Chapter 7
Tracking Social Life and Crime

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7.1 Introduction

The interaction of individual characteristics and environment is a recognisably under-researched question in criminological literature (e.g. Gottfredson et al. 1991; Wikström and Loeber 2000). This is partly a consequence of the lack of well-developed theoretical models for how social environments influence people's engagement in acts of crime. Research has also lacked adequate methodologies to study and measure people's exposure to social environments and how it interacts with people's crime propensity (Wikström et al. 2010). The use of spatial information and space-related methods can be of help here. Techniques of visualisation allow the representation of individual movement patterns over time–space using, for example, lines or polygons. Individuals can be tracked by measures of exposure to environments using methods that simultaneously take an individual's location, activity and type of socialisation into account. GIS allow a flexible combination of data of different types using information on the unique location of individual (x,y coordinates) with aggregated data (combining individual point or line data into larger areal units, such as a city's statistical units).

The use of spatial information in criminology research is not new. The intensity of its use is directly linked to the technological development of spatial techniques in academia and in practice (police officers and practitioners). Decades ago, the use of computerised mapping systems as part of police command and control led to the creation of a large variety of software for visualising the growing amounts of geocoded crime data. In addition, GIS have, since the 1980s, made geographical

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analyses of crime data possible for a great number of users, facilitating the integration of many types of data into a common spatial framework. The value of GIS has become even more apparent when enhanced with spatial statistical techniques and modelling. More recently, GIS have adapted to the need to visualise data on individual movement patterns, generated by space–time budgets or other, more technology-based tracking devices. Some of these spatial applications in criminology are illustrated later in this chapter.

The objective of this chapter is twofold. The first aim is to report advances of spatial methodologies to capture the complexity of individuals' movement patterns and exposure over space and time. This chapter starts by illustrating the potential of GIS and spatial analysis techniques for visualisation and tracking individual activity patterns over time and space. This is particularly important in urban criminology since traditionally analyses are focused on individuals' place of residence, rarely taking into consideration the fact that people spend a large share of their waking time outside their home. This first section describes several GIS-based visualisation methods for handling spatial and temporal dimensions of human activity patterns: 2-D and 3-D visualisation, space–time aquariums and activity density surfaces.

The second objective is to show how GIS, combined with space–time budgets, can be used to generate measures of exposure to environments for a group of individuals. In combination with individual propensity and settings, this environmental measure of exposure has the potential to explain differences in levels of offending between groups of individuals.

The structure of this chapter is as follows. Section 7.2 sets out the theoretical background for the study. The literature on urban criminology, with particular focus on the role of environment on crime causation, is reviewed first, followed by a discussion of the current spatial methodologies for visualisation and support for measuring and analysing environmental exposure. A new theory (situational action theory – SAT) and new methodologies to address and overcome these problems are discussed. Section 7.3 presents the Peterborough Adolescent and Young Adult Development Study (PADS+) as a case study. Sections 7.4 and 7.5 report the use of spatial methods for both visualisation and analysis of individual-level data. A summary of the results and conclusions is presented in the final section of this chapter.

7.2 Theoretical Background

We provide in Sect. 7.2.1 a historical review of the development of urban criminology theory, from social disorganisation theory (Shaw and McKay 1942; Kornhauser 1978) to situational action theory (SAT) by Wikström (2005; 2006). Since SAT requires news ways of capturing the influence of environment on human behaviour (Wikström et al. 2011: 113), we therefore discuss in Sects. 7.2.2 and 7.2.3 the potential of GIS and space–time budgets to illustrate individuals' movement patterns and capture their environmental exposure over time and space.

7.2.1 *The Environment Effect: From the* Tyranny of Zones *to Individual Measures of Environmental Exposure*

Most criminological theory (and research) focuses on either the role of personal factors or the role of environmental factors in crime causation (Wikström 2010: 215). Here we focus only on theories that suggest ways to interpret the *environment effect* on one's decision to commit crime.

The role of the environment in crime causation has traditionally been studied mostly in terms of the relationship between neighbourhood structural characteristics and neighbourhood levels of crime or offenders (Wikström et al. 2011). Traditionally, aggregated data are attached to spatial entities that are thought to be ecologically exposed to different sorts of crimes. Such data may be ecological (a group-level property) or contextual (an aggregation of a property belonging to the individuals comprising the group). Census and land-use data provide only limited information on theoretically relevant aspects of the environment. Theoretically, most studies of this type derive from the work by Shaw and McKay (1942) on Chicago. They argued that low economic status, ethnic heterogeneity and residential instability led to *community disorganisation*, which in turn resulted in subcultures of violence and high rates of delinquency. Social disorganisation theory suggests that structural disadvantage breeds crime. The main focus is placed on offenders and motivation (often indicated by an offender's place of residence).

