STARS: Space–Time Analysis of Regional Systems

Sergio J. Rey[1,2], Mark V. Janikas[1]

[1]Department of Geography, San Diego State University, San Diego, CA, [2]Regional Economics Application Laboratory, University of Illinois, Urbana, IL

Space–Time Analysis of Regional Systems (STARS) is an open-source package designed for the dynamic exploratory analysis of data measured for areal units at multiple points in time. STARS consists of four core analytical modules: Anselin (1995) exploratory spatial data analysis; Anselin (2003) inequality measures; Carlino and Mills (1993) mobility metrics; and Christakos, Bogaert, and Serre (2001) spatial Markov. Developed using the Python object-oriented scripting language, STARS lends itself to three main modes of use. Within the context of a command line interface (CLI), STARS can be treated as a package which can be called from within customized scripts for batch-oriented analyses and simulation. Alternatively, a graphical user interface (GUI) integrates most of the analytical modules with a series of dynamic graphical views containing brushing and linking functionality to support the interactive exploration of the spatial, temporal, and distributional dimensions of socioeconomic and physical processes. Finally, the GUI and CLI modes can be combined for use from the Python shell to facilitate interactive programming and access to the many libraries contained within Python. This article provides an overview of the design of STARS, its implementation, functionality, and future plans. A selection of its analytical capabilities are also illustrated that highlight the power and flexibility of the package.

Introduction

One of the active areas in the field of geographic information sciences (GIS) is the development of new methods of exploratory spatial data analysis. A number of impressive efforts have recently appeared to provide researchers with powerful tools for both geospatial statistical analysis, data mining, as well as geovisualization. Well-known efforts include the GeoDa environment (Anselin 2003), the GeoVista Studio (Takatsuka and Gahegan 2002), Cartographic Data Visualizer

Correspondence: Sergio J. Rey, Department of Geography, San Diego State University, San Diego, CA 92182-4493
e-mail: serge@rohan.sdsu.edu

(Dykes 1995), SAGE (Haining, Wise, and Ma 2001) and the ArcView-XGobi project (Symanzik et al. 1998).

A new addition to this field is the package Space–Time Analysis of Regional Systems (STARS). STARS is an open-source environment written in Python that supports exploratory *dynamic* spatial data analysis. Dynamic takes on two meanings in STARS. The first reflects a strong emphasis on the incorporation of time into the exploratory analysis of space–time data. To do so, STARS combines two sets of modules, *visualization* and *computation*. The visualization module consists of a family of geographical, temporal, and statistical views that are interactive and interdependent. That is, they allow the user to 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. On the computational front, STARS contains a set of exploratory spatial data analysis (ESDA) modules, together with several newly developed measures for space–time analysis.

This article provides the first detailed introduction to STARS and is organized as follows. The motivation giving rise to the creation of STARS is discussed in the following section. A detailed overview of the analytical components of the package are presented in ''Components and design.'' The capabilities of these components are then illustrated in a series of examples drawing from the study of regional income dynamics in ''Illustrations.'' The article closes with an outline of future plans for the continued development of STARS.

Motivation

As is common with many open-source packages, STARS was born out of a need to scratch an itch. In this instance the itch was the lack of an integrated statistical toolkit that supported the analysis of both the spatial and temporal dimensions of regional income growth and convergence. Regional convergence or divergence has both temporal and spatial dimensions, and in studying these processes researchers have relied on either spatial analysis (Rey and Montouri 1999) or time series methods (Carlino and Mills 1993).[1]

To consider both dimensions jointly requires the use of two different sets of methods, yet with the existing software this meant having to switch between software packages. This turns out to be a rather awkward way to do exploratory data analysis. It is clear that new tools are needed for an EDA toolkit that truly integrates *space and time*. While the question of time in GIS has attracted much conceptual attention (Egenhofer and Golledge 1997; Peuquet 2002), operational systems implementing both geocomputational and geovisualization components that also incorporate time are few in number.[2] STARS is an attempt to fill this niche. Although the initial motivation for STARS was the study of regional income dynamics, the methods and tools it contains can be applied to a wide set of socioeconomic or physical processes with data measured for areal units over multiple time periods.

