Ann Reg Sci (2013) 50:315–339
DOI 10.1007/s00168-011-0470-4

ORIGINAL PAPER

A framework for exploratory space-time analysis of economic data

Xinyue Ye · Sergio Rey

Received: 11 September 2010 / Accepted: 24 July 2011 / Published online: 11 August 2011

Abstract The development of exploratory spatial data analysis methods is an active research domain in the field of geographic information science (GIS). At the same time, the coupled space-time attributes of economic phenomena are difficult to be represented and examined. Both GIS and economic geography are faced with the challenges of dealing with the temporal dynamics of geographic processes and spatial dynamics of economic development across scales and dimensions. This paper thus suggests a novel way to generalize the characteristics and the structure of space-time data sets, using regional economic data as the example. Accordingly, a reasonable number of general questions (data analysis tasks) can be abstracted. Then, tools (methods) may be suggested on that basis. The cross-fertilization between exploratory spatial data analysis (ESDA) and spatial economics is also identified and illustrated by the capabilities of these components, which have uncovered some interesting patterns and trends in the spatial income data of China and the United States. Through exploratory analysis of economic data, the detection of rich details of underlying geographical and temporal processes would be the first step toward such cross-fertilization. In addition, this exploratory analytical framework can be applied to other data sets that are also measured for areal units at multiple points in time.

JEL Classification C21 · C88

X. Ye (✉)
Center for Regional Development & School of Earth, Environment, and Society,
Bowling Green State University, 109 South Hall, Bowling Green,
OH 43403-0181, USA
e-mail: xye@bgsu.edu

S. Rey
School of Geographical Sciences and Urban Planning, Arizona State University,
Tempe, AZ 85287-5302, USA

1 Introduction

The role of temporal GIS in data analysis is aptly explained by Wachowicz and Healey (1994) who argue that, "by producing a lineage of data to track the historical information associated with real-world phenomena, temporal GIS will provide analytical tools for the recognition of patterns of change through time as well as the prediction of future changes, by implementing dynamic simulations." Hence, the application of GIS to the domain of changing phenomena such as ecosystem dynamics, oceanic process, and economic growth seems to have a promising future. GIS and economic geography, however, are faced with the challenges of dealing with the temporal dynamics of geographic processes and spatial dynamics of economic development across scales and dimensions. The coupled space-time attributes of economic phenomena are difficult to be represented and examined under a single umbrella that integrates space, time, and attributes. Despite some initial advances, the technical and conceptual difficulties of temporal GIS still require a large amount of attention (Peuquet 2002; Goodchild 2008; Goodchild and Janelle 2010). As Goodchild et al. (2007) argue, "a simpler set of building blocks for geographic representation would give better support for the scientific investigation and management of the surface and near-surface of the Earth, including its description, representation, analysis, visualization, and simulation." The design of these building blocks can dramatically reduce the difficulty of representing the complex geographic world.

This paper suggests a novel exploratory approach to generalize the characteristics and the structure of space-time data sets using various types of unit of analysis across multiple scales and dimensions. These units of analysis serve as the building blocks, which are used to construct the space-time system representing the geographic world. Accordingly, a reasonable number of general questions (data analysis tasks) can be systematically abstracted for space-time data sets. Taxonomy of methods is then suggested, and tool can be developed on that basis.

To demonstrate the potential of this idea in both methodological and theoretical advances, regional economic data set is used as an example. The cross-fertilization between exploratory spatial data analysis (ESDA) and spatial economics is thus identified and illustrated by the capabilities of the components of the suggested framework. As Rey and Ye (2010) state, "in order to develop a more spatially explicit growth theory it is first necessary to develop operational measures that capture the spatial dynamics inherent in regional datasets." In other words, the tool is developed (operational measures are designed) in order to better understand space-time economic systems. Regarding "spatial dynamics inherent in regional datasets," a global description of datasets is far from detecting the multilevel dependence and heterogeneity embedded in the system. Hence, this framework aims to contribute to temporal GIS by revealing and quantifying hidden space-time dynamics at finer levels of scales and dimensions. In addition, this paper argues that ESDA will remain as a technique instead of a solution to pressing economic development issues without the cross-fertilization between ESDA and spatial economics. The choice of appropriate tools (methods) should be jointly decided by ESDA procedures (Andrienko and Andrienko 2006 call it "understanding") and domain-specific knowledge related to economic growth.

This paper is organized as follows. The next section gives a literature review of ESDA for spatial economics. The third section explores the nature of space-time economic data set. It includes a framework for generating research questions based on 12 units of analysis. The fourth section includes taxonomy of methods which will address the corresponding research questions. This is followed by an illustration of some analytical methods. This paper closes with some final points. The purpose of this paper is to build a framework to conduct exploratory space-time analysis of economic data, which is viewed as an initial step toward the goal of spatially explicit growth theory.

2 Literature review

It is the research question, not the methodology that should drive the design of scientific studies. Most of empirical studies are motivated by certain well-defined research questions. Then, the researcher chooses the appropriate analytical methods while also obtaining the data needed for application of the methods. Only at the end of the process does the analyst interpret and evaluate the results. However, traditional research methods tend not to be very useful in revealing space-time patterns in new, large, and complicated space-time data set. As pointed out by Goodchild and Glennon (2008), spatial pattern is associated with time-dependent aspects, and the processes that transform and modify spatial structure should also be investigated in order to understand geographic dynamics which is represented by space-time data sets. Hence, the analyst has to get acquainted with the data before formulating novel questions. As such, the procedure of "getting acquainted with data" is the basis of exploratory data analysis (EDA) (Andrienko and Andrienko 2006).

EDA is a philosophy of conducting data analysis, which originates from Tukey's seminal work (Tukey 1977). As argued by Tukey, EDA is to analyze data for the purpose of interactively formulating hypotheses instead of testing hypotheses. Under the framework of EDA, exploratory spatial data analysis (ESDA) is defined to be "detecting spatial patterns in data, formulating hypotheses based on the geography of the data, assessing spatial models" (Haining and Wise 1997). Le Gallo and Ertur (2003) consider it as "a set of techniques aimed at describing and visualizing spatial distributions, at identifying atypical localizations or spatial outliers, at detecting patterns of spatial association, clusters or hot spots, and at suggesting spatial regimes or other forms of spatial heterogeneity." Abundant evidence has illustrated that the effects of spatial dependence and heterogeneity tend to be the rule rather than the exception (Rey and Ye 2010). ESDA can reveal complex spatial phenomenon not identified otherwise (Anselin 1993), and it forms the basis for formulating novel research questions. The development of new methods of ESDA has stimulated a number of research efforts (Anselin and Getis 1992; Getis et al. 2004; Rey and Anselin 2006; Ye and Carroll 2011).

At the same time, there is increasing awareness of the importance of space in the studies of economic convergence and inequality (Rey and Ye 2010). Goodchild and Janelle (2010) summarize spatial turns in the sciences and social sciences, arguing the importance of the integration of geographically referenced information into conceptual frameworks and applied uses in these domains. However, recent work in economic geography has also been criticized for failing to deal with the major problems of economic development and inequality, as well as for including fuzzy concepts, using shaky evidence, and generating findings that are irrelevant to policy formulation (Hamnett 2003). The existing economic and regional growth theories do not fully account for the rich details of spatial patterns encountered in empirical work (Fingleton 2004). In addition, it is not surprising that geography (such as spatial autocorrelation) matters in different economic systems. However, it is more interesting to what extent that geography matters in a comparative context. Hence, Bode and Rey (2006) call for "further research on integrating space into formal theoretical models of growth and convergence as well as on developing the next generation of analytical methods needed to implement those models." Furthermore, they maintain that these are "the preconditions for reliable policy recommendations, one of the primary goals of economic research" (Bode and Rey 2006). The treatment of space and time in the analysis of economic growth has only recently begun to receive attention (Rey and Janikas 2005; Ye and Carroll 2011). Moreover, the findings of economic growth are usually mixed and sometimes conflicting for a same economic system, because economic development is a multi-dimensional and multi-scale phenomenon (Ye and Wei 2005).