More recent investigations have drawn on new concepts (such as social cohesion and collective efficacy) but are still linked to crime locations or an offender's places of residence as discrete zones (Sampson et al. 1997). According to Wikström et al. (2011: 113), the possibility of combining census (and land use) data with data on theoretically relevant area social conditions gathered from community surveys was, however, an important methodological step forward. The development of *ecometrics* by Sampson and colleagues (e.g. Raudenbush and Sampson 1999) further helped to improve the study of environmental factors by providing advanced techniques to assess the reliability of community survey measures of environmental conditions.

Although ecological studies have continued to reveal strong associations between characteristics of urban areas and the locations of certain types of offences, there is little evidence (e.g. Reiss 1961; Wikström and Loeber 2000) to show how exposure to different urban environments (beyond place of residence or crime location) can influence an individual's decision to commit a crime. This is problematic since people are mobile and may spend a large share of their time outside in different parts of the city and hence are subjected to environmental influences from a range of environments, other than their own neighbourhoods. Even those who live in the same neighbourhood may have different lifestyles, which means that they may be exposed to very different environments.

Other limitations are methodological: the use of *zones* as a unit of analysis. Despite using more accurate modelling strategies, such as nested models that partially deal with the impact of zones, it is unclear how the shape and size of these geographical units affect the results (the modifiable areal unit problem – MAUP) as well as the risk for ecological fallacy (Fotheringham and Wong 1991; Robinson 1950). Using cross-sectional aggregated zone data, we are able to ascertain the links between the occurrence of crime and small-area socio-economic and demographic characteristics (conclusions are drawn at ecological level only). However, what cannot be done is to observe how these causal mechanisms take place at an individual level within zones and over time.

Attempts to portray a more dynamic view of the causes behind crime causation have played an important role in criminology. The *routine activity theory* (Cohen and Felson 1979) suggests that an individual's activities and daily habits are rhythmic and comprise repetitive patterns. Space is like a structural backcloth that generates certain types of social interactions that may lead to crime. These social interactions do not happen in a vacuum. The vast majority of crime occurs within the *offender's awareness and activity space* (Brantingham and Brantingham 1995). There was a genuine will in these studies to direct work away from static ecological correlations between socio-economic characteristics and crime towards a more dynamic view of crime within the context of human activity patterns. Critics argue that the theory may work more effectively for property crime than for violence and is not able to capture why some individuals choose crime as an alternative and others do not in spite of being *in the right place at the right time*. An important problem is that the dynamic aspect of this theory has never been properly tested empirically because of limited access to individual-level data over time and space. Instead, empirical studies have so far taken land-use indicators (e.g. location of city centre, resident population density) as proxies for an individual's mobility or potential social interactions that may lead to crime (Roncek and Maier 1991; Osgood et al. 1996; Ceccato 2009).

Criminology has also focused on the importance of environment as a synonym of distance between places to explain where crime happens (for instance, the distance between crime location and offender's place of residence). These studies might be simple average distance analysis (a bipolar connection of offender's residence and crime location) or complex methodological proposals to predict an individual's offending behaviour, such as geographic profiling of sexual offenders (e.g. Amir 1971; LeBeau 1987; Canter and Larkin 1993; Rossmo 2000). The work of White (1932) is regarded as a basis for many scholars in this field (Turner 1969; Rhodes and Conly 1981; Lundigran and Canter 2001; Costello and Wiles 2001; Fritzon 2001; Gore and Pattavina 2004). None of these studies, however, regards crime in relation to an individual's mobility within the city, either prior or subsequent to the crime event. They also disregard the potential effect of a particular setting/environment on an individual's decision to commit an offence.

In order to make a contribution to the need to theoretically integrate and develop key criminological insights about crime propensity and criminogenic exposure, Wikström (2005, 2006) suggests *situational action theory* (SAT). The theory proposes that acts of crime are an outcome of a perception–choice process initiated by the interaction between an individual's crime propensity and his/her exposure to a criminogenic setting.

SAT makes an important contribution to the understanding of a city's geography of crime. The theory suggests that concentrations of crime events in time and space (the so-called *hot spots*) in an urban area are essentially consequences of concentrations in time and space of interactions between crime prone individuals and criminogenic settings (against the backdrop of a set of particular temptations and provocations of relevance for what kinds of crimes may occur at a particular location), creating the situations to which crime prone people may (habitually or after deliberation) respond with acts which break the rules of conduct stated in law. Changes in the level of crime in a particular urban area (or in certain parts of an urban area) are seen to be a result of (1) changes in the prevalence of crime prone people among its population (and its visitors), (2) changes in the extent of its criminogenic settings or (3) changes in the nature of the selection processes that affect the rate by which crime prone people are exposed to its criminogenic settings. Such changes are an outcome of changes in processes of social emergence (as they affect the prevalence of criminogenic settings), changes in processes of personal emergence (as they affect people's crime propensity) or changes in contemporaneous processes of social and self-selection which, in turn, may be related to political and economical changes in the larger society in which the urban area is embedded and on which it depends.

