Geovisualization of Human Activity Patterns Using 3D GIS: A Time-Geographic Approach

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Abstract. The study of human activities and movements in space and time has long been an important research area in social science. One of the earliest spatially integrated perspective for the analysis of human activities patterns and movement in space-time is time-geography. Despite the usefulness of time-geography, there are very few studies that actually implemented its constructs because of a lack of detailed individual-level data and analytical tools. With the increasing availability of georeferenced individual-level data and improvement in the representational and geocomputational capabilities of Geographical Information Systems (GIS), the operationalization of time-geographic constructs has become more feasible recently. This chapter illustrates the value of time-geographic methods in the description and analysis of human activity patterns using GIS-based three-dimensional (3D) geovisualization methods. These methods are used to study gender/ethnic differences in space-time activity patterns using an activity diary data set collected in the Portland (Oregon) metropolitan area. The study shows that geovisualization methods are not only effective in revealing the complex interaction between the spatial and temporal dimensions in structuring human spatial behavior. They are also effective tools for exploratory spatial data analysis that can help the formulation of more realistic computational or behavioral models.

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Human Activities in Space-Time

The study of human activities and movements in space and time has long been an important research area in social science. It covers a wide range of topics such as migration, residential mobility, shopping, travel, and commuting behavior. One of the earliest spatially integrated perspectives for the analysis of human activity patterns and movement in space-time is time-geography. Developed by a group of Swedish geographers associated with Torsten Hägerstrand (1970), the time geographic perspective has inspired generations of social scientists, especially geographers and transportation researchers, in the description and analysis of human activities in space-time. It conceives and represents an individual's activities and travel in a 24-hour day as a continuous temporal sequence in geographical space. The trajectory that traces this activity sequence is referred to as a space-time path, while the graphical representation of the three-dimensional space in which this path unfolds is referred to as the space-time aquarium. The number and location of everyday activities that can be performed by a person are limited by the amount of time available and the space-time constraints associated with various obligatory activities (e.g., work) and joint activities with others (Carlstein et al. 1978; Parkes and Thrift 1975; Thrift 1977).

Time-geography not only highlights the importance of space for understanding the geographies of everyday life. It also allows the researcher to examine the complex interaction between space and time and their joint effect on the structure of human activity patterns in particular localities (Cullen et al. 1972). This perspective has been particularly fruitful for understanding women's everyday lives because it helps to identify the restrictive effect of space-time constraints on their activity choice, job location, travel, as well as occupational and employment status (Dyck 1990; England 1993; Friberg 1993; Hanson and Pratt 1995; Kwan 1999a,b, 2000a; Laws 1997; Palm 1981; Tivers 1985). Time geography has also been used as a framework for the study of migration and mobility behavior (Odland 1998), as well as the everyday life of children, dockworkers and homeless people (Mårtensson 1977; Pred 1990; Rollinson 1998).

Despite the usefulness of time-geography in many areas of social science research, there are very few studies that actually implemented its constructs as analytical methods excepts some early attempts (e.g., Lenntorp 1976). The limited development of time-geographic methods can be attributed to the lack of detailed individual-level data and analytical tools that can realistically represent the complexities of an urban environment (e.g., the transportation network and spatial distribution of urban opportunities). Another difficulty is that individual movement in space-time is a complex trajectory with many interacting dimensions. These include the location, timing, duration, sequencing, and type of activities and/or trips. This characteristic of activity patterns has made the simultaneous analysis of its many dimensions difficult (Burnett and Hanson 1982). However, with increasing availability of georeferenced individual-level data and improvement in the representational and geocomputational capabilities of Geographical Information Systems (GIS), it is now more feasible than ever before to operationalize and implement time-geographic constructs. Further, the use of GIS also allows the incorporation of a large amount of geographic data that are essential for any meaningful analysis of human activity patterns. Because of these changes, time-geographic methods are undergoing a new phase of development as several recent studies indicate (Kwan 1998, 2000b; Miller 1999, Ohmori et al. 1999; Takeda 1998; Weber and Kwan 2002). Although the primary focus of these studies is on individual accessibility, there are many areas in social science research where time-geography can be fruitfully applied.

This chapter illustrates the value of time-geographic methods in the description and analysis of human activity patterns. It describes several GIS-based three-dimensional (3D) geovisualization methods that avoid the interpretative difficulties of conventional quantitative methods. These methods are used to study gender/ethnic differences in space-time activity patterns using an activity diary data set collected in the Portland (Oregon) metropolitan area. The study shows that these geovisualization methods are effective in revealing the complex interaction between the spatial and temporal dimensions in structuring human behavior. They are also effective tools for exploratory spatial data analysis that can help the formulation of more realistic computational or behavioral models. Several significant substantive insights derived from using these methods will be discussed.

Scientific Visualization and Interactive 3D Geovisualization

Scientific visualization is the process of creating and viewing graphical images of data with the aim of increasing human understanding (Hearnshaw and Unwin 1994). It is based on the premise that humans are able to reason and learn more effectively in a visual setting than when using textual and numerical data (Tufte 1990; 1997). Visualization is particularly suitable for dealing with large and complex data sets because conventional inferential statistics and pattern recognition algorithms may fail when a large number of attributes are involved (Gahegan 2000). In view of the large number of attributes that can be used to characterize human activity patterns, and given the capability of scientific visualization in handling a large number of attributes, visualization is a promising direction for exploring and analyzing large and complex data sets.

Geovisualization (visualization of geographic information), on the other hand, is the use of concrete visual representations and human visual abilities to make spatial contexts and problems visible (MacEachren et al. 1999). Through involving the geographical dimension in the visualization process, geovisualization greatly facilitates the identification and interpretation of spatial patterns and relationships in complex data in the geographical context of a particular study area. For the visualization of geographic data, conventional GIS has focused largely on the representation and analysis of geographic phenomena in two dimensions (2D). Although 3D visualization programs with advanced 3D modeling and rendering capabilities have been available for many years, they have been developed and applied largely in areas outside the GIS domain (Sheppard 1999). Only recently has GIS incorporated the ability to visualize geographic data in 3D (although specialized surface modeling programs have existed long before). This is so not only in the digital representation of physical landscape and terrain of land surfaces, but also in the 3D representation of geographic objects using various data structures.

Despite the use of GIS-based 3D geovisualization in many areas of research in recent years, its application in the analysis of human activity patterns is rather limited to date. In many early studies, 2D maps and graphical methods were used to portray the patterns of human activity-travel behavior (e.g., Chapin 1974; Tivers 1985). Individual daily space-time paths were represented as lines connecting various destinations. Using 2D graphical methods, information about the timing, duration, and sequence of activities and trips was lost. Even long after the adoption of the theoretical constructs of the time-geographic perspective in the 1970s and 1980s, the 3D representation of space-time aquariums and space-time paths seldom went beyond the schematic representations used either to explain the logic of a particular behavioral model or to put forward a theoretical argument about human activity patterns. They were not intended to portray the real

experience of individuals in relation to the concrete geographical context in any empirical sense.