In spatial economic data, region is used to record both spatial and non-spatial attributes. The region has served as a useful unit of observation to test those competing economic growth theories as well as a host of regional economic hypothesis (Quigley 2001). The increased globalization of the world's economic, social, and political realms has increased interest further in the study of regional phenomena. The debate on the trajectories and mechanisms of regional development has focused on the scope and consequences of regional policies, as well as the extent and sources of regional inequality (Sidaway and Simon 1990; Fan and Casetti 1994; Ye and Wei 2005; Wei and Ye 2009). It is reflected in numerous empirical studies of specific nations and continents (Wei and Ye 2004; Rey and Janikas 2005). Such studies provide evidence concerning the convergence or divergence of regional economies, which help to plan and evaluate the regional policies.

Quah (1993) argues that traditional empirical strategies might be misleading because of the arbitrary assumptions about the dynamics as a whole. Distribution dynamics refer to the difference among the overall shape characteristics of the regional income distribution and the evolution of these characteristics over time, as well as the amount of internal mixing or rank mobility taking place within these same distributions. Quah (1996b) comments that the distribution dynamics empirics will lead to new theories on economic growth.

In response, a number of EDA techniques have been applied to regional income distributions. Using Markov chain techniques, Quah documents the degree to which this instability characterizes the data. Markov chains have been applied to study steady-state trends (Magrini 1999), modality (Quah 1996b), and rank mobility (Hammond and Thompson 2002). Stochastic kernels are considered as extensions of the Markov chain to a continuous field. Bianchi (1997) employs Markov chain approach in the analysis of modality, and its application in the internal mixing is carried out by Tsionas (2000). Although the empirics of distribution dynamics have been used both descriptively and inferentially, these methods have ignored the physical locations and geographical distributions of attributes, which can matter more than traditional macroeconomic factors (Quah 1996a). Some recent works point out that the dominant focus in the empirical literature on shape regularities may mask some interesting patterns that are internal to those distributions (Overman and Ioannides 2001; Ioannides and Overman 2004). Hence, underlying geographical and temporal processes may be ignored (Rey and Ye 2010).

To understand the role of geography in economic phenomena, many novel methods of spatial data analysis and visualization are becoming increasingly valuable in analyzing the location of economic activities and the allocation of scarce resources over space (Church 2002; Getis et al. 2004; Anselin et al. 2006). Based on a critical review of empirical approaches and methodological advances in spatial econometrics and spatial statistics, Rey and Janikas (2005) highlight the important roles of spatial dependence, spatial heterogeneity, and spatial scale in the analysis of regional income distribution dynamics. Rey (2001, 2004) and Rey and Ye (2010) suggest a series of spatial empirics for distributional dynamics. Applying GIS analysis and computational geometry approaches to summarize spatial patterns of distributional dynamics has just begun to attract attention (Rey and Anselin 2007; Rey and Ye 2008; Ye and Carroll 2011).

It is clear that a space-time perspective has become increasingly relevant to our understanding of economic development, and novel methods are needed to truly integrate space and time (Rey and Ye 2010). Space-time methods can be created by either incorporating spatial dependence into the evolution of regional income distributions or extending static spatial associations to a dynamic context. Hence, it is valuable to have a framework to fully explore the interactions among space, time, and economic attributes across scales on one hand and to generate a systematic group of research questions that can guide the design of ESDA on the other hand.

In many disciplines, researchers are asked to compare and contrast two things, such as two theories, two temporal trends, two spatial processes, and so on. When one or two space-time income data sets are presented, it is interesting to detect crucial differences or surprising commonalities between two regions or across two groups of regions, which can be refined to generate many important research questions. These research interests span a variety of disciplines that include any domains concerned with change in geographic space (Goodchild and Glennon 2008). Faced with a daunting list of differences and similarities, it is necessary to design research questions more logically and comprehensively. However, existing exploratory approaches to space-time analysis, from data mining to visualization, are limited to building a framework to generate research questions for one space-time data set, let alone two data sets (Rey and Ye 2010).

Despite a very rich empirical literature on regional convergence and income distribution dynamics, comparative analysis of income distribution dynamics and the role of space in the dynamic context are relatively few (Rey and Janikas 2005; Janikas 2007). Researchers and policy makers will gain better understanding of different economic development mechanisms and policy implementation schemes through comparative analysis. Additionally, economic development is a multi-scale phenomenon, because distributional characteristics at one scale might impact the distribution at another scale

(Rey and Janikas 2005). Moreover, applications of comparative analysis among one economic system and across different economic systems are currently lacking an inferential basis (Rey and Ye 2010).

3 A framework of research questions

3.1 Unit of analysis

Methods developed in the mainstream social science disciplines have been applied with little attention paid to the potential challenges posed by spatial autocorrelation, let alone the spatial effects over time at multiple scales. Though rich conceptual frameworks have highlighted the spatial dynamics and unevenness of income distribution processes, the gap has been widening between the empirical studies and economic growth models. Many implementations of growth theories in estimable econometric specifications do not appropriately treat dynamic spatial effects in the data (Rey and Janikas 2005). Hence, the most crucial step is to systematically understand the data before testing hypotheses. It is worth noticing that data are also collected based on our understanding of the systems including hypotheses. However, the definitions of the unit of analysis and the unit of observation should be distinguished before the structure of the space-time data set can be characterized.

The unit of analysis is the major entity that is being analyzed in the research, while the unit of observation is the basic entity that the data are reported upon. The unit of analysis is the "what" that is being studied, which is designed by the researcher. However, the unit of observation is decided by the way how the data set was collected, which cannot be fully controlled by the researcher. In most studies, the difference between the unit of analysis and the unit of observation is not emphasized. Although this has been an issue for some time, it is important to recognize the difference between the unit of analysis and the unit of observation in the framework for comparative space-time analysis. The main reason is that the unit of analysis involves the issues of scales and aggregation of data, which are very useful for designing data analysis tasks. Census data, for instance, serve as the unit of observation for many socioeconomic studies. Census data may be aggregated into census enumeration districts (block, block group, census tract, place, county, MSA, State, and so on), by postcode areas (Zip Code Tabulation areas), with considerable difficulty into other geographic subdivisions such as police beats or flood zones.

Various spatial partition schemes lead to different types of unit of analysis, which in turn generate different perspectives of looking at the same data. Hence, it is valuable to consider all possible spatial perspectives before formulating research questions. At the same time, it is worth noticing that all possible temporal configurations should be considered. Monthly unemployment counts (the unit of observation), for instance, can be aggregated into quarterly or yearly periods. Many types of units of analysis can be generated when both spatial and temporal partition schemes are considered. Unemployment issues, for instance, can be analyzed at the county level using monthly counts, or at the state level using yearly counts, or at the level of any other spatial partition with any other temporal partition.

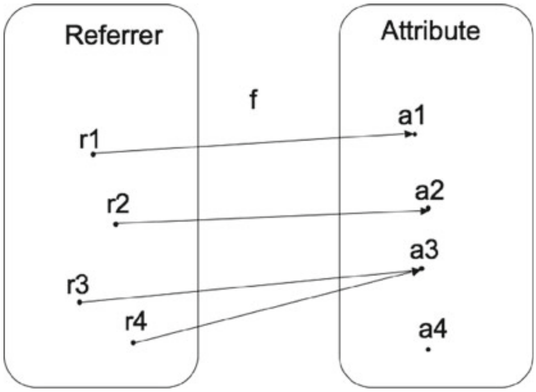

Fig. 1 The functional view of a dataset (Andrienko and Andrienko 2006)

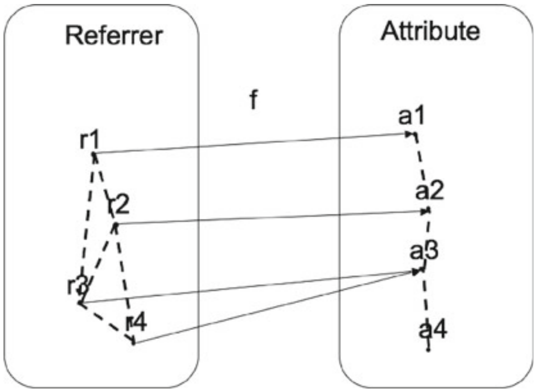

Fig. 2 Missing structures in the functional view of a dataset

Andrienko and Andrienko (2006)'s diagram (Fig. 1) represents a common view of space-time data set in the current ESDA literature. Characteristic and referential components of data are distinguished: the former (Attribute) reflects measurements while the latter (Referrer) specifies where and/or when the measurements are recorded. For example, median household income in San Diego County was $61,724 in 2007. Both San Diego County (space) and 2007 (time) serve as the context (r1) for the income of $61,724 (a1). However, the assumption here is that characteristic/referential elements are independent from each other. In other words, the relationships (structures) among the referrers/attributes are not considered in Fig. 1. According to Waldo Tobler, "everything is related to everything else, but near things are more related than distant things" (Tobler 1970). Besides space, things near in time or near in statistical distribution should also be more related than distant things. Hence, the interdependence among the referrers/attributes should be the rule instead of the exception, as shown by the dotted segments in Fig. 2. Ignoring these relationships leads to overlooking many possible interactions and dependence among space, time, and attributes.