Components and design

It was decided in the genesis of the STARS project that the exploratory geocomputational methods and the visualization techniques used to express them be developed separately. This facilitated the development of the STARS package in a modular fashion which has enabled users to interact with the program in a number of ways. First, the geocomputational and visualization modules can be linked together in a user-friendly, interactive, graphical interface. Second, the individual modules can be used as a library and combined with scripts written in Python (or other scripting languages). The modularity also permits easy extension of STARS through the development of specialized modules. We shall return to this issue later on. Next we discuss the two core modules of STARS, geocomputation and visualization.

Geocomputation

The methods used to explore the dynamics of space–time data have been broken into distinct categories, which are outlined in Table 1. While STARS has many of the standard summary statistic capabilities that one would find in any number of data analysis packages, it is its inherent ability to identify and analyze the space–time characteristics of the data that makes it a unique environment.

STARS has focused on incorporating recent advances in the analysis of spatial dependence. Global measures of spatial autocorrelation are included for the analysis of dependence over a region. The program also contains Local Indicators of Spatial Autocorrelation (LISAs) which give a more disaggregated view at the nature of dependence (Anselin 1995). These have been extended to a dynamic context in a number of new empirical measures such as Spatial Markov matrices, LISA Markov matrices, and indicators of spatial cohesion and flux introduced by Rey (2001).

Table 1 Geocomputational Methods Contained in STARS

Category	Description
Descriptive statistics	This category contains distribution and summary measures for variables by cross-section, time period, or pooled
Exploratory spatial data analysis	Includes various methods specifically designed to analyze spatial dependence. Global and local versions of Moran's I, Geary' c and the G statistic are provided
Inequality	Techniques that quantity and decompose inequality over time and space. Includes classic and spatial Gini Coefficients as well as Theil decomposition
Mobility	Recent advances in internal mobility dynamics are presented through the τ and θ statistics
Markov analysis	Transitional dynamics of distributional attributes are examined through the use of classic Markov and spatial Markov techniques

A series of alternative computational categories that deal with inter/intradistributional dynamics are also contained in STARS. Measures such as Theil's (1996)T can be used to evaluate and decompose inequality over time and space (see Rey 2004a, for an illustration). STARS also incorporates enhanced methods that identify various aspects of mobility within a distribution. These include spatially explicit rank-correlation measures and regime-based mobility decompositions introduced by Rey (2004b), as well as spatialized Gini coefficients. All these new measures provide insights as to the role of spatial context in the evolution of variable distributions over time and space.

STARS also provides a host of data and matrix utility functions. These can be used to create new or transform existing variables as well as to construct alternative forms of spatial weights matrices, network representations of spatial structure, and temporal covariance matrices. The latter allow for detailed investigation and comparison of the implied relationships between spatial observations as reflected in various spatial weights matrices and those revealed from the temporal comovement of variables for different cross-sectional units.

Visualization

A list of the visualization capabilities of the STARS module is presented in Table 2. STARS contains some views that are standard to an exploratory data package, however, the dynamic linking mechanisms enhance the user's ability to analyze data over various dimensions (see ''Illustrations'' for examples).

Table 2 Visualization Capabilities in STARS

Category	Description
Map	A variety of sequential, categorical, and user-defined choropleth maps
Scatter plot	A basic two-dimensional view, the scatter plot can be used to analyze cross-sectional, time period, or bivariate correspondence in $X–Y$ space
Conditional scatter plot	Extends the traditional scatter plot to three dimensions by conditioning the color of the data points by the level of a third variable
Parallel coordinate plot	Allows the user to view multivariate relationships over space and time
Time-series plot	Plot the evolution of a variable for a given spatial unit
Time–path plot	Demonstrates the comovement of a variable for two spatial units over time
Histogram	Creates a basic partitioning of a variable into respective bins
Density	Contains empirical kernel density estimation for the analysis of dispersion, modality, and skewness
Box plots	Another distributional view with an added focus on quantiles and outliers

Figure 1. Space–time analysis of regional systems in the graphical user interface mode.

Some of the views are multidimensional by nature. The conditional scatter plot can provide an additional facet to its traditional counterpart through a color weighting scheme based on a requisite variable. This supports the use of categorical variables for regime-based analysis and a simple time variable which can identify hidden evolutions.