There is, however, noticeable change in recent years. As more georeferenced activity-travel diary data become available, and as more GIS software incorporate 3D capabilities, it is apparent that GIS-based 3D geovisualization is a fruitful approach for examining human activity patterns in space-time. For instance, Forer (1998) and Huisman and Forer (1998) implemented space-time paths and prisms based on a 3D raster data structure for visualizing and computing space-time accessibility surfaces. Their methods are especially useful for aggregating individuals with similar socioeconomic characteristics and for identifying behavioral patterns. However, since the raster data structure is not suitable for representing the complex topology of a transportation network, the implementation of network-based computational algorithms is difficult when using their methods. On the other hand, Kwan (2000b,c) implemented 3D visualization of space-time paths and aquariums using vector GIS methods and activity-travel diary data. These recent studies indicate that GIS-based geovisualization has considerable potential for advancing the research on human activity patterns. Further, implementing 3D visualization of human activity patterns can be an important first step in the development of GIS-based geocomputational procedures that are applicable in many areas of social science research. For example, Kwan (1998, 1999b), Miller (1999), Miller and Wu (2000) and Weber and Kwan (2002) developed different network-based algorithms for computing individual accessibility using vector GIS procedures.

There are several advantages in using GIS-based 3D geovisualization in the analysis of human activity patterns. First, since GIS has the capability to integrate a large amount of geographic data in various formats and from different sources into a comprehensive geographic database, it is able to generate far more complex and realistic representations of the urban environment than conventional methods. The concrete spatial context it provides can greatly facilitate exploratory spatial data analysis and the identification of spatial relations in the data. Results can also be exported easily to spatial analysis packages for performing formal spatial analysis (Anselin and Bao 1997). Second, 3D geovisualization provides a dynamic and interactive environment that is much more flexible than the conventional mode of data analysis in transportation research. The researcher can directly manipulate the attributes of a scene and its features, and change the views, alter parameters, query data, and see the results of any of these actions easily. Third, unlike quantitative methods that tend to reduce the dimensionality of data in the process of analysis, 3D geovisualization may retain the complexity of the original data to the extent that human visual processing is still capable of handling. Lastly, with many useful navigational capabilities such as fly-through, zooming, panning, and dynamic rotation, as well as the multimedia capabilities to generate map animation series such as 3D "walk-throughs" and "fly-bys", the researcher can create a "virtual world" that represents the urban environment with a very high level of realism (Batty et al. 1998).

Study Area and Data

Most examples described in this chapter are based upon an activity-travel diary data set collected in the Portland metropolitan region. This region consists of Multnomah, Washington, and Clackamas counties in Oregon and Clark County in Washington. These four counties had a population of 1.6 million in 1995, making up 93.15 percent of the population of the metropolitan region. Much of this area is included within the urban growth boundary of the Portland Metropolitan Service District (commonly known as Metro), which

is the local metropolitan planning organization (MPO) for the Portland urban area. The urban growth boundary encompasses a total of 24 municipalities, of which the city of Portland is by far the largest city (with 498,747 people in 1995). A considerable portion of the study area population resides within a large number of suburban municipalities, including Gresham, Beaverton, Hillsboro, Tigard, Lake Oswego, Milwaukie, and Tualatin. The study area includes geographic features that may have significant influence on human travel and mobility behavior. For instance, it is traversed by two major rivers, which are potentially important barriers to mobility. The Columbia River crosses from East to West along the north edge of the study area and the Willamette River bisects the study area as it flows from south to north and into the Columbia, northwest of the study area.

The activity data set was collected through a survey conducted in the Portland metropolitan region in 1994 and 1995. See Cambridge Systmatics, Inc. (1996) for details of the survey. The survey used a two-day activity diary to record all activities involving travel and all in-home activities with a duration of at least 30 minutes for all individuals in the sampled households. Of the 7,090 households recruited for the survey, 4,451 households with a total of 10,084 individuals returned completed and usable surveys. The data set logged a total of 129,188 activities and 71,808 trips. Besides the information commonly collected in a travel diary survey, this data set also provides the geocodes (geographical coordinates) of all activity locations, including the home and workplace of all individuals in the sample. This not only facilitates the incorporation of these data into a comprehensive geographic database of the study area but also allows analysis of the space-time behavior of the sampled individuals in fine spatial and temporal resolution.

In addition to the activity-travel diary data, geographic information about the Portland metropolitan region is also used in this study. Data for Oregon was obtained from Metro's Regional Land Information System (RLIS), while similar data for Clark County, Washington, was obtained from the local planning agency. The digital GIS database assembled from these two sources provides comprehensive data on many aspects of the urban environment and transportation system of the study area. These contextual data allow the activity-travel data to be related to the geographical environment of the region during visualization. A 3D representation of three geographical data layers used in the geovisualization sessions described in this chapter is shown in Figure 1. These layers are the residential parcels (top layer), commercial and individual parcels (bottom layer) and the transportation network. The next two sections describe several methods for the 3D geovisualization of human activity-travel patterns in space-time. These methods are implemented using ArcView 3D Analyst where various segments of the original sample are used.

Geovisualization of Activity Density Patterns in Space-Time

The GIS-based 3D geovisualization methods discussed here are based upon the time-geographic perspective of Hägerstrand (1970) and his associates. In time-geographic conception, an individual's activities and trips in a day can be represented as a daily space-time path within a 'prism' defined by a set of constraints (Burns 1979; Hägerstrand 1970; Lenntorp 1976; Parkes and Thrift 1975). This time-geographic conception is valuable for understanding human activity patterns because it integrates the temporal and spatial dimensions of human activity patterns into a single analytical framework. Although both time and space are significant factors structuring individual activity patterns, past approaches mainly focus on only one of two dimensions. Further, the significance of the interaction between the spatial and temporal dimensions in structuring individual daily space-time

trajectories are often ignored. Yet, using the concepts and methods of time-geography that focus on the 3D structure of space-time patterns of activities, this kind of interaction can be examined, and many important behavioral characteristics of different population subgroups can be revealed.

This section focuses on interactive 3D geovisualizations of activity intensity in space-time. Geovisualizations of space-time paths will be discussed in the next section. Color versions of the figures are available on Web site http://geog-www.sbs.ohio-state.edu/faculty/mkwan/figures/best_links.htm. Since the dynamic process of knowledge discovery through interactive 3D geovisualizations cannot be illustrated using static 2D screen captures, the figures in this chapter cannot convey the same amount and quality of information enabled by interactive 3D geovisualizations. The reader may find it difficult to follow the discussion simply by looking at these figures because the text is based on observations enabled by the computer-aided interactive 3D visualization environment (which allows very complex manipulation of 3D objects or surfaces).