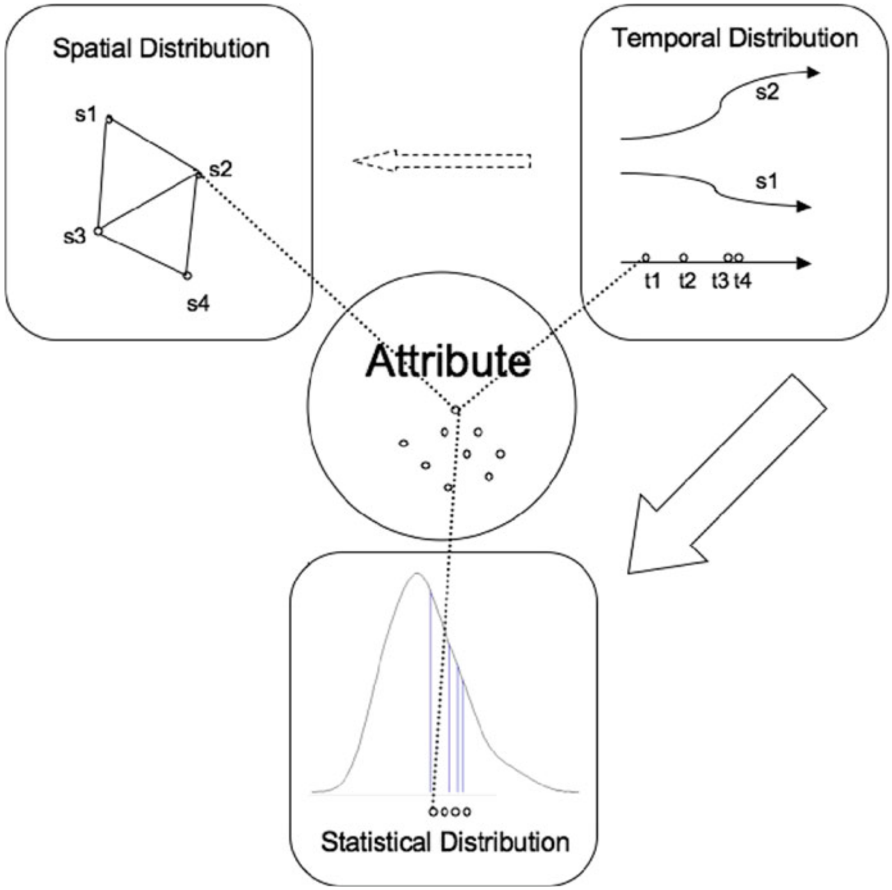

Fig. 3 A general view of space-time data

3.2 Dimensions and scales

To reveal these relationships, the distributions of space, time, and attributes should be treated as the context in which a measurement is made (Fig. 3), instead of specifying a single space and/or time as the context. The "distribution" of space (the dimension of space) refers to the spatial distribution of attributes while the "distribution" of attributes (the dimension of statistical distribution) implies the arrangement of attributes showing their observed or theoretical frequency of occurrence. In addition, the "distribution" of time (the dimension of time) signifies the temporal trend of attributes. As revealed by Fig. 4, California's per capita income in 1970 can be mapped to a place in the spatial distribution (the top right view), to a time point in the temporal trend (the bottom left view), and to a location in the statistical distribution (the top left view). Arizona's per capita income can also be viewed in these three dimensions. It is worth noticing that though these two incomes in 1970 were located in the two neighboring states (spatial relationship), their locations in the statistical distribution

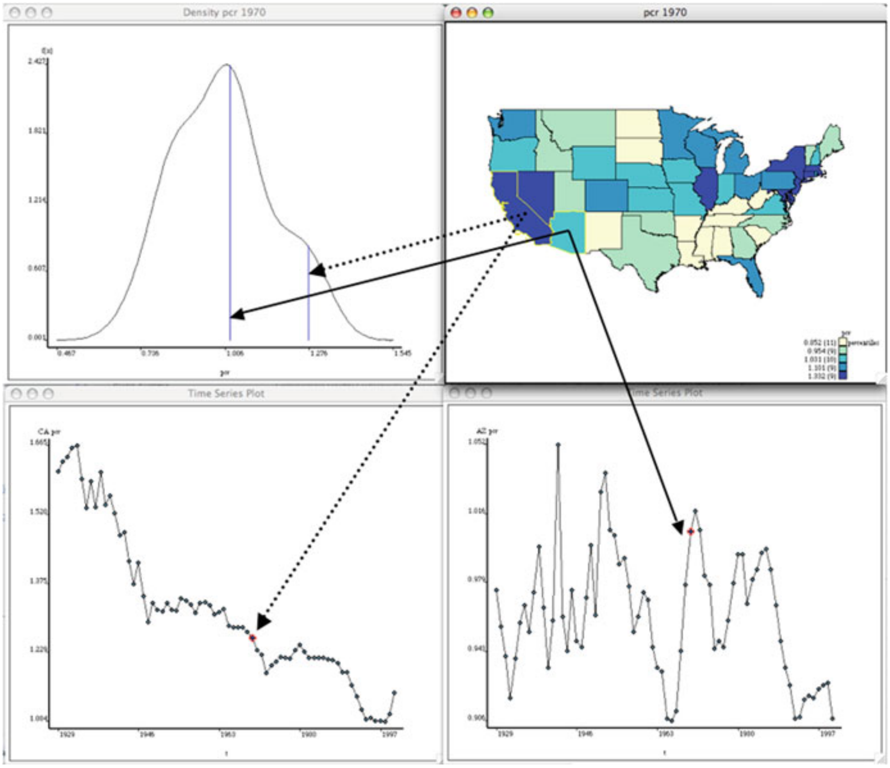

Fig. 4 Spatial distribution, temporal trend, and statistical distribution of incomes in the United States

were not close at all. From the temporal perspective, the income of California in 1970 was at a time point during the era of economic decay (the bottom left view in Fig. 4) while Arizona reported great economic growth in the same year (the bottom right view in Fig. 4). These similarities and differences cannot be detected if the distributions do not serve as the context for these two incomes. A list of data analysis tasks can then be generated through summarizing these phenomena. In other words, if the relationships among referrers/attributes (the dotted segments in Fig. 2) are ignored, many interesting research questions cannot be developed.

Besides the dimensions, it is also important to recognize the issue of scales. Four scales are taken into consideration. The unit of analysis at the individual scale signifies the geographical location of an attribute (A1, Table 1), the temporal label of an attribute (A5, Table 1), or the rank of an attribute (A9, Table 1). In other words, individual-scale unit of analysis does not take into accounts any relationship among observations. The unit of analysis at the local scale explores a group of units which is formed by the focal observation and its neighboring observations in one of these three dimensions. A focal state and its neighboring states, for example, can be considered as a unit of analysis from the perspective of the spatial dimension (distribution) at the local scale (A2, Table 1). A focal year, the previous year, and the following year can be considered as a unit of analysis from the perspective of the temporal dimension at

Table 1 Examples for unit of analysis

		Levels			
		Individual	Local	Meso	Global
Distributions	Spatial	California (A1)	California and its neighboring states (A2)	Spatial distribution of rich states (A3)	Spatial distribution of all the states that belong to the first income quartile (A4)
	Temporal	1988 (A5)	1987, 1988 and 1989 (A6)	the 1980s (A7)	1978–1998 (the study period) (A8)
	Statistical	No. 3 income (A9)	No. 2, 3, and 4 incomes (A10)	The first income quartile (A11)	Statistical distribution of all the state incomes (A12)

the local scale (A6, Table 1). A focal rank and the two immediate higher/lower ranks can be considered as a unit of analysis from the perspective of the statistical dimension (distribution) at the local scale (A10, Table 1). Researchers have the flexibility to define which observations are neighbors to a focal observation in spatial, temporal, or statistical distribution. For example, various types of spatial weight matrix can be used to define the neighboring spatial units of a focal observation.