To be tested, SAT requires individual-level data and innovative methods that can measure individual exposure to settings/environments. We first review the literature of visualisation techniques in GIS and the use of space–time budgets as examples. Then we apply them to real-life examples from data from a case study based in Peterborough, UK.

7.2.2 Visualisation of Individual Activity Patterns in Space

Although the study of human mobility has been a growing research area (e.g. Hägerstrand 1970; Tomlinson et al. 1973; Lenntorp 1976; Janelle et al. 1988; Mey and Heide 1997; Gonzalez et al. 2008; Ratti et al. 2010), it was only recently that the field experienced a powerful resurgence after its popularity in the 1970s and early 1980s. One reason for the revival is the availability of data from opportunistic sensors that create new means to track individual movement patterns by facilitating the continuous and relatively inexpensive collection of mobility data that can be used to develop continuous models of spatial interaction (e.g. GPS, data of mobile phone users). Data of this kind can be useful, for instance, in predicting real-time risk in different types of environment in the city.[1] Another reason for the rebirth of

[1] The possibility of using real-time location data has, for instance, opened up a number of new research questions and, perhaps, answers to old ones. Examples include work by MIT's *Senseable City Lab*, *UrbanSense* at UCLA, *Spatial Information Design Lab* at Columbia University and the i-Mobility lab at KTH, Sweden. These projects serve as examples to illustrate the unlimited opportunities mobile communications offer today to understand urban activities and monitor them over time.

the field is the continual advances in spatial analysis technology, such as GIS, which provides a toolkit for analysis and visualisation of space–time phenomena.

The tradition of visualising people's movement over time and space dates back to the late 1960s, when Hägerstrand (1970) suggested the concept of *space–time prisms* to illustrate how an individual navigates his/her way through the spatial–temporal environment (e.g. a city) – a field of research called time-geography. In practice, however, our understanding of the basic laws governing human behaviour in space remains limited, owing to the lack of tools and appropriate methods to monitor and predict the time location of individuals. New evidence shows however that although our daily mobility seems to be characterised by a deep-rooted regularity (Song et al. 2010), explicit predictions on people's whereabouts can in the future be explored by using data-mining algorithms (e.g. Eagle and Pentland 2006), turning the patterns of regularities into actual mobility predictions. Whilst space–time prisms and other concepts in time-geography have been empirically tested in different fields of research (for a review, see Corbett 2001), they have been neglected in most of criminology literature. The few empirical attempts are limited to appraisal of offenders' distance to crime (e.g. White 1932; Fritzon 2001; Gore and Pattavina 2004) and trajectory analysis (e.g. Groff et al. 2009).

A simple way to gain an indication of how much time is spent in different types of environments is by using visualisation techniques. Standard GIS provide different tools that allow spatial representation of people's movement, either on a bi-dimensional or a 3-D plan. Section 7.4 illustrates individual activity patterns both in bi and three dimensions, space–time prisms and activity density surfaces. The literature is rich in this area. Studies have been devoted to activity–travel behaviour and accessibility (e.g. Janelle et al. 1988; Kwan 1998, 2000; Takahashi et al. 2001), individuals' lifestyles (e.g. Huisman and Forer 1998; Kwan 1999) activity patterns in both time and space (Peuquet 1994; Huisman and Forer 1998; Miller 2003) and space–time visualisation of group of individuals (e.g. Kwan 2000; Krak 2003; Schönfoelder and Axhausen 2003; Song et al. 2010).

7.2.3 Individual's Environmental Exposure

How can *environmental exposure* be measured at individual level? The methodological literature shows examples of how data can be gathered, from which later measures can be made. They vary from traditional surveys and questionnaires, time diaries, time budgets and, more recently, methods that rely on ICT technology, such as GPS, interactive location gadgets and mobile phones. Of relevance here are time budgets since they deal with time and space windows that are more appropriate to the measurement of exposure. Moreover, they allow data gathering simultaneously on activity, space and time that other techniques may not.