Simple activity patterns in space-time

A relatively simple method for visualizing human activity patterns in 3D is to use the two-dimensional (2D) activity-travel data provided in the original data set and to convert them to a format displayable in three dimensions. An important element in this conversion process is to identify the variable in the original data file that will be used as the Z value, which represents the value of a particular activity in the vertical dimension (besides the geographical coordinates X and Y). For a meaningful representation of activity patterns in space-time, the Z variable in this study represents the temporal dimension of activities and trips. In this particular example, activity start time is used as the Z variable in the conversion process. Using this Z value, each activity is first located in 3D space as a point entity using its geographic location (X,Y) and activity start time (Z). To represent the duration of each activity, the activity points in 3D are extruded from their start times by a value equal to the duration of the activity. In 3D visualization, extruding a feature extends its geometric dimension and changes its form - for instance, from points into vertical lines, lines into vertical walls, and polygons into 3D blocks.

Figure 2 shows the result of this method for the 11,559 out-of-home, non-employment activities performed by the 3,147 European-American (white) men in the subsample. In the figure, the length of the vertical line that represents the temporal span of an activity indicates activity duration. Activity start time can be color-coded to represent the temporal distribution of activities during interactive visualization. A helpful background for relating the activity patterns to various locations in the study area is created by adding several layers of geographic information into the 3D scene. These layers include the boundary, freeways, and rivers of the Portland metropolitan region. For better visual anchoring and locational referencing during visualization, a 3D representation of downtown Portland, which appears as a partially transparent 3D pillar derived from extruding its 2D boundary along the Z dimension, is also added. For easier identification of the temporal span of these activities, two 3D grid lines representing noon and midnight are added in the 3D scene.

Interactive geovisualization of the activity patterns, shown in Figure 2, suggests that the highest concentrations of non-employment activities for the selected individuals are found largely in areas close to downtown Portland inside the “loop”, east of downtown in the north, and south of Freeway 84. Important clusters of non-employment activities are also

found in Beaverton in the west and Gresham in the east. Most of the non-employment activities are of very short duration (95.4 percent of them have durations under 5 minutes, and less than 1.6 percent have durations over 10 minutes). Further, non-employment activities were undertaken throughout the day with a rather even temporal distribution. This not only corroborates the findings of Kwan's (1999a) Columbus study that men's non-employment activities tend to be less temporally concentrated than women's, but also that there is a significant gender difference in activity patterns in space-time.

Activity density patterns in geographic space

Comparison of the patterns of different activities for the same population subgroup or the patterns of the same activity between different population subgroups using this simple representation, however, is difficult. As the number of activities involved will increase considerably when more population subgroups are included and the patterns may be difficult to compare visually, other methods that facilitate inter-group or inter-activity comparisons are needed. This subsection explores the use of 3D activity density surfaces for representing and comparing the density patterns of different activities in real geographic space. The same group of respondents discussed above is also used here. The purpose is first to represent the spatial intensity of the locations of workplace, home, and non-employment activities of these individuals, and then to examine the spatial relationships between these density patterns.

To generate a density surface from a point distribution of n activity locations, a nonparametric density estimation method called kernel estimation is used (Gatrell, 1994; Silverman, 1986). Following Bailey and Gatrell's (1995) formulation, if $\Re$ represents the study area, x represents a general location in $\Re$ and $x_1, x_2 .... x_n$ are the locations of the n activities, then the intensity or density, $\lambda(x)$, at x is estimated by:

$$\lambda_h(\boldsymbol{x}) = \frac{1}{\delta_h(x)} \sum_{i=1}^{n} \frac{w_i}{h^2} k\left(\frac{(\boldsymbol{x} - \boldsymbol{x}_i)}{h}\right), \qquad \boldsymbol{x} \in \Re$$

where $k(.)$ is the kernel function, the parameter $h > 0$ is the bandwidth determining the amount of smoothing, w_i is a weighing factor, and $\delta_h(x)$ is an edge correction factor (Cressie 1993). In this study, the quartic kernel function

$$k(\boldsymbol{x}) = \begin{cases} 3\pi^{-1}(1 - \boldsymbol{x}^T\boldsymbol{x})^2 & \text{if } \boldsymbol{x}^T\boldsymbol{x} \le 1 \\ 0 & \text{otherwise} \end{cases}$$

described in Silverman (1986) is used for generating space-time activity density surfaces. The method is implemented through covering the study area by a 1371x2105 grid structure (with 2.89 million cells) and using a bandwidth of 0.86. The density surfaces, originally created in the grid data structure, are then converted to 3D format and added into a 3D scene (Figure 3).

In Figure 3, the density surface of non-employment activities is displayed transparently on top of the density surface of home locations of the selected individuals. To help identify the location of density peaks and troughs, three geographic data layers, namely freeways, major arterials, and rivers, are draped over the density surface of home locations. The figure, oriented towards west, shows that the major peak of non-employment activities is centered at downtown Portland within the "loop", and there are also considerable

concentrations northeast of downtown and around Beaverton. The highest density of home locations for the selected individuals is found at two peaks in the northwest and east of downtown Portland.

Figure 4 provides a close-up view of the same 3D scene in which the transparent density surface of non-employment activities is not shown. Three distinctive peaks of home locations can be clearly seen in the figure. They are located at downtown Portland inside the "loop", in areas northwest and east of downtown. Other areas with high concentration of home locations are found in Beaverton and in the area north of Milwaukee. The major advantage of this visualization method is its capability for examining the spatial relationships between different surfaces in their concrete geographical context. To explore the temporal dimension and its interaction with the spatial dimension, another visualization method is needed.

Space-time activity density surfaces

For representing the intensity of activities in space-time, kernel estimation is used again to generate 'space-time activity density surfaces' (Gatrell 1994; Silverman 1986). In this implementation, a space-time region $\Re$ is established with a locational system similar to an x-y geographic coordinate system. The time-axis of this coordinate system covers a 24-hour day from 3 a.m. and the space-axis represents the distance of an activity from home. A fine grid structure of 1920x1920 space-time grids (with 3.69 million cells) is then created by dividing a day into 1920 0.75-minute time slices and distance from home into 1920 20.1-meter (66-foot) blocks. The quartic kernel function described above is also used here with a bandwidth of 0.6. This method is used to generate three space-time activity density surfaces for individuals in the sample. One is for women employed full-time (Figure 5); the second one is for men employed full-time (figure not shown); and the third portrays the difference between these two density surfaces (Figure 6).