Both local and meso scales deal with a subgroup of observations. A meso-scale analysis studies a group of entities which shares similar feature(s) in spatial, temporal, or statistical distributions. In other words, the local-scale analysis differs from the meso-scale analysis in the way how a subset of space-time data is retrieved for analysis. The former emphasizes that the rest of the subset are "near things" to the focal element while the latter does not have a focal element in the subset. In addition, the latter usually has a larger subset (larger in space and lengthier in time) as the unit of analysis than the former does. The spatial distribution of rich states, for example, can be considered as a unit of analysis from the perspective of the spatial dimension (distribution) at the meso scale (A3, Table 1). All the years since a policy was implemented can be considered as a unit of analysis from the perspective of the temporal dimension at the meso scale (A7, Table 1). An income quartile can be considered as a unit of analysis from the perspective of statistical dimension (distribution) at the meso scale (A11, Table 1). As illustrated by the above three examples, meso scale can be treated as a scale between local and global scales from the perspective of the size of observations.

The analysis at the global scale examines the distributions of all the regions, times, or attributes. Spatial distribution of all the incomes, for example, can be considered as a unit of analysis from the perspective of the spatial dimension (distribution) at the global scale (A4, Table 1); all the years can be considered as a unit of analysis based on the temporal dimension at the global scale because the research of the space-time dynamics is very sensitive to the selected starting and ending years (A8, Table 1); the

Table 2 Spatial-temporal task

		Temporal			
		Individual	Local	Meso	Global
Spatial	Individual	A1 + A5	A1 + A6	A1 + A7	A1 + A8
	Local	A2 + A5	A2 + A6	A1 + A7	A2 + A8
	Meso	A3 + A5	A3 + A6	A3 + A7	A3 + A8
	Global	A4 + A5	A4 + A6	A4 + A7	A4 + A8

Table 3 Statistical-temporal task

		Temporal			
		Individual	Local	Meso	Global
Statistical	Individual	A9 + A5	A9 + A6	A9 + A7	A9 + A8
	Local	A10 + A5	A10 + A6	A10 + A7	A10 + A8
	Meso	A11 + A5	A11 + A6	A11 + A7	A11 + A8
	Global	A12 + A5	A12 + A6	A12 + A7	A12 + A8

Table 4 Statistical-spatial task

		Spatial			
		Individual	Local	Meso	Global
Statistical	Individual	A9 + A1	A9 + A2	A9 + A3	A9 + A4
	Local	A10 + A1	A10 + A2	A10 + A3	A10 + A4
	Meso	A11 + A1	A11 + A2	A11 + A3	A11 + A4
	Global	A12 + A1	A12 + A2	A12 + A3	A12 + A4

statistical distribution of all the incomes can be considered as a unit of analysis based on statistical dimension (distribution) at the global scale (A12, Table 1). Limiting attention to only one of these dimensions or scales may result in a misguided or partial understanding of the economic growth dynamics.

Thus, 12 basic units of analysis can be conceptualized through combining three dimensions and four scales (Table 1). This view of a space-time data set helps to describe patterns of economic activities such as geographical spillover occurring across scales, which may be more significant than traditional macroeconomic factors (Quah 1996a). By identifying the unit of analysis, a general task typology can build on top of Table 1. Three conceptual tables involve various possible research questions based on the combination of these 12 units of analysis (Tables 2, 3, and 4). Hence, such a framework has a significant appeal for exploratory data analysis because it generates a comprehensive list of research questions. During the course of analysis, as something interesting to researchers is detected in the data, new research questions arise, causing specific regions or relationships to be scrutinized in more detail. It is worth pointing out that such a list of examples in Tables 5, 6, and 7 includes a limited number of data analysis task that can be formulated according to Tables 2, 3, and 4. A set of comparative analysis questions can then be built on these examples (Tables 8, 9, and 10).

Table 5 Examples of spatial-temporal task

		Temporal			
		Individual	Local	Meso	Global
Statistical	Individual	What was California's income in 1988? (A1A5)	Was California's income in 1988 different from 1987 and from 1989? (A1A6)	Was California characterized by steady growth in the 1980s? (A1A7)	What was the trend of California's economic growth during the study period (1978–1998)? (A1A8)
	Local	What was the income of California and its neighboring states in 1988? (A2A5)	Was the income of California and its neighboring states in 1988 different from 1987 and from 1989? (A2A6)	Were California and its neighboring states characterized by steady growth in the 1980s? (A1A7)	Were California and its neighboring states characterized by steady growth during the study period (1978–1998)? (A2A8)
	Meso	Where were the five richest states located in 1988? (A3A5)	Was the spatial distribution of the five richest states in 1988 different from 1987 and from 1989? (A3A6)	Was the spatial distribution of the five richest states stable in the 1980s? (A3A7)	Was the spatial distribution of the five richest states stable during the study period (1978–1998)? (A3A8)
	Global	Were incomes in the United States clustered in 1988? (A4A5)	Were temporal dynamics of incomes in the United States clustered from 1987 to 1989? (A4A6)	Were temporal dynamics of incomes in the United States clustered during the 1980s? (A4A7)	Were temporal dynamics of incomes in the United States clustered during the study period (1978–1998)? (A4A8)

In these examples, income signifies per capita income at the state (province) level while rank implies a state (province)'s ranking of per capita income in the nation. The era of the 1980s is an important period of new economic policies for both the United States and China, so it is considered a meso-scale temporal unit.

The units of analysis suggested here use regional economic data sets as the example. However, it can be extended to other categories of space-time data sets by modifying the terms. For instance, the states in Fig. 4 can be replaced with the polygons which represent neighborhoods in a city. The dimensions and scales can thus be used to explore space-time dynamics of socioeconomic indicators within an urban area. Similar to what Fig. 4 reveals, a neighborhood's homicide rate, for example, can be viewed in three different contexts: space, time, and attribute (Ye and Wu 2011). Criminologists can use the suggested 12 basic units of analysis to investigate scales and dimensions of homicide rate at the neighborhood level.

Table 6 Examples of temporal-statistical task

		Temporal			
		Individual	Local	Meso	Global
Statistical	Individual	Which state was ranked No. 3 in 1988? (A9A5)	Was the same state ranked No. 3 from 1987 to 1989? (A9A6)	How many different states were ranked No. 3 during the 1980s? (A9A7)	How many different states were ranked No. 3 during the study period (1978–1998)? (A9A8)
	Local	Which three states were ranked No. 2, 3, and 4 in 1988? (A10A5)	Were the same three states rank No. 2, 3, and 4 from 1987 to 1989? (A10A6)	How many different states were ranked No. 2, 3, and 4 during the 1980s? (A10A7)	How many different states were ranked No. 2, 3, and 4 during the study period (1978–1998)? (A10A8)
	Meso	Which states were in the first income quartile in 1988? (A11A5)	Were the same three states in the first income quartile from 1987 to 1989? (A11A6)	How many different states were in the first income quartile during the 1980s? (A11A7)	How many different states were in the first income quartile during the study period (1978–1998)? (A11A8)
	Global	What was the skewness of the U.S.' income distribution in 1988? (A12A5)	Was the shape of the U.S.' income distribution stable from 1987 to 1989? (A12A6)	How did the modality of the U.S.' income distribution change in the 1980s? (A12A7)	How did the modality of the U.S.' income distribution change in the study period (1978–1998)? (A12A8)

This framework can also be incorporated into cellular automata modeling of land use change, where spatial dimensions across scales can be used specifically to test various scenarios in constructing the rules of forming neighborhoods, and temporal dimension across scales would be well conceptualized as the life cycle of land use change. In addition, the attributes can be used as the threshold for development at different stages (statistical distribution at various scales). Hence, cellular automata transition rules can be systematically explored, which is an important task in modeling complexity (Ye et al. 2005).

