasingly vector data as well) that contains spatial information; (ii) data for agent attributes (e.g., an ASCII or Excel spreadsheet for agent information), and (iii) rules and parameters that make the actions or processes play out. ABM models can be used for either prediction or explanation purposes. The output of ABMs can be different graphs (e.g., population dynamics over time), maps (e.g., shapefiles, ASCII files), or numbers (e.g., An *et al.* 2005). Each agent contains a number of the attributes that characterize it, and behaviors that can cause changes to the agent itself, to other agents, and to the environment as time passes. As in a CA model, ABMs function based on a set of decision rules. As these decision rules play out over time steps and agents interact with other agents and the environment, they update the attributes of themselves, other agents, and the environment. Consequently, the system represented by the ABM will evolve over time.

When applied to human-environment systems, urban systems, or other geographical systems, agents can include individuals, households, neighborhoods, or other hierarchical groupings.

The spatial domain in which the agents operate is often made up of GIS data layers that can include pixel-based or sometimes vector-based representations of the landscape. The representation of time is via time steps, or ticks. At each tick, which coincides with a real-world time interval such as a month or year, agents make decisions regarding themselves, other agents, and the environment. In a human-environment ABM, for example, these decisions can relate to things such as marriage, childbirth, the decision to collect fuelwood in a forest, or the decision to create a new household where there had previously been forest (An *et al.* 2005).

ABMs are especially suited for modeling complex systems, allowing the investigation of emergent properties, due to the fact that each agent has autonomy, intelligence, ability to communicate and interact with other agents and the environment, and ability to make informed decisions regarding the environment (Parker *et al.* 2003). These features allow ABM to characterize further features of complexity such as feedbacks, nonlinearity, thresholds, time lags, and resilience. In doing this, they demonstrate strengths in integrating heterogeneous, multiscale data, including a diverse array of agent types at different hierarchical scales. Despite these strengths, challenges in ABM implementation include steep learning curves for new modelers, high data requirements, challenging verification methodologies due to path dependence, equifinality, and multifinality (Brown *et al.* 2005; NRC 2014).

Verification, validation, and other aspects in spatiotemporal analysis

All of the spatiotemporal methods above purport to have utility in understanding, describing, and/or predicting spatiotemporal patterns of interest. In order to show this utility, the degree to which models demonstrate agreement among their theoretical frameworks, model predictions, and real-world observations needs to be established. Verification refers to the task of making sure that the construction of the model (usually in computer code) reflects the design intentions of the modeler, and is achieved partly through debugging (NRC 2014) and a set of other techniques (An *et al.* 2005). Validation can jointly refer to "structural validation," or demonstrating that model processes largely reflect or approximate real-world processes, and "outcome validation," in which model outputs are compared to real-world data of the same outcome through, for example, map comparison if the outcomes are maps (NRC 2014). One of the most-used methods is to compile an error matrix and calculate a Kappa statistic based on a sample of points, tabulating cases of agreement and disagreement between types. However, other methods for outcome validation have arisen that allow more sophisticated comparison. These include fuzzy set approaches, multiple resolution map comparison, and the variant-invariant method (Brown *et al.* 2005; Pontius, Peethambaram, and Castella 2011). These methods are crucial in examining outcomes of spatiotemporal analysis.

Conclusion

The aforementioned models represent some, though not all, of the methodologies used in spatiotemporal analysis in geography, environmental studies, and related disciplines. Other techniques, including some geovisualization and land-change models, contain overlap with these spatiotemporal analysis techniques but are less explicitly focused on looking at changes over both space and time. Despite the strengths of the demonstrated methods in appropriately dealing with spatiotemporal systems, there are a number of future research directions and challenges that the discipline faces.

In traditional spatiotemporal analysis, there has always been a dominant focus on space. Most analysis techniques are built around GIS software packages that give a good representation of space, at the expense of offering an adequate representation of time. Indeed, in many applications of spatiotemporal analysis in geography, the decision regarding the number and resolution of time steps to include is based on convenience or data availability. While space can be represented in a continuous way, time steps are broken up and included without much thought as to what the most appropriate time span and/or temporal resolution might be (An and Brown 2008; Wang *et al*. 2013), which might cause important patterns and processes to be overlooked and thereby generate biased or even misleading conclusions.

Spatiotemporal analysis, with limited capability to handle temporal variability, has a bunch of other implications. First, changes in state are often limited to low temporal accuracy, as it can only be said that a change happens before or after a time step, or between two time steps. Survival analysis models offer one potential solution to this problem by appropriately dealing with censored data. Second, the common methods of storing data based on consecutive time steps may be inefficient in data processing and data storage when compared to time-based storage techniques that are organized by the times an event happens (Peuquet and Niu 1995). Finally, it has been noted that spatiotemporal models are generally conceptualized using an absolute conception of space and time. Relative conceptions of space and time, focusing on where and when events happen in relation to other events rather than in relation to fixed space time stamps (latitude/longitude, clock time), should be further developed. Fuzzy land-change methods are one methodology moving in a direction toward relative space–time conception and deserve more attention in the future (An *et al*. 2015).

The techniques discussed in this entry offer an introduction to the many methods used for spatiotemporal analysis in geography, environmental studies, and related disciplines. An important note is that many of these models can be combined to create hybrid models (NRC 2014). Some, such as CA/Markov models, or the use of statistical methods in parameterizing an ABM, have been demonstrated here, though other hybrid combinations exist. When undertaking spatiotemporal analysis, the selection of a proper model is key to characterizing the desired pattern or processes. Understanding the models listed above, each with their advantages and drawbacks, provides a starting point for conducting spatiotemporal analysis.

SEE ALSO: Agent-based modeling; Geographic information system; Spatial analysis; Time geography and space–time prism

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