The density surface for full-time employed women (Figure 5) shows that there is a considerable amount of non-employment activities close to home (largely within 8 km) around noon and 5:00 p.m. This suggests that most of the non-employment activities undertaken by these women are performed during lunch hours and shortly after work. There are two intensive peaks of non-employment activities. One is found at noon about 6 km from home, and the other happens around 5 p.m. about 6 km from home. There are considerable amount of non-employment activities within 8 km from home during the evening hours between 6 to 9 p.m. The density surface for full-time employed men (not shown) reveals a very similar space-time pattern when compared to that of the full-time employed women. The main difference is that the space-time density of non-employment activities for these full-time employed men is not as intensive as that of the full-time employed women.

Figure 6 shows the difference between these two density surfaces. It is obtained by using the map algebraic operator "minus" for the two surfaces, where the value in a cell in the output grid is obtained by deducting the value of the corresponding cell in the surface for men from the value of the corresponding cell in the surface for women. Peaks in this "difference surface" indicate areas where the intensity of women's non-employment activities is much higher than that of men, and vice versa. Since the two density surfaces are very similar, the resulting difference surface reveals only minor and random modulations. The greatest gender difference is found around 6:00 p.m. within 8 km from home.

There are two major advantages in using these 3D space-time activity density surfaces. First, they reveal the intensity of activities in space and time simultaneously, thus facilitating the analysis of their interaction. Second, the grid-based method is amenable to many map-algebraic operations that can be used to adjust the computed raw density for highlighting the distinctiveness in the activity patterns of a particular population subgroup. It also makes the derivation of a "difference surface" for two population subgroups relatively easy, thus facilitating the examination of inter-group differences. The next section explores the 3D geovisualization of space-time paths.

Geovisualization of Individual Space-Time Paths

The space-time aquarium

The earliest 3D method for the visualization of individual space-time paths is the space-time aquarium conceived by Hägerstrand (1970). In a schematic representation of the aquarium, the vertical axis is the time of day and the boundary of the horizontal plane represents the spatial scope of the study area. Individual space-time paths are portrayed as trajectories in this 3D aquarium. Although the schematic representation of the space-time aquarium was developed long ago, it has never been implemented using real activity-travel diary data. The main difficulties include the need to convert the activity data into "3Dable" formats that can be used by existing visualization software, and the lack of comprehensive geographic data for representing complex geographic objects of the urban environment. The recent incorporation of 3D capabilities into GIS packages and the availability of contextual geographic data of many metropolitan regions have ameliorated these two difficulties.

To implement 3D geovisualization of the space-time aquarium, four contextual geographic data layers are first converted from 2D map layers to 3D format and added to a 3D scene. These include the metropolitan boundary, freeways, major arterials, and rivers. For better close-up visualization and for improving the realism of the scene, outlines of commercial and industrial parcels in the study area are converted to 3D polygons and vertically extruded in the scene. Finally, the 3D space-time paths of the African and Asian Americans in the sample are generated and added to the 3D scene. These procedures created the scene shown in Figure 7.

The overall pattern of the space-time paths for these two groups shown in Figure 7 indicates heavy concentration of day-time activities in and around downtown Portland. Using the interactive visualization capabilities of the 3D GIS, it can be seen that many individuals of these two ethnic groups work in downtown Portland and undertake a considerable amount of their non-employment activities in areas within and east of the area. Space-time paths for individuals who undertook several non-employment activities in a sequence within a single day tend to be more fragmented than those who have long work hours during the day. Further, ethnic differences in the spatial distribution of workplace are observed using the interactive capabilities provided by the geovisualization environment. The space-time paths of Asian Americans are more spatially scattered throughout the area than those of the African Americans, whose work and non-employment activities are largely concentrated in the east side of the metropolitan region. This seems to suggest that racial segregation may involve dimensions other than residential segregation since it may have a significant restrictive effect on the activity space of specific minority groups.

A close-up view from the west of the 3D scene is given in Figure 8, which shows some of the details of downtown Portland in areas within and around the "loop" and along

the Willamette River. Portions of some space-time paths can also be seen. With the 3D parcels and other contextual layers in view, the figure gives the researcher a strong sense about the geographical context through a virtual reality-like view of the downtown area. This interactive virtual environment not only contextualizes the visualization in its actual geographical surroundings but also enables the analysis of local variations at fine spatial scales. For instance, color codes can be used to represent different types of landuse or buildings to provide the analyst a better sense of the urban environment and its context, which can then be used to compare the activities and paths of each individual in the sample. This approach will, therefore, have considerable potential for the analysis and understanding of individual activity patterns at fine spatial scales.

Space-time paths based on GPS data

Although the 3D space-time paths shown in Figures 7 and 8 are helpful for understanding the activity patterns of different population subgroups, these paths are not entirely realistic since they only connect trip ends with straight lines and do not trace the travel routes of an individual. This limitation is due to the lack of route data in the Portland data set. When georeferenced activity-travel data collected by GPS are available and used in the geovisualization environment, the researcher can examine the detailed characteristics of an individual's travel pattern as actual travel routes. Figure 9 illustrate this possibility using the GPS data collected in the Lexington Area Travel Data Collection Test conducted in 1997 (Battelle 1997). The original data set contains information of 216 licensed drivers (100 male, 116 female) from 100 households with an average age of 42.5. In total, data of 2,758 GPS-recorded trips and 794,861 data points of latitude-longitude pairs and time were collected for a 6-day period for each survey participant.

To prepare for 3D geovisualization, three contextual geographic data layers of the Lexington metropolitan area are converted from 2D map layers to 3D format and added to a 3D scene. These include the boundary of the Lexington metropolitan region, highways, and major arterials. As an illustration, the 3D space-time paths of women without children under 16 years of age in the sample are generated and added to the 3D scene. These procedures created the scene shown in Figure 9. The overall pattern of the space-time paths for these women indicates that trips were undertaken using largely highways and major arterials. There is some regularity as indicated by the daily repetition of trips in more or less the same time throughout the 6-day survey period. This suggests that distinctive activity-travel patterns can be revealed by 3D geovisualization.

Conclusions

The dynamic and interactive GIS-based 3D geovisualization methods discussed in this chapter are useful for the exploratory analysis of activity-travel patterns. They allow the researcher to interact and explore the 3D scene. The visual properties of objects can be altered to reflect their various attributes and the highly flexible viewing and navigational environment is also a great help to the researcher. As shown by the examples, these methods are capable of revealing many important characteristics of the space-time activity patterns of different population subgroups in relation to the concrete urban environment. They also facilitate the identification of complex spatial relations and the comparison of patterns generated by individuals of different gender/ethnic subgroups. As the rhythm of everyday life and life cycle events, such as migration, can be portrayed by these methods, they can be used to gain insight into the everyday life of a particular place and time (Hanson and Hanson 1993). As individual-level, geo-referenced data become increasingly available, the

development and implementation of these kind of 3D geovisualization methods is a promising direction for many areas of social science research.