4 Taxonomy of methods

4.1 Taxonomy

The previous section presents a general framework for pattern discovery and hypothesis exploration in space-time data sets. This framework allows the behavior of a

Table 7 Examples of spatial-statistical task

		Temporal			
		Individual	Local	Meso	Global
Statistical	Individual	Has California been ranked No. 3? (A9A1)	Have California and its neighboring states been ranked No. 3? (A9A2)	How many coastal states have been ranked No. 3? (A9A3)	What was the spatial distribution of the states that have been ranked No. 3? (A9A4)
	Local	Has California been ranked No. 2, 3, or 4? (A10A1)	Have California and its neighboring states been ranked No. 2, 3, or 4? (A10A2)	Has any coastal state been ranked No. 2, 3, or 4? (A10A3)	What was the spatial distribution of the states that have been ranked No. 2, 3, or 4? (A10A4)
	Meso	Has California always been in the first income quartile? (A11A1)	Have California and its neighboring states always been in the first income quartile? (A11A2)	Has any state in the first income quartile not located in the coastal area? (A11A3)	Was the spatial distribution of the states in the first income quartile stable over time? (A11A4)
	Global	Which ranks has California experienced? (A12A1)	Which ranks have California and its neighboring states experienced? (A12A2)	Which ranks have the coastal states experienced? (A12A3)	What was the spatial distribution of ranks? (A12A4)

dynamic system to be reconstructed from a group of units of analysis. The key aspect of the work is to integrate the three dimensions of a space-time data set in a four-scale environment.

Spatial data analysis, temporal data analysis, and probability distribution analysis are three fundamental analytical methods for space-time data set. Taxonomy of methods can then be built by combining any two methods at any two scales, which aims to address the tasks raised by the framework of research task. This section tries to extend the generality attained to the consideration of the methods for space-time tasks, using income data as the example (Table 11). It is worth noticing that this section does not cover all the types of potential research task because the objective of this research is to suggest taxonomy instead of discussing every analytical method in detail.

The concept of exploratory data analysis is strongly associated with visualization because graphical presentation enables the analyst to open-mindedly explore the structure of the data set and gain some new insights. According to Shneiderman (1996), exploratory data analysis can be generalized as a three-step process: “overview first, zoom and filter and then details-on-demand.” In the first step, an analyst must obtain an overview of the entire data set, which is referred to as global-scale methods. In

Table 8 Examples of comparative spatial-temporal task

		Temporal			
		Individual	Local	Meso	Global
Spatial	Individual	Was California's income higher than New York in 1988? (A1A5)	Compared to New York, was California's income in 1988 more different from 1987 and from 1989? (A1A6)	Compared to New York, was California characterized by more steady growth in the 1980s? (A1A7)	Did California grow faster than New York during the study period (1978–1998)? (A1A8)
	Local	Was the income of California and its neighboring states higher than New York and its neighboring states in 1988? (A2A5)	Compared to New York and its neighboring states, was the income of California an its neighboring states more different from 1987 and from 1989? (A2A6)	Compared to New York and its neighboring states, did the income of California and its neighboring states grow faster in the 1980s? (A1A7)	Compared to New York and its neighboring states, did the income of California and its neighboring states grow faster in the study period (1978–1998)? (A2A8)
	Meso	Compared to the five richest provinces in China, were the five richest states in the United States. more clustered in 1988? (A3A5)	Compared to the five richest provinces in China, was the spatial distribution of the five richest states in the United States more stable in 1987, 1988, and 1989? (A3A6)	Compared to the five richest provinces in China, was the spatial distribution of the five richest states in the United States more stable in the 1980s? (A3A7)	Compared to the five richest provinces in China, was the spatial distribution of the five richest states in the United States more stable during the study period (1978–1998)? (A3A8)
	Global	Compared to China, were incomes in the United States more clustered in 1988? (A4A5)	Compared to China, were temporal dynamics of incomes in the United States more clustered from 1987 to 1989? (A4A6)	Compared to China, were temporal dynamics of incomes in the United States more clustered during the 1980s? (A4A7)	Compared to China, were temporal dynamics of incomes in the United States more clustered during the study period (1978–1998)? (A4A8)

the second step, the analyst zooms in on the items of interest, which is referred as meso-scale methods. At the third stage, the analyst selects an item and/or its vicinity for examination of more details, which is referred as local-scale or individual-scale

Table 9 Examples of comparative temporal-statistical task

		Temporal			
		Individual	Local	Meso	Global
Statistical	Individual	What was the difference between the No. 3 income and the No. 4 income in 1988? (A9A5)	Was the difference between the No. 3 income and the No. 4 income stable from 1987 to 1989? (A9A6)	Was the difference between the No. 3 income and the No. 4 income stable during the 1980s? (A9A7)	Was the difference between the No. 3 income and the No. 4 income stable during the study period (1978–1998)? (A9A8)
	Local	What was the difference between two income groups (the No. 2, 3, 4 and No. 5, 6, 7) in 1988? (A10A5)	Was the difference between two income groups (the No. 2, 3, 4 and No. 5, 6, 7) stable from 1987 to 1989? (A10A6)	Was the difference between two income groups (the No. 2, 3, 4 and No. 5, 6, 7) stable during the 1980s? (A10A7)	Was the difference between two income groups (the No. 2, 3, 4 and No. 5, 6, 7) stable during the study period (1978–1998)? (A10A8)
	Meso	What was the difference between the first income quartile and the second income quartile in 1988? (A11A5)	Was the difference between the first income quartile and the second income quartile stable from 1987 to 1989? (A11A6)	Was the difference between the first income quartile and the second income quartile stable during the 1980s? (A11A7)	Was the difference between the first income quartile and the second income quartile stable during the study period (1978–1998)? (A11A8)
	Global	Was the U.S.' regional income distribution more skewed than that of China in 1988? (A12A5)	Was the skewness of the U.S.' regional income distribution stable than that of China from 1987 to 1989? (A12A6)	Was the skewness of the U.S.' regional income distribution stable than that of China in the 1980s? (A12A7)	Was the skewness of the U.S.' regional income distribution stable than that of China during the study period (1978–1998)? (A12A8)

methods. It is worth noticing that this process is iterative, and the analyst can frequently return to the previous steps.

4.2 Illustrations

In the rest of this section, some methods are highlighted drawing on examples from income distribution studies in China and the United States. As Rey and Janikas (2006) state, "explore patterns through various interfaces and the views are dynamically integrated with one another, giving rise to the second meaning of dynamic spatial data analysis (the first meaning is incorporating time to spatial data analysis)." The scales and dimensions suggested in this framework enrich the formats of interfaces and views. At the global scale, the network approach visualizes the covariance matrix of

Table 10 Examples of comparative spatial-statistical task

		Spatial			
		Individual	Local	Meso	Global
Statistical	Individual	Has California been more frequently ranked No. 3 than any other state? (A9A1)	Compared to New York and its neighboring states, have California and its neighboring states been more frequently ranked No. 3? (A9A2)	Compared to the inland states, have the coastal states been more frequently ranked No. 3? (A9A3)	Was the states that have been ranked No. 3 more clustered than those ranked No. 4? (A9A4)
	Local	Has California been more frequently ranked No. 2, 3, and 4 than any other state? (A10A1)	Compared to New York and its neighboring states, have California and its neighboring states been more frequently ranked No. 2, 3, and 4? (A10A2)	Compared to the inland states, have the coastal states been more frequently ranked No. 2, 3, and 4? (A10A3)	Were the states that have been ranked No. 2, 3, and 4 more clustered than those ranked No. 5, 6, and 7? (A10A4)
	Meso	Has California been more frequently in the first income quartile than the second quartile? (A11A1)	Have California and its neighboring states been more frequently in the first income quartile than the second quartile? (A11A2)	Have the coastal states been more frequently in the first income quartile than the second quartile? (A11A3)	Was the spatial distribution of the first income quartile more clustered than the second quartile? (A11A4)
	Global	Compared to New York, has California experienced more different types of ranks? (A12A1)	Compared to New York and its neighboring states, have California and its neighboring states experienced more different types of ranks? (A12A2)	Compared to the inland states, have the coastal states experienced more different types of ranks? (A12A3)	Compared to China, did the United States have a more clustered spatial distribution of ranks? (A12A4)

economic growth on a single map (Fig. 5). The covariance matrix is a matrix of covariance between the dynamics of incomes of each state (province). Covariance provides a measure of the strength of the correlation between two sets of incomes. This pairwise temporal covariance between two sets of incomes can be represented geographically using the network approach (Rey and Janikas 2006). The edges (covariance links) between the centroid of each region are based on a predefined spatial weights matrix. In Fig. 5, first-order contiguity is employed as it can be determined easily on the basis