The time–path plot illustrates the pair-wise movement of two variables and/or observations over time. This view is helpful in identifying levels of stability across a given structural process. Individual aspects of the comovement progression can be dissected by interval gaps and distinct directional movements.

STARS also contains a series of maps which can be created and altered through the use of various commands. One example involves the visualization of covariance matrices over space. The covariance structure of a variable is portrayed as a series of links between the centroids of each polygon. Positive correlations are colored differently than negative ones to more distinctly identify cross-sectional relationships. Threshold capabilities assure that the user can map covariance links based on specified criterion. These are illustrated later in the article.

```
000                    Terminal — python2.3 — 98x54
For help on classes: from ModuleName import *
>>> shelp(Tau)
Classic Tau rank correlation

    Arguments:
        variable: STARS variable
        interval: integer for length of time interval (default=1)
        w:  STARS sparse weight matrix (optional)

    Attributes:
        concord: number of concordant pairs for each period
        discord: number of disconcordant pairs for each period
        T:  number of unique pairs
        tau:    tau statistic (concord/T) for each period

        (if w is specified)
        nContiguities: number of unique contiguous pairs
        contConcordCount: number of contiguous concordant pairs
        contTau:    tau statistic for contiguous pairs
        nonContConcordCount: number of noncontiguous concordant pairs
        nonContTau:    tau statistic for noncontiguous pairs

    Example Useage:
        >>> from stars import Project
        >>> s=Project("s")
        >>> s.ReadData("csiss")
        >>> income=s.getVariable("pcincome")
        >>> r=s.getVariable("bea")
        >>> w=spRegionMatrix(r)
        >>> taus=Tau(income,w=w)
        >>> taus.tau[0]
        0.6313405797101449
        >>> taus.contTau[0]
        0.6875
        >>> taus.nonContTau[0]
        0.62291666666666667
        >>> tau=Tau(income,interval=10)
        >>> tau.tau
        array([ 0.55978261, 0.5923913 , 0.60869565, 0.54076087, 0.55253623, 0.57880435,
                0.56612319, 0.58967391, 0.50724638, 0.59692029, 0.56431159,
                0.52083333, 0.52173913, 0.51449275, 0.42844203, 0.4692029 ,
                0.55615942, 0.47735507, 0.58152174, 0.5317029 , 0.52626812,
                0.53713768, 0.48822464, 0.58423913, 0.57427536, 0.47101449,
                0.61865942, 0.5615942 , 0.51539855, 0.5        , 0.61956522,
                0.51539855, 0.53623188, 0.5923913 , 0.5951087 , 0.47373188,
                0.51539855, 0.51358696, 0.51811594, 0.39945652, 0.50996377,
                0.43387681, 0.49456522, 0.63677536, 0.49184783, 0.54981884,
                0.44384058, 0.53623188, 0.4701087 , 0.52173913, 0.58423913,
                0.50362319, 0.44112319, 0.55706522, 0.48460145, 0.58695652,
                0.45742754, 0.48731884, 0.62228261, 0.48460145, 0.55253623,
                0.5        ])

For help on classes: from ModuleName import *
>>>
```

Figure 2. Space–time analysis of regional systems in command line interface mode.