There are, however, several difficulties in the development and use of these 3D methods. First, the researcher may encounter barriers to the effective visualization of large and complex activity-travel data sets. Four such potential barriers identified by Gahegan (1999) are: (1) rendering speed - the ability of the hardware to deliver satisfactory performance for the interactive display and manipulation of large data sets; (2) visual combination effects - problems associated with the limitation in human ability to identify patterns and relations when many layers or variables are simultaneously viewed; (3) large number of visual possibilities - the complexity associated with the vast range of possibilities that a visualization environment provides (i.e., the vast number of permutations and combinations of visual properties the researcher can assign to particular data attributes); and (4) the orientation of the user in a visualized scene or virtual world. Implementation of the interactive 3D methods in this study shows that a geovisualization environment that provides a geographical context for the researcher may alleviate the fourth problem. However, the other three barriers may still remain a significant challenge to researchers who want to use such methods. For instance, rendering the density surface in Figure 6, which involves a TIN (triangulated irregular network) of 494,076 triangles and 247,256 nodes, can be taxing on the hardware. Further, identifying patterns from the space-time paths covering 129,188 activities undertaken by the survey respondents may push our visual ability beyond its limit. It is therefore important for future research to examine how human cognitive barriers involved in the interpretation of complex 3D patterns may be overcome.

Second, there is the challenge of converting many types of data into "3Dable" formats for a particular geovisualization environment. Since every visualization software may have its unique data format requirements, and the activity and geographic data currently available are largely in 2D formats, the data preparation and conversion process can be time consuming and costly. For example, considerable data preparation and pre-processing was required for converting the Portland activity-travel data for display as 3D space-time paths. Future research should investigate how the effort and time spent on data conversion could be reduced when data from various sources are used.

Third, the use of individual-level activity-travel data geocoded to street addresses, given their reasonable degree of positional accuracy, may lead to considerable risk of privacy violation. As Armstrong and Ruggles (1999) demonstrated, although "raw" maps comprised of abstract map symbols do not directly disclose confidential information, a determined data spy can use GIS technology and other knowledge to "hack" the maps and make an estimate of the actual address (and hence, a good guess of the identify of an individual) associated with each point symbol. This practice, called "inverse address-matching", has the potential for serious confidentiality or privacy violation. As "map hackers" may be able to accurately recover a large proportion of original addresses from dot maps, any use of such kind of individual-level geocoded data should be conducted with great concern in protecting the privacy of survey respondents and maintaining the confidentiality of information. As apparent in the 3D geovisualization examples in this chapter (e.g., the details in Figure 7), releasing a 3D scene created from several accurate data layers in VRML (virtual reality markup language) format may lead to significant risk of privacy violation because map hackers may be able to recover the identity of a particular survey respondent. This may further lead to the disclosure of other confidential information. As a result, researchers using 3D geovisualization methods should pay attention to this potential risk.

Recent research on geographical masking as a method of privacy protection is particularly relevant and important in this context (Armstrong et al. 1998).

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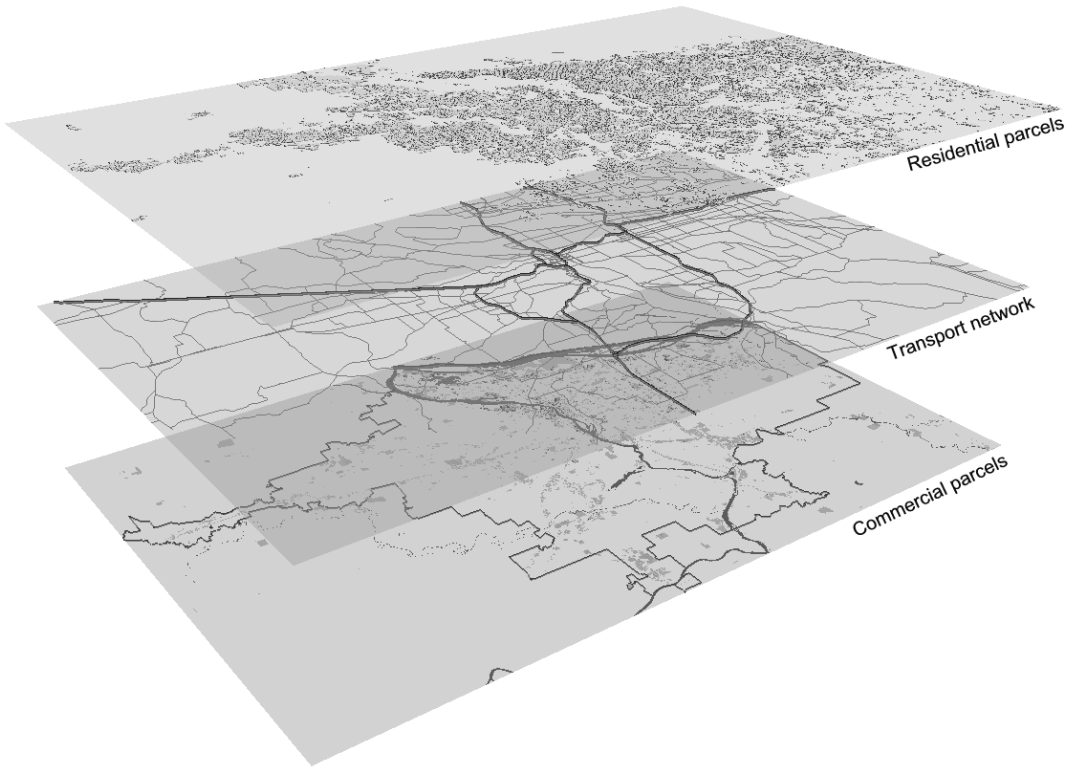

Figure 1. Three layers of geographical data used in the study.