Table 11 Methods for spatial-temporal task

Spatial scales	One time point (individual)	Multiple time points (Local, Meso, and Global)
Individual	Analyze the geometry of a region at a time point	Detect geometrical change of a region (such as annexation); Summarize the change trajectory of a region (such as economic growth trend)
Local	Summarize local spatial statistics at a time point	Extend local spatial statistics into a dynamic context; Summarize local spatial statistics based on temporal dynamics of incomes
Meso	Summarize the spatial distribution of a group of attributes at a time point	Detect the change of the spatial distribution of a group of attributes over time; Summarize the spatial distribution of a group of temporal dynamics of incomes
Global	Summarize global spatial statistics at a time point of a group of attributes at a time point	Detect the change of the spatial distribution of all the attributes over time; Summarize the spatial distribution of all the temporal dynamics of incomes

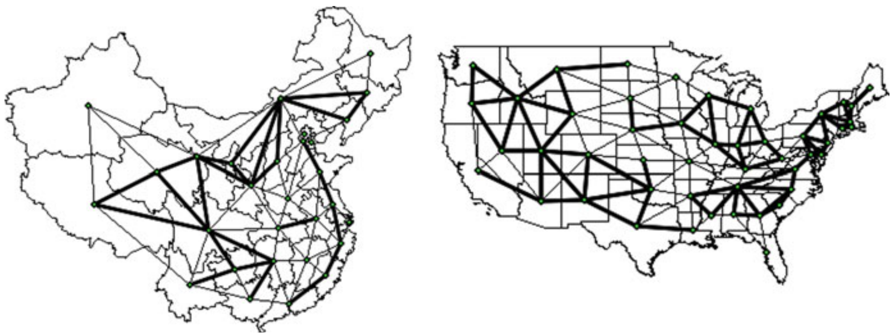

Fig. 5 Covariance networks of per capita incomes in China and the United States, 1978–1998

of states (provinces) that have shared borders. Covariance links are conditioned on the strength of the temporal covariance between two contiguous spatial units. Two bordering regions are defined to be similar in the temporal dynamics (have strong temporal linkages) if the covariance of their time series of incomes is above the national average. If two temporal dynamics of incomes are similar, there might exist some types of interaction between the two involved economies.

Since the covariance between each pair of regions is known, the strength of temporal linkages is measured for each possible region-pair. The relationships between a focal economy and any of its surrounding economies are then divided into two groups. Thick segments indicate strong temporal linkages while thin segments signify weak temporal linkages (Fig. 5). This method displays the temporal dynamics of incomes by integrating a spatial component. More specifically, this network graph identifies

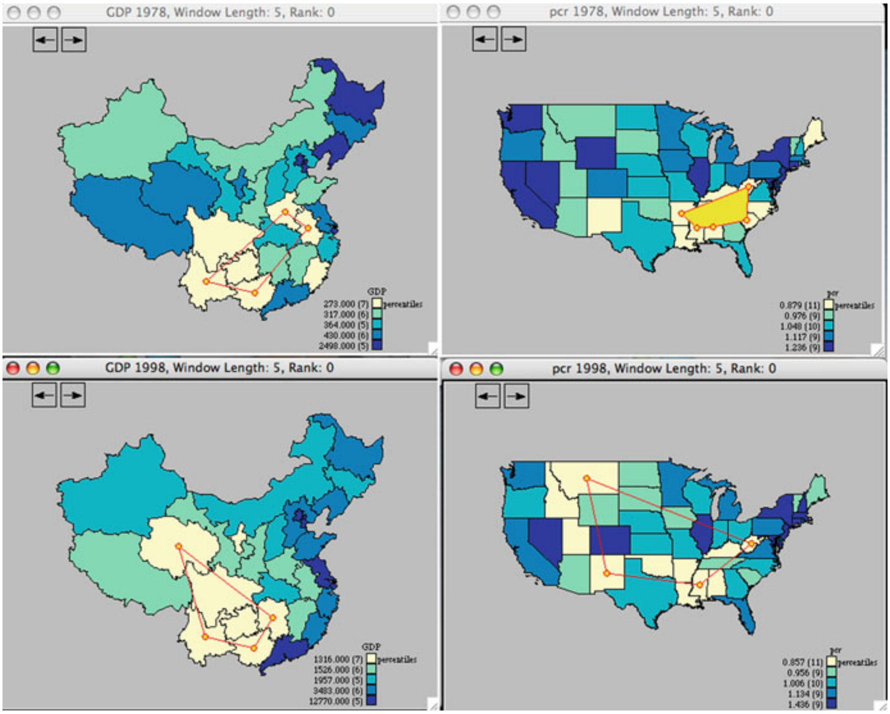

Fig. 6 The convex hulls of poor regions in China and the United States, 1978 and 1998

both similar and dissimilar economic growth trends across regions (Rey and Ye 2010). In addition, various levels of correlation can also be visualized, which will more distinctly identify cross-sectional relationships. At the meso scale, spatial properties of a group of regions can be summarized by characterizing the "shape" of a point set using the convex hull (Rey et al. 2005). The centroids of these selected regions form such a point set. The convex hull of such a point set is the smallest convex set containing these centroids. Based on a requisite variable, a group of regions can be retrieved as a subset of the whole space-time data set for further analysis. The study of a convex hull based on a group of poor regions, for example, can be used to summarize the spatial distribution of these regions. In addition, the temporal stability of this convex hull might reveal a hidden spatial diffusion process or a spatial interaction process, through detecting the change of the size, compactness, and location of this convex hull. For example, the five poorest states (provinces) in terms of per capita income are identified each year, and the convex hull can be formed based on the centroids of these polygons (the convex hulls in 1978 and 1998 are shown in Fig. 6). Because the five poorest states (provinces) might not be the same group of regions each year, the convex hulls possibly change in size and location over time. The size of the convex hull in the United States in 1978 (shown as a highlighted convex hull on the upper right view of Fig. 6), for instance, is much smaller than what is expected if the convex hull is formed by any five states. Hence, it indicates a significant spatial cluster of the

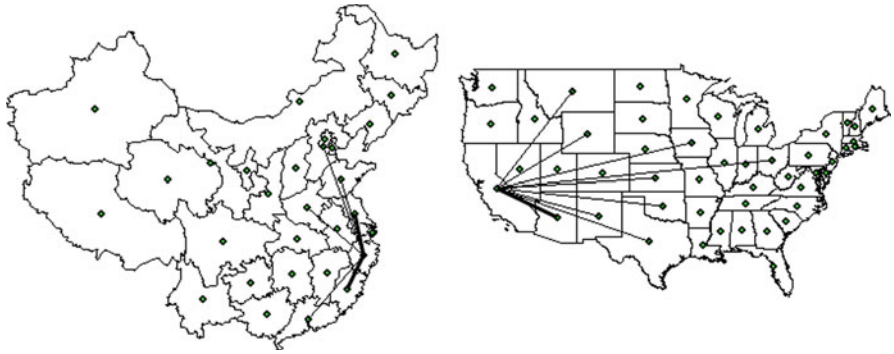

Fig. 7 Spider graphs of Zhejiang Province (China) and California (the United States)

five poorest states in 1978. Change detection based on the convex hulls might reveal the spatial association of the selected regions.

A spider graph reflects the specific temporal covariance of incomes between a region and the rest of the regional system (Fig. 7) (Rey and Janikas 2006). This is illustrated in the spider graphs of two regions: Zhejiang Province in China and California in the United States. The spider graph reveals the possible economic integration of each focal region with their respective national systems. This graph identifies the specific regions with which they share common dynamics, as reflected in high standardized pairwise temporal correlations. These are indicated by edges connecting each focal region to the dynamically similar region. The links indicate strong temporal linkages, and those regions that are also spatially contiguous to the focal region are indicated by thicker edges. Based on the spider graph, if an economy has strong temporal linkages with all of its spatial neighbors (display similar temporal dynamics), there might exist very strong space-time integration for the focal economy.