Design

As mentioned previously, STARS is written entirely in the Python language. Python is an object-oriented scripting language gaining widespread acceptance as a language for scientific computing (Hinsen 2000; Schliep, Hochstättler, and Pattberg 2001; Saenz, Zubillaga, and Fernandez 2002; Langtangen 2004). As Python is open-source and cross-platform, researchers interested in using STARS are not limited in their choice of operating system or hardware platform. Moreover, Python has a
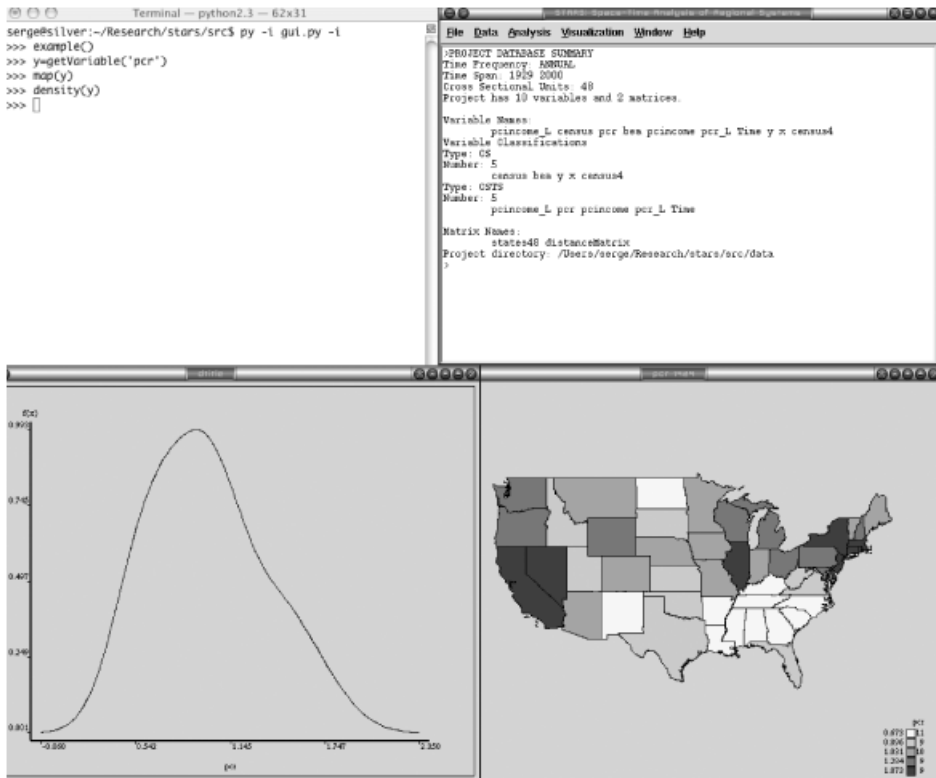
Figure 3. Space–time analysis of regional systems in command line interface+graphical user interface mode.

clean and simple syntax which facilitates collaboration by researchers wanting to add extensions to STARS.

STARS is designed from the ground up as an object-oriented system. This has a number of advantages. First, the internal architecture is accessible at a high level, supporting the relatively easy enhancement of STARS via new specialized modules. Second, from an end-user's perspective, models, variables, matrices, and other core elements of the system are all objects (i.e., instances of classes in Python parlance), and thus are closer to the user's problem domain than is the case in a system designed around procedural programming.

In addition to being object-oriented in design, STARS is also highly modularized. The geocomputational and visualization modules are orthogonal, that is, they can be used independently of one another, or they can be combined depending on the requirements of a particular project. This modularity permits the use of STARS in three different modes. The first is the graphical user interface (GUI) mode, where the two sets of modules are tightly integrated. Here the user accesses the analytical capabilities from a series of menu items as displayed in Fig. 1. This mode is well
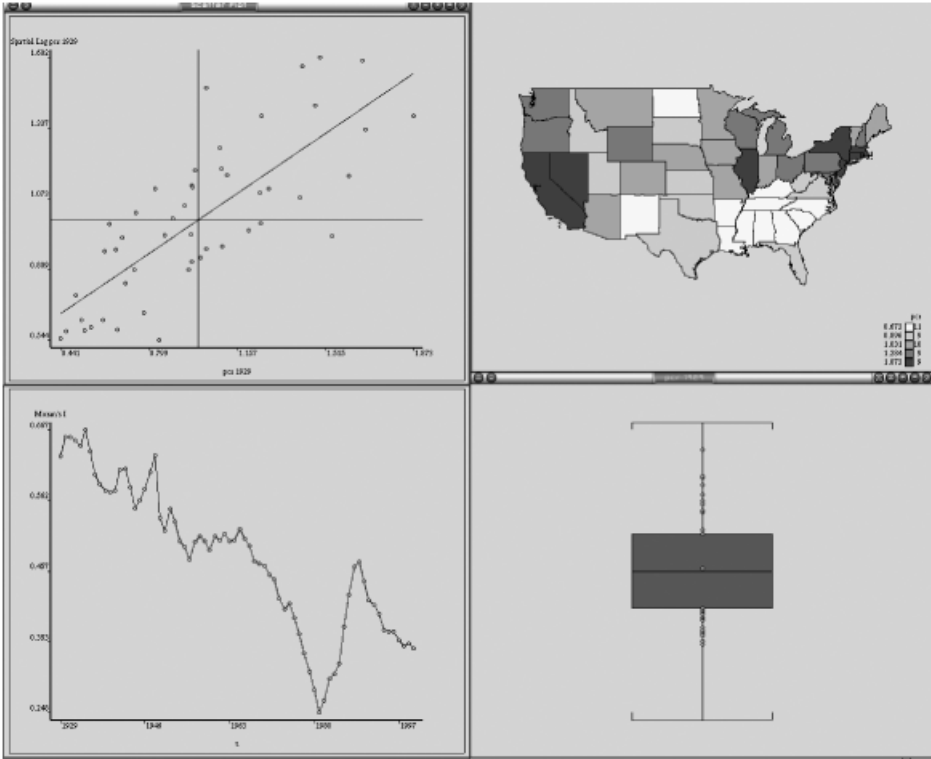
Figure 4. Multiple views of the U.S. per capita income data.