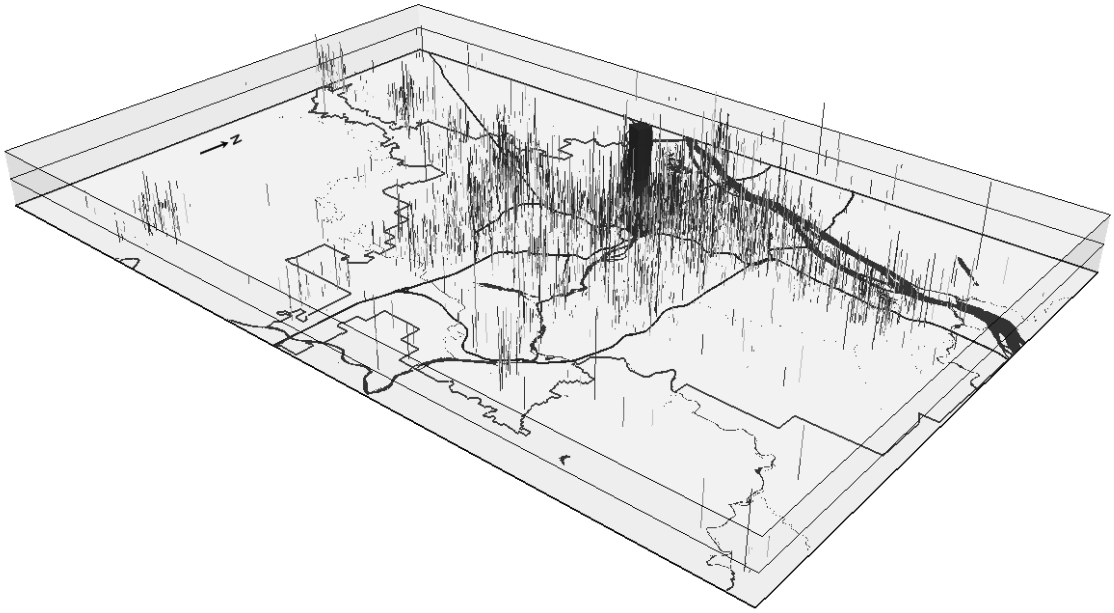

Figure 2. Simple activity patterns in space-time.

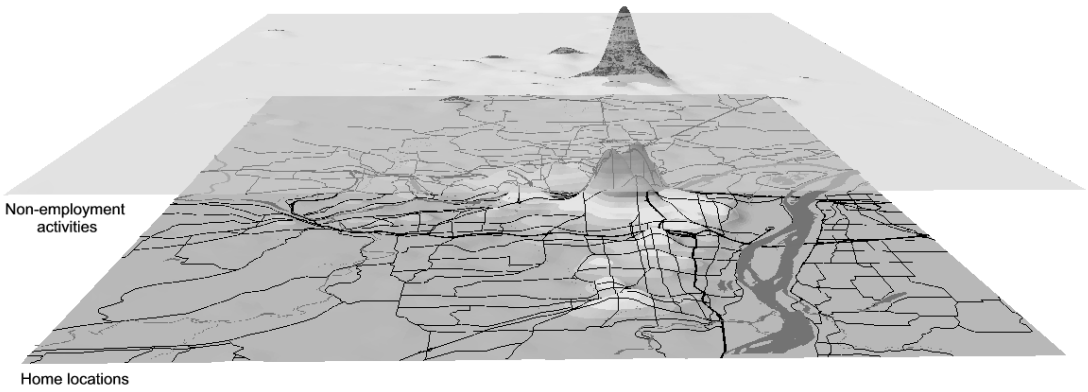

Figure 3. Activity density patterns in geographic space. The transparent surface for non-employment activities is above the surface of home locations.

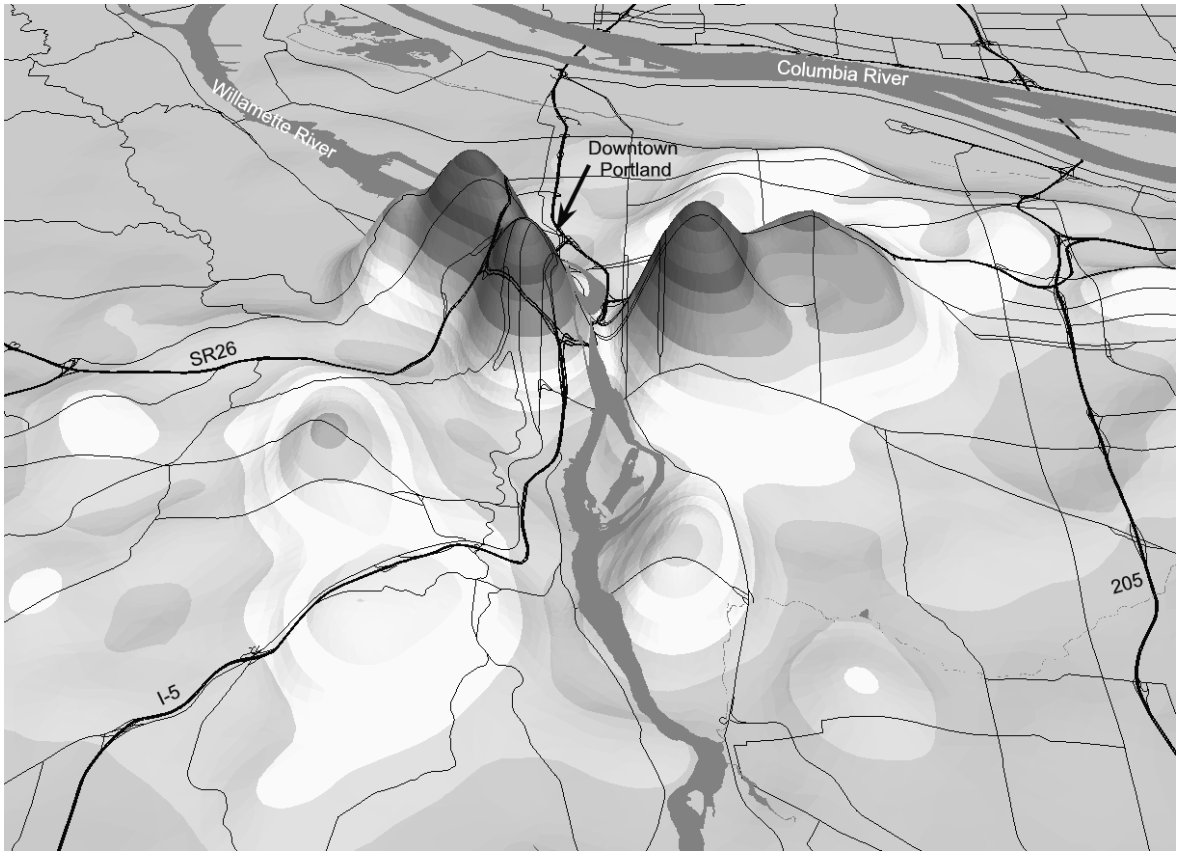

Figure 4. A close-up view of the density surface of home locations of the elected individuals.