At the local scale, Luc Anselin's LISA (local indicator of spatial association) is an indicator to examine local autocorrelation (Anselin 1995). By extending such a static view of local spatial dependence into the dynamic context, the LISA Time-Path Plot illustrates the pair-wise movement of a focal unit's income value and its spatial lag (the average of the focal unit's first-order neighbors) over time (Rey et al. 2005). The path of observation i over time can be written as $[(yi, 1, yli, 1), (yi, 2, yli, 2), \ldots, (yi, T, yli, T)]$. yi, t is the value of observation I at time t and yli, t is its spatial lag at time t. That is, at a given time t, each region i can be identified with a position whose coordinates on the Moran Scatter Plot are known. Hence, each region i has associated with it a directional path connecting all the coordinates by temporal order (Fig. 8). Since individual aspects of the same contemporaneous process can be dissected by interval gaps, some geometric properties of the time path can be summarized for each region. The LISA time path can be considered a continuous representation of Markov transition matrices.

This multi-scale and multi-dimension framework can reveal some hidden space-time patterns that otherwise would be very difficult to detect. Hence, this framework is an ideal and powerful environment for exploring data that has both temporal and spatial dimensions. An example of this can be seen in Fig. 5 where at the global level

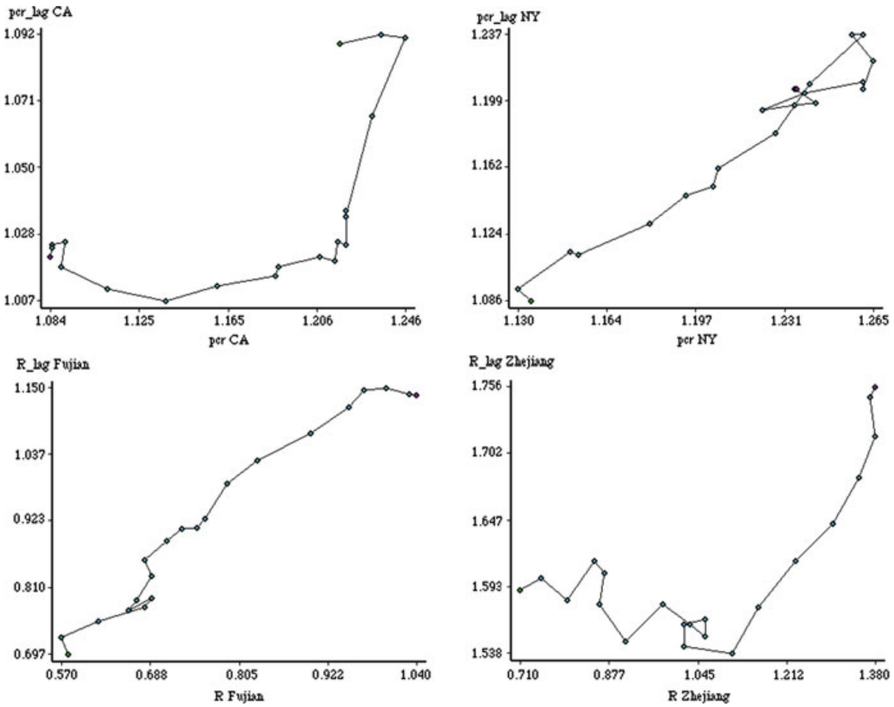

Fig. 8 LISA time paths in California (*top left*) and New York (*top right*) in the United States, Fujian (*bottom left*) and Zhejiang (*bottom right*) in China, 1978–1998

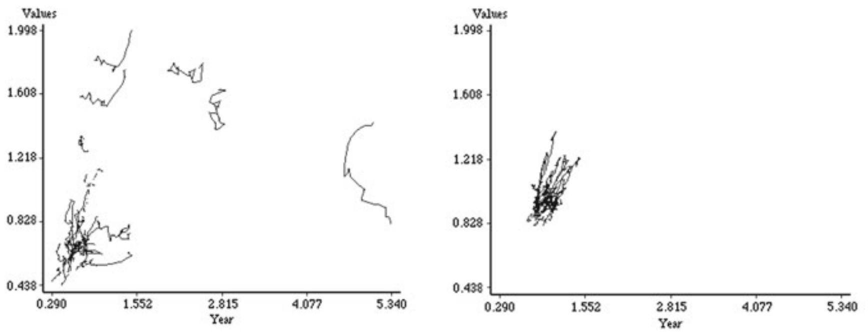

Fig. 9 LISA time paths in China (*left*) and the United States (*right*)

there is some evidence that the spatial dynamics of incomes are more integrated in the United States than in China. However, this macro structure can frequently mask a great deal of turbulence at finer scales. Figure 9 demonstrates the LISA time paths of all the states/provinces in the United States and China, which contrasts the LISA time paths of these two economic systems at the same scale (the x-axis refers to a province/state's per capita income relative to the national average, and the y-axis refers to its spatial lag). It reveals that China has much more dispersed spatial dynamics, which might indicate the existence and practice of various economic development models in China. Both outliers and clusters of the LISA time paths can also be easily identified in Fig. 9. Hence, researchers can further identify which provinces or states might have very different economic development paths from the other economic units, as well as the extent to which the difference is. This figure provides important insights to the finer-scale aspects of stability and distinct directional movement within multiple regional income distributions over time, because the convergence hypothesis is concerned with the temporal dynamics of these distributions (Rey 2001). At the individual scale, a particular economy might move up and down the statistical distribution. At the local scale, a focal region might have a different pace of economic development rate from its neighboring regions (Fig. 7). At the meso level, some intervals of statistical distribution might reveal interesting spatial processes over time (Fig. 6). This meso-scale structure provides insights as to the possible spatial impact of the selected statistical interval on the global spatial clustering over time, temporal dynamics of associated regions, and economic growth of a specific region. The sincere hope here is that this dialogue between spatial/regional economics and ESDA will extend beyond the area of developing ESDA to visualize and summarize income distribution dynamics from various scales and dimensions—that it will embrace the real-world challenges of economic development issues—and that, as a consequence, this might foster a spatially integrated research on economic analysis.

5 Summary

Many socioeconomic systems involve a number of interacting elements across scales. The realistic representation of such systems and the rigorous quantitative analysis of these interactions are crucial parts of human beings' efforts to understand the world. At the same time, the importance of space to many socioeconomic theories has been widely noted (Goodchild 2008). This paper stresses the need to study the three dimensions and four scales underlying space-time data sets, using income data sets as the example. ESDA is not new to economic convergence and inequality studies, but there are nevertheless good reasons to extend ESDA into a dynamic context and explore the data set from a systematic perspective. Comparative space-time framework enables access to a much broader thinking which addresses fundamental research questions and identifies the research gaps and opportunities for more in-depth study. This framework borrows the strength of scientific visualization techniques and develops a general task topology by combining spatial, temporal, and statistical distributions with individual, local, meso, and global scales. One research question can thus engender many follow-up research questions. This paper also explores the potential for this framework to function in spatial economics studies, specifically, in the comparison of income distribution dynamics between different economic systems. In other words, the current framework is mainly from an exploratory perspective, and the systematically generated data analysis tasks can motivate regional scientists to design a series of economic analysis questions and formulate new hypotheses from theoretical and policy perspectives.

On this basis, this paper argues that ESDA and spatial economics could benefit from each other in the following procedures: First, the analyst has the specific reason for investigating distinct economic development issues, which can be expressed as a general question or a set of general questions. Second, this nature of the investigation is checked against the task topology of the data set. Third, the analyst carries out the matched tasks and detects something both interesting and relevant to this investigation. Fourth, new, more specific questions appear and these questions motivate the analyst to look for more details. These questions affect what details will be viewed and in what ways. Lastly, the general questions in Step 1 are revised, and the investigator goes through the procedures again. Hence, this work procedure will facilitate the interdisciplinary research, for example, exploratory space-time analysis of local economic development (Ye and Carroll 2011).