suited to researchers wanting to apply exploratory space–time data analysis to a substantive problem.

The second mode uses a command line interface (CLI) in which the computational module can be called directly from the Python interpreter. An example of such use is seen in Fig. 2. This supports very efficient interactive computation, similar to that found in other data analysis environments such as R Development Core Team (2004). This mode also supports the wrapping of STARS modules inside larger Python scripts to implement simulation programs through batch processing.[3]

STARS can also be used in a combined CLI+GUI mode as shown in Fig. 3. In this mode the user has access to the Python interpreter via the terminal window (upper left) and can create views either from that interpreter, or from the GUI (upper right). Results of interactive commands entered in the shell are reported in the text area of the GUI.

Illustrations

In this section a subset of the graphical and analytical capabilities of STARS is highlighted drawing on examples from regional income convergence

Figure 5. Linking multiple views.

studies. STARS stresses the need to study multiple dimensions underlying the data used in exploratory analysis. An illustration of this is provided in Fig. 4 which contains four different views of data on U.S. regional incomes for the lower 48 states. The upper left view is a quintile map for incomes in 1929. Next to this is the Moran scatter plot (Anselin 1995), indicating strong positive spatial autocorrelation. Below the scatter plot, a histogram provides an a-spatial view of the income distribution, while the view to the left of the histogram portrays the time series for the global Moran statistic for the years 1929–2000. The latter figure reveals that the level of spatial clustering fluctuates substantially over time.

Linking and brushing views
In addition to providing views of the different dimensions (time, space, distribution), the views in STARS are also interactive. Interactivity can take on multiple forms. The first is *linking* in which the selection of observations in an origin view leads to the highlighting of associated observations in other destination views. An example of this can be seen in Fig. 5, where the selection occurs on the origin view

Figure 6. Brushing multiple views.

(map) using a rectangle created and sized with the mouse. When the user releases the mouse button, the polygons underneath the selection rectangle are selected and observations associated with these selected polygons are then highlighted in the three destination views.[4]

The second form of interaction is *brushing* which is illustrated in Fig. 6. Here observations are selected in the same fashion as with linking, however the impact of the selected set is different, and results in a refitting of the global autocorrelation trend in the scatter plot to omit the states selected on the map. This provides insights as to the leverage of the selected states on the level of spatial clustering for that time period.

Space–time traveling and roaming
Linking and brushing can also be combined with a third form of interaction referred to as *roaming*. When roaming, the selection rectangle remains on the screen and the user can move it around the origin view, as is reflected in Fig. 7. Movement of the selection rectangle creates a new selection set of observations on the origin view to trigger the corresponding interaction signal (brushing or linking) on the destination views.

Figure 7. Roaming a map with brushing.

Similar to roaming, linking and brushing can also be combined with *traveling*. Traveling on an origin view selects observations in a sorted order and triggers linking or brushing on the destination views. The traveling is done automatically over the entire set of observations on the origin view, giving the user a full depiction of the particular type of interaction (linking or brushing). An example of this is shown in Fig. 8 which combines cumulative brushing on the scatter plot and box plot resulting from spatial traveling on the map.