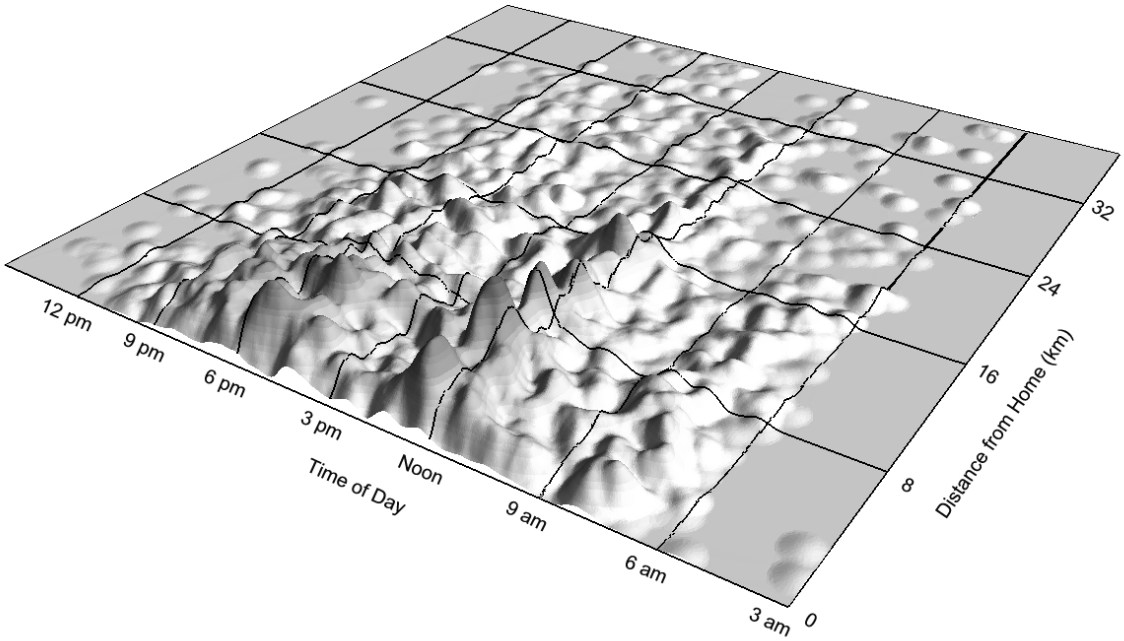

Figure 5. Space-time activity density of the non-employment activities of the full-time employed women in the sample.

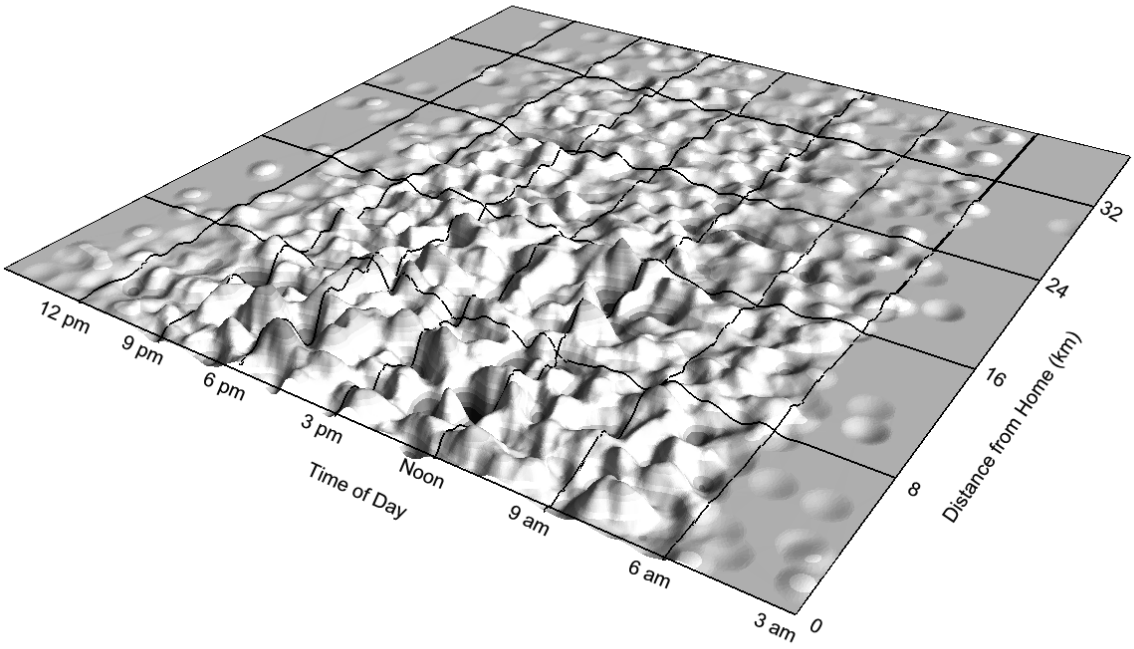

Figure 6. Gender difference in the space-time density of non-employment activities between the full-time employed women and men in the sample.

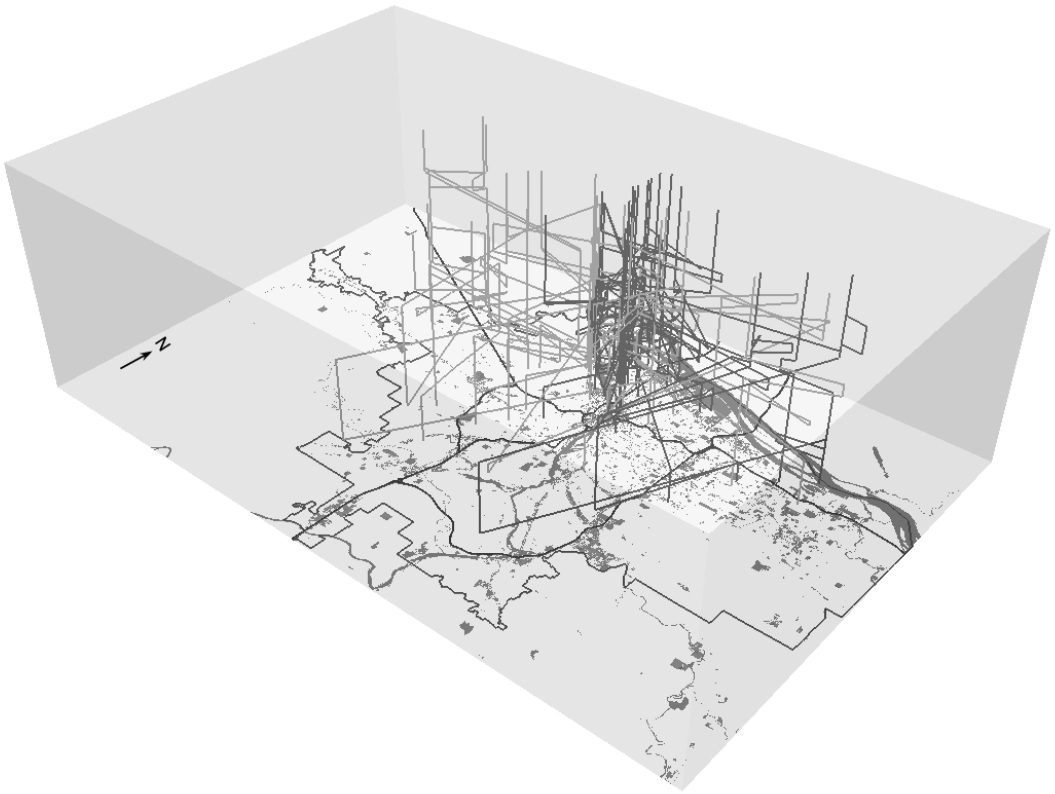

Figure 7. Space-time aquarium showing the space-time paths of African and Asian Americans in the sample.