This space-time framework provides an important contribution to the current economic convergence and inequality literature, which lacks in systematic comparative space-time studies (Rey and Ye 2010). Although this comparative framework arose in the study of income distribution dynamics, it can also be applied to a wide set of socioeconomic processes with geo-referenced data measured over areal units at multiple time periods, such as crime rate dynamics, housing market dynamics, and among others (Rey and Janikas 2005; Ye and Wu 2011). In other words, the framework and the selected demonstrated tool can be directly applied to disciplines and topics with discrete-object conceptualization. It is a vast field encompassing most social science disciplines, where the data sets have been increasingly featured with spatial and temporal footprints. As such, the devised operational typology of space-time data and analytical tasks are potentially helpful for data analysts and users in these various domain-specific fields to anticipate the typical questions that may arise in data exploration. If certain task types are insufficiently supported by the existing tools, the gaps in methodological developments can thus be identified and filled (Ye and Carroll 2011).

Goodchild and Glennon (2008) suggest “in the context of geographic dynamics, it seems appropriate that GIScience focus similarly on the generic: the tools, data models, software, and other resources that facilitate analysis and modeling of dynamic phenomena.” The research conducted in this paper is among the efforts by integrating “the tools, data models, software” through systematically-designed data analytical tasks and research questions. Comparative space-time analysis suggested in this paper aims to develop research questions to compare space-time patterns and trends within one data set, as well as across two data sets. This framework can provide a useful platform for further discussion in the characterization, understanding, and prediction of geographic dynamics (Goodchild and Glennon 2008; Ye 2010).

Acknowledgments Portions of this research were supported by National Science Foundation Grant BCS-0826594. We have also benefited from the suggestions and comments of the anonymous reviewers.

References

Andrienko N, Andrienko G (2006) Exploratory analysis of spatial and temporal data: a systematic approach. Springer, Berlin

Anselin L (1993) Exploratory spatial data analysis and geographic information systems. Technical Report 1, Regional Research Institute, West Virginia University

Anselin L (1995) Local indicators of spatial association-LISA. Geograph Anal 27:93–115

Anselin L, Getis A (1992) Spatial statistical analysis and geographic information systems. Ann Reg Sci 26:19–33

Anselin L, Syabri I, Kho Y (2006) GeoDa: an introduction to spatial data analysis. Geograph Anal 38:5–22

Bianchi M (1997) Testing for convergence: evidence from non-parametric multimodality tests. J Appl Econom 12(4):393–409

Bode E, Rey SJ (2006) The spatial dimension of economic growth and convergence. Pap Reg Sci 85(2): 171–176

Church R (2002) Geographical information systems and location science. Computers and Operation Research

Fan C, Casetti E (1994) The spatial and temporal dynamics of US regional income inequality, 1950–1989. Ann Reg Sci 28:177–196

Fingleton B (2004) Theoretical economic geography and spatial econometrics: bridging the gap between theory and reality. In: Getis A, Múr J, Zoeller H (eds) Spatial econometrics and spatial statistics. Palgrave, Hampshire, pp 8–27

Getis A, Múr J, Zoeller H (eds) (2004) Spatial econometrics and spatial statistics. Palgrave, Hampshire

Goodchild MF (2008) Geographic information science: the grand challenges. In: Wilson J, Fotheringham A (eds) The hand-book of geographic information science. Blackwell, Malden, MA, pp 596–608

Goodchild MF, Glennon A (2008) Representation and computation of geographic dynamics. In: Hornsby KS, Yuan M (eds) Understanding Dynamics of geographic domains. CRC Press, Boca Raton, pp 13–30

Goodchild MF, Janelle DG (2010) Toward critical spatial thinking in the social sciences and humanities. GeoJournal 75(1):3–13

Goodchild MF, Yuan M, Cova TJ (2007) Towards a general theory of geographic representation in GIS. Int J Geograph Inf Sci 21(3):239–260

Haining R, Wise S (1997) Exploratory spatial data analysis. NCGIA Core Curriculum in GIScience

Hammond G, Thompson E (2002) Mobility and modality trends in U.S. state personal income. Reg Stud 36:375–387

Hamnett C (2003) Contemporary human geography: fiddling while Rome burns? Geoforum

Ioannides YM, Overman HG (2004) Spatial evolution of the US urban system. J Econ Geogr 4:131–156

Janikas M (2007) Comparative regional income dynamics: clustering, scale, and geocomputation. PhD thesis, University of California, Santa Barbara and San Diego State University

Le Gallo J, Ertur C (2003) Exploratory spatial data analysis of the distribution of regional Per Capita GDP in Europe, 1980–1995. Pap Reg Sci 82:175–201

Magrini S (1999) The evolution of income disparities among the regions of the European Union. Reg Sci Urban Econ 29:257–281

Overman HG, Ioannides YM (2001) The cross-sectional evolution of the US city size distribution. J Urban Econ 49:543–566

Peuquet DJ (2002) Representations of space and time. Guilford, New York

Quah DT (1993) Empirical cross-section dynamics in economic growth. Eur Econ Rev 37:426–434

Quah DT (1996a) Regional convergence clusters across Europe. Eur Econ Rev 40:951–958

Quah DT (1996b) Twin peaks: growth and convergence in models of distribution dynamics. Econ J 106:1045–1055

Quigley JM (2001) The renaissance in regional research. Ann Reg Sci 35(2):167–178

Rey SJ (2001) Spatial empirics for regional economic growth and convergence. Geograph Anal 33(3): 195–214

Rey SJ (2004) Spatial dependence in the evolution of regional in-come distributions. In: Getis A, Múr J, Zoeller H (eds) Spatial econometrics and spatial statistics. Palgrave, Hampshire, pp 194–213

Rey S, Anselin L (2006) Recent advances in software for spatial analysis in the social sciences. Geograph Anal 38:1–4

Rey S, Anselin L (2007) PySAL: a python library for spatial analytical functions. Rev Reg Stud 37:5–27

Rey SJ, Janikas MV (2005) Regional convergence, inequality, and space. J Econ Geogr 5:155–176

Rey SJ, Janikas MV (2006) STARS: space-time analysis of regional systems. Geograph Anal 38:67–86

Rey S, Ye X (2008) Dynamic pseudo weighted voronoi: integrating cartogram and voronoi diagrams. In: Working paper, Annual meeting of association of American Geographers, Boston

Rey SJ, Ye X (2010) Comparative spatial dynamics of regional systems. In: Páez A, Gallo JL, Buliung R, Dall'Erba S (eds) Progress in spatial analysis: methods and applications. Springer, Berlin, pp 441–463

Rey S, Janikas M, Smirnov O (2005) Exploratory geo-visualization of spatial dynamics. In: Geocomputation 2005 proceedings (CD-ROM)

Shneiderman B (1996) The eyes have it: a task by data type taxonomy for information visualizations. In: Burnett M, Citrin W (eds) Proceedings of the 1996 IEEE symposium on visual languages. IEEE Computer Society Press, Piscataway, pp 336–343

Sidaway JD, Simon D (1990) Spatial policies and uneven development in the 'Marxist-Leninist' states of the third world. In: Simon D (ed) Third world regional development. Paul Chapman, London

Tobler W (1970) A computer movie simulating urban growth in the Detroit region. Econ Geogr 46(2): 234–240

Tsionas EG (2000) Regional growth and convergence: evidence from the United States. Reg Stud 34(3):231–238

Tukey J (1977) Exploratory data analysis. Addison-Wesley, Reading, MA

Wachowicz M, Healey R (1994) Towards temporality in GIS. In: Worboys MF (ed) Innovation in GIS I, vol 1. Taylor and Francis, London, pp 105–115

Wei YHD, Ye X (2004) Regional inequality in China: a case study of Zhejiang Province. Tijdschrift voor Economische en Sociale Geografie. J Econ Soc Geogr 95:44–60

Wei YHD, Ye X (2009) Beyond convergence: space, scale, and regional inequality in China. Tijdschrift voor Economische en Sociale Geografie. J Econ Soc Geogr 100:59–80

Ye X (2010) Comparative space time dynamics. PhD thesis, University of California, Santa Barbara and San Diego State University

Ye X, Carroll M (2011) Exploratory space-time analysis of local economic development. Appl Geogr 31:1049–1058

Ye X, Wei YD (2005) Geospatial analysis of regional development in China: the case of Zhejiang Province and the Wenzhou model. Eurasian Geogr Econ 46:342–361

Ye X, Wu L (2011) Analyzing the dynamics of homicide patterns in Chicago: ESDA and spatial panel approaches. Appl Geogr 31:800–807

Ye X, Xie Y, Batty M (2005) Modeling transition rules in Urban cellular automata. In: Geocomputation 2005, Proceedings, CD-ROM