Traveling can also be done on a time series view to trigger temporal updating of destination views. The traveling proceeds from earliest period to the latest period given the user views of all destination views for each time period in the sample. Alternatively, the user can control the temporal updating by switching to roaming on a time series view. This is illustrated in Fig. 9 where the vertical selector has been moved over the year 1990. Again the three destination views (scatter plot, map, and box plot) are updated to this year, which reveals an outlier in the box plot. The user then selects that outlier observation on the box plot to trigger linking on the destination views (map, time series, scatter plot) to reveal that the outlier observation is Connecticut.

The combination of linking and brushing with either space–time roaming or traveling provides a powerful approach to exploratory visualization that can reveal

Figure 8. Spatial traveling with brushing.

patterns that otherwise would be very difficult to detect. An example of this can be seen in Fig. 10 where a conditional scatter plot in the lower right corner is used to combine the Moran scatter plots from each year in a single view. The observations on each state's income and that of its spatial lag are then conditioned on a third variable, in this case time, and the conditioning uses color depth to indicate early (light color) versus more recent (dark color) observations. The conditioning reveals that the dispersion in state incomes has declined substantially over time. The figure also reflects the result of the user selecting Illinois on the map to trigger linking in the destination views. The own-lag pairs for all time periods for Illinois are then highlighted in the conditional scatter plot to reveal that the spatial dynamics between Illinois and its neighbors have been qualitatively and quantitatively different from the overall space–time dynamics in the U.S. space economy.

View-generated views
The view interactivity can be exploited to more fully explore these space–time instabilities depicted in the conditional scatter plot. While the latter shows that Illinois and its geographical neighbors have income dynamics moving in different directions, additional insights on these dynamics can be obtained by the user

Figure 9. Time roaming.

combining a key press (control) with a mouse click on the Illinois-specific obser-vation in the Moran scatter plot which generates a new view called a TimePath as shown in the upper left of Fig. 11. The TimePath shows the comovement of Illinois per capita income and its spatial lag of per capita income for all time periods with subsequent time periods linked together.

The ability to generate new views through user actions on existing views offers a powerful exploratory device. View-generated views can also be obtained from a map origin view as seen in Fig. 12, where the user has issued the same selection event on Illinois in the map to generate the time series view of relative income for Illinois. This isolates the dynamics of Illinois income from the comovement dy-namics in the TimePath, in a similar manner to the way the comovement dynamics for Illinois were isolated in the TimePath from the full set of state-lag comovement dynamics depicted in the conditional scatter plot.

Distributional dynamics

In addition to exploring spatial and temporal dimensions via view interactivity, the distributional dynamics can also be examined. One approach is displayed in Fig. 13 in which two densities for state relative per capita incomes are displayed,

Figure 10. Space–time instabilities.

one for the beginning of the period (1929) and one for the last year of the sample (2000). To explore the movement of individual economies within the income distribution the user can trigger spatial traveling on the map serving as the origin view. This then highlights each state (from lowest income to highest income) on the map and identifies the positions of that state in the initial and terminal income densities. As the traveling is done automatically for the entire set of spatial units, the user sees the full extent of distributional dynamics. Following the automated traveling, the user can then select individual states on the map to isolate on their mobility characteristics. This is shown for Virginia which initially was a relatively poor economy but has shown substantial upward movement in the income distribution.