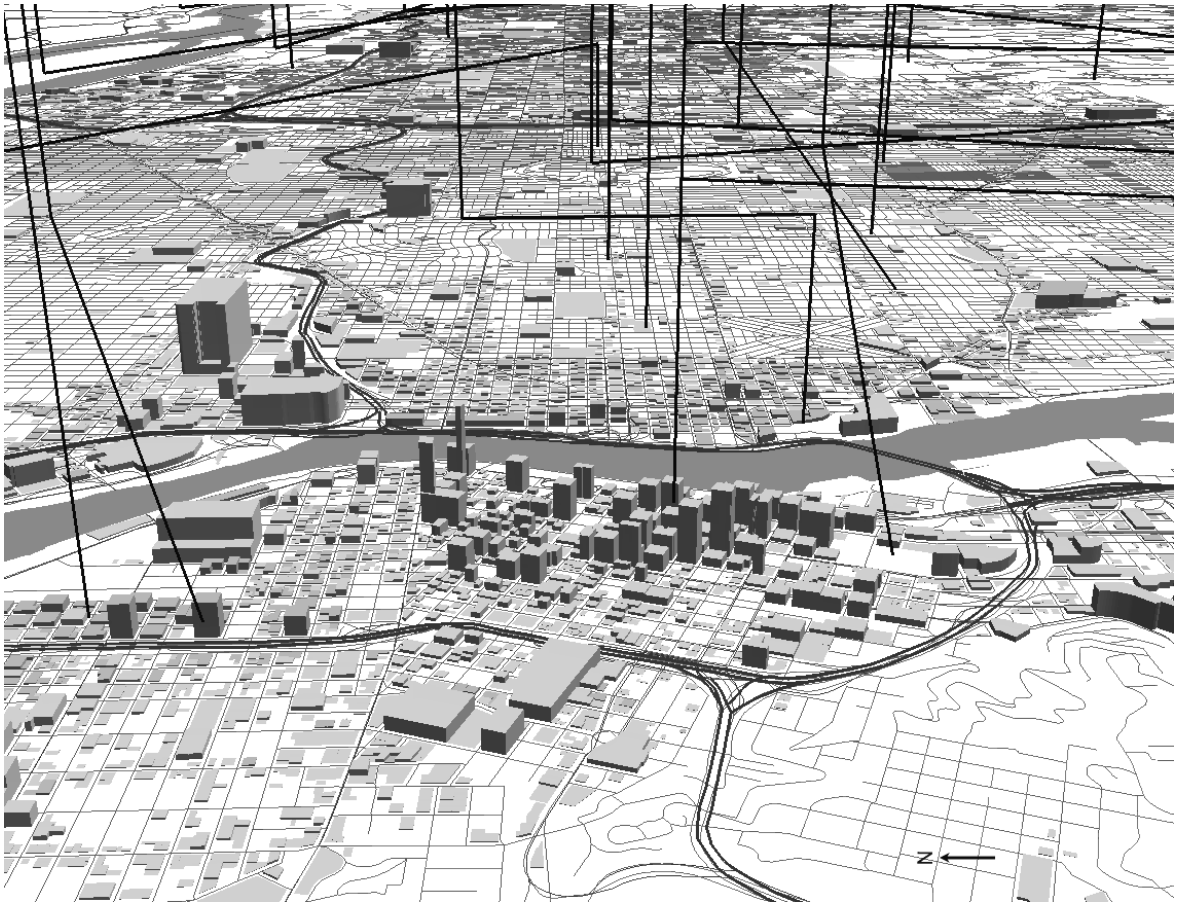

Figure 8. A close-up view of downtown Portland.

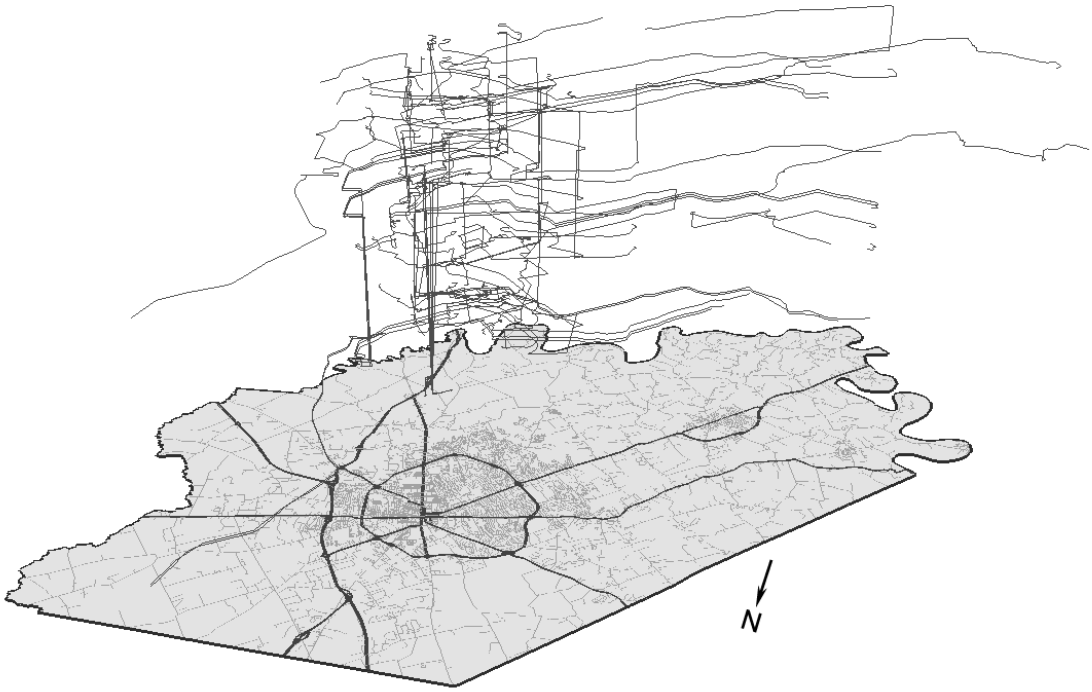

Figure 9. Space-time paths based on GPS data collected in Lexington, Kentucky.