Spatial and temporal dependencies

In addition to providing dimension-specific views, such as a TimePath or box plot or quintile map, STARS enables the depiction of multiple dimensions on a single view. This is illustrated in Fig. 14 which contrasts two forms of covariance in a graph representation. The linkages reflected in a spatial weights matrix based on contiguity are recorded as edges between polygon centroids for each state. These
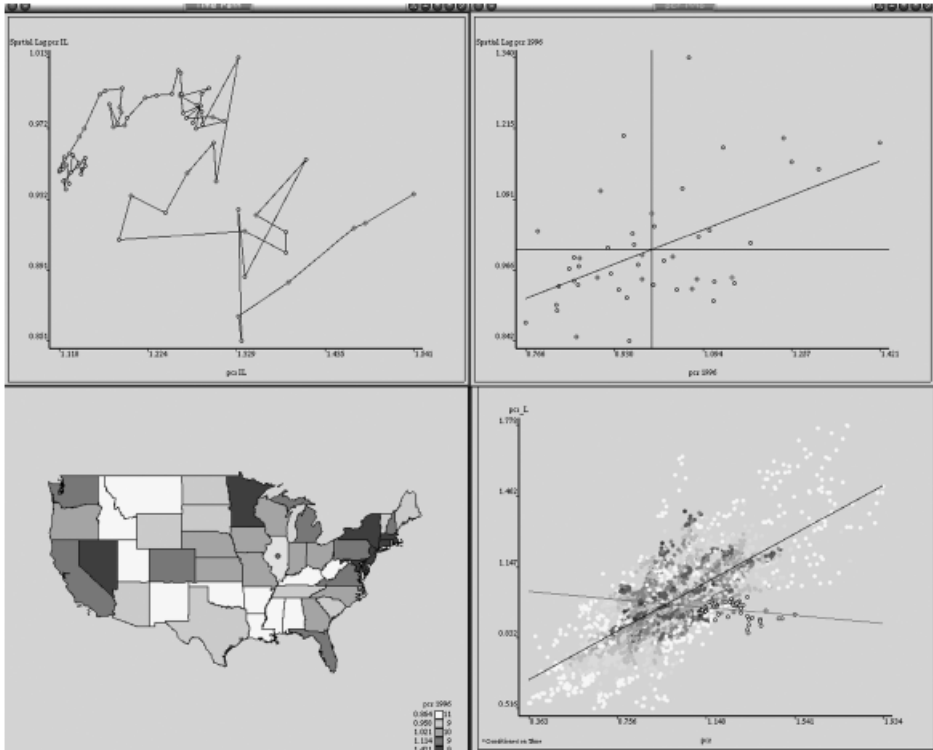
Figure 11. Scatter-plot-generated TimePath.

linkages are then conditioned on the strength of the temporal covariance between each pair of contiguous states, with red lines indicating strong temporal linkages.

The nature of the specific temporal covariances between a state and the rest of the system can then be explored using the spider graph depicted in Fig. 15. Here the user can step through each state to determine which other states it has the strongest temporal comovements with. In this case the spider graph reveals that California income dynamics have not only been similar to some of its geographical neighbors, but also in sync with the northeast states. This type of interaction is useful for uncovering covariance relations that may not be obvious with traditional ESDA techniques.

Future directions

STARS has evolved quickly from its origins as a specialized program to support research on regional income dynamics to now being used by researchers, outside of the development team, to examine such issues as spatial dynamics of fertility, land-use cover change, segregation dynamics, migration, commodity flow patterns, and housing market dynamics, among others. Each new application raises new

Figure 12. Map-generated time series.

demands for increased functionality and enhancement of STARS. Currently there are a number of such enhancements that are major priorities for the development team.

The first enhancement is the creation of a new type of map view to visualize substantive flows between cross-sectional observations.[5] There has been a growing interest in the extension of flow maps to include temporal–spatial dynamics which we believe STARS is quite posed to introduce. In short, the goal of this extension is to demonstrate how flows between cross-sectional units evolve over time. Although often used to study migration, the notion of flows is by no means confined to the movement of people. Flows of commodities, for example, could be considered a driver for many socioeconomic processes, and the inclusion of which could present some interesting research avenues, such as the covariation between these flows and economic growth and the construction of hybrid weight matrices based on spatial constructs coupled with a-spatial flow linkages.

Another analytical front for the STARS module is cluster analysis. Although some basic forms of spatial clustering are identifiable by a number of graphs and maps produced in the current version of STARS, more analytical features on a-spatial cluster analysis seem a fruitful avenue for future work. The research team has an extensive body of code implementing agglomerative, partitive, and medoid

Figure 13. Distributional mixing.

clustering methods written in a variety of languages (*R*, Octave, Python) in support of ongoing research on industrial cluster analysis (Rey and Mattheis 2000; Rey 2000a–e, 2002). The integration of these methods in STARS is currently underway.

We are also exploring new approaches to recasting conventional measures of distributional dynamics, such as the so-called σ-convergence measure, to incorporate spatially explicit dimensions (Rey and Dev 2004). Coupled with this is work on developing inferential methods for new space–time empirics based on both analytical distributions as well as computationally based approaches.

STARS is a powerful environment for exploring data that has both temporal and spatial dimensions. The interactivity of the various views helps to identify dependencies across various dimensions that may otherwise go unnoticed. These views are also tied to a suite of recently developed advanced methods for ESDA and ESTDA. Moreover, STARS has been designed for users with a wide range of demands and skill sets. Researchers looking for a user-friendly GUI environment for exploratory space–time analysis should feel at home with STARS. Others who are developing new methods for exploratory analysis can easily integrate these into the modular framework underlying STARS. In between these two groups are researchers comfortable with writing simple macro-type scripts (in Python) to use STARS for
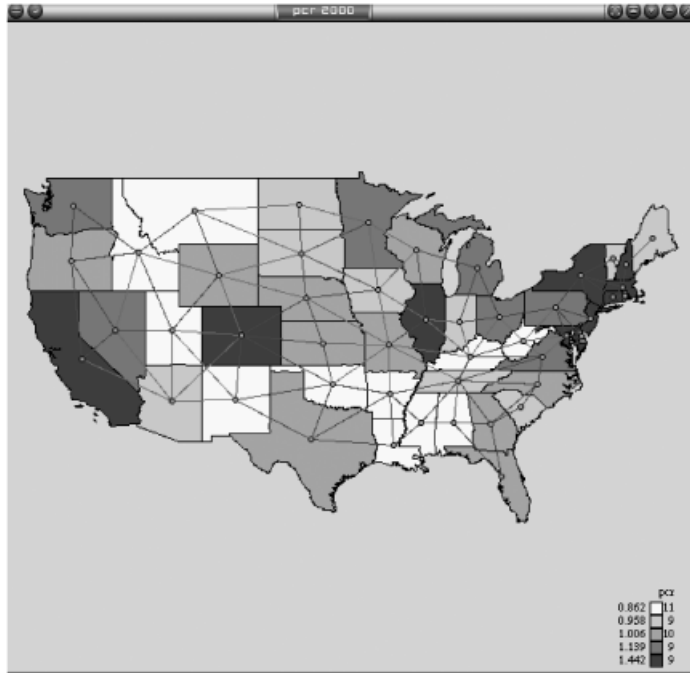
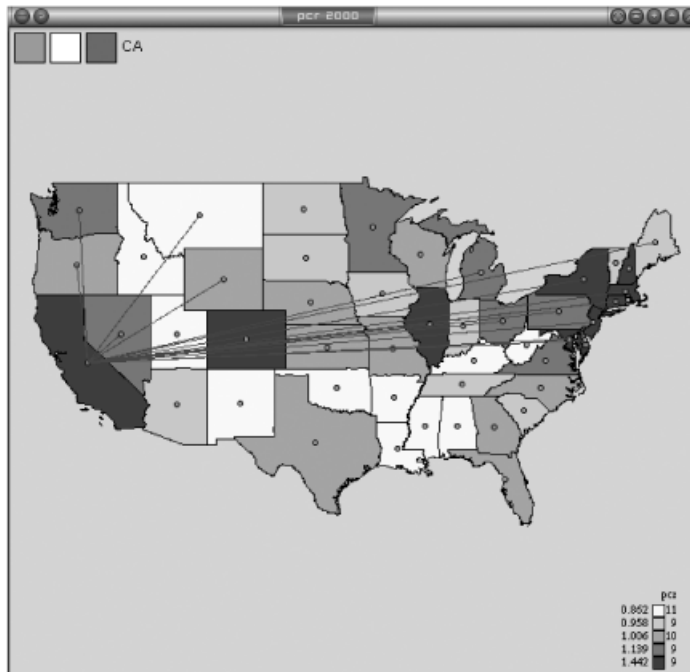**Figure 14.** Spatial and temporal covariance networks.

Figure 15. Spider graph of temporal covariance networks.

simulation experiments as well as for linkages with other model systems and statistical packages. We hope this design, together with the commitment to the open-source development model, will attract researchers to collaborate on the enhancement and future development path of STARS.

Acknowledgements

Notes

1 For a recent overview of the empirical literature on spatial convergence, see Rey and Janikas (2005).
2 For an example of such a system focusing on geophysical data, see Christakos, Bogaert, and Serre (2001).
3 An example of such an application is reported in Rey (2004a).
4 The selection rectangle is not seen in Fig. 5 as it is erased upon completion of the selection.
5 See Tobler's Flow Mapper at http://csiss.ncgia.ucsb.edu/clearinghouse/FlowMapper/for a program designed for the sole purpose of studying flows.

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