Time budgets or time diaries constitute a set of techniques for data acquisition that provides a basis for detailed description and analysis of individual behaviour over time. They record information of individuals either continuously or by time periods that can be used for the reconstruction of the timing, sequence and frequency of activities (see Pentland et al. 1999 for an extensive review). The spatial dimension has being incorporated into the time budget toolkit with the advent of studies of individual travel behaviour and urban planning policies since the early 1970s, adding up *space* to the existent term time budget (e.g. Tomlinson et al. 1973; Forer and Kivell 1981; Janelle et al. 1988; Mey and Heide 1997; Schönfoelder and Axhausen 2003). The incorporation of GIS techniques and database capabilities to space–time budget is, however, new, particularly in criminology (see, e.g. Wikström et al. 2010). Figure 7.1 illustrates an example of a space–time budget framework (See electronic version for colour figures).

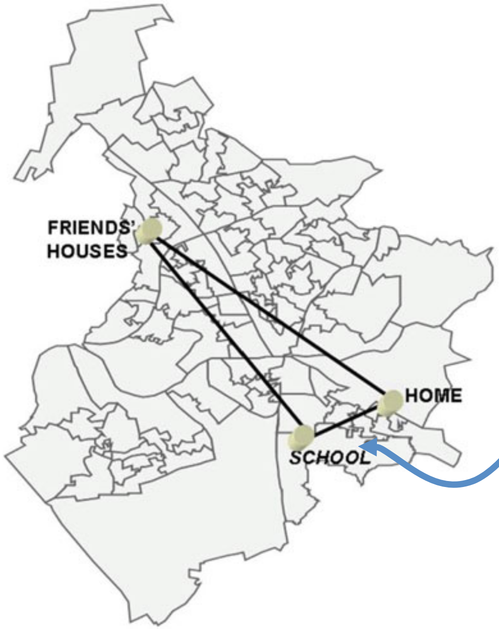
A space–time budget methodology gathers very detailed time diary data linked to a spatial unit and can therefore be used to calculate complex measures of exposure to a range of settings. This method collects information about which individuals interact with which settings (who goes where, under what circumstances, for how long). This provides a more dynamic sense of why particular individuals are in particular places and the circumstances they encounter (Wikström et al. 2011).

Section 7.5 shows how GIS can be used to generate measures of environmental risk for a group of individuals over time using data gathered by space–time budgets. In combination with individual characteristics and behaviour settings, measures of individual exposure help explain differences in levels of offending between groups of individuals. For further reading on the applications and technicalities of space–time budgets within criminology, see Wikström et al. (2011).

7.3 The Peterborough Study

The data for this study are taken from the Peterborough Adolescent and Young Adult Development Study (PADS+), an ongoing ESRC-financed longitudinal study of a randomly selected sample of young people who were 11 years old and living in the UK city of Peterborough and nearby villages in 2002. Peterborough is a medium-sized city with considerable social diversity, encompassing some of the most highly advantaged and disadvantaged neighbourhoods in the East of England. About a third of all Cambridgeshire offences are committed in Peterborough, but not homogenously over space (Cambridgeshire Constabulary 2005). Typical individual offences, such as vandalism and violent offences, are clustered in inner-city areas and in a couple of neighbourhoods in the northeast and west of Peterborough (e.g. Dogsthorpe, Paston, Bretton, which are deprived neighbourhoods).

Data were obtained by interviewing each child for about half an hour on his/her previous week's activities. For example, if the interview was done on Tuesday, the interview started with questions about Monday and then moved on to Sunday. Pupils were asked to indicate on a map of Peterborough at what location they were



Time	Geo Location	Place	Activity	Socialisation	Alcohol/ Drug Use	Risk	Fear	Victim	Weapon	Offend	Truancy
6	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
7	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
8	NK08	Home	Breakfast	Siblings+Pare	No	No	No	No	No	No	No
9	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
10	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
11	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
12	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
13	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
14	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
15	NP01	***School***	Studying	Guardian	No	No	No	No	No	No	No
16	NK08	Home	TV watch	Siblings	No	No	No	No	No	No	No
17	NK08	Home	TV watch	Siblings	No	No	No	No	No	No	No
18	NK08	Home	Dinner	Siblings	No	No	No	No	No	No	No
19	NC07	Friend	Homework	peer	No	No	No	No	No	No	No
20	NC07	Friend	PlayingPC	peer	No	No	No	No	No	No	No
21	NC07	Friend	Talking	peer	No	No	No	No	No	No	No
22	NK08	Home	Sleeping	Siblings+Pare	No	Yes	No	No	No	No	No
23	NK08	Home	Sleeping	Siblings+Pare	No	Yes	No	No	No	No	No
24	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
1	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
2	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
3	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
4	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No
5	NK08	Home	Sleeping	Siblings+Pare	No	No	No	No	No	No	No

Interview code ____________________
Date of interview__________________
Day of the week___________________

Home Output Area code ______________________
School Output Area code _____________________

Fig. 7.1 The structure of the space–time budget hourly (coded for the study initially by enumeration districts (ED)[2]), then asked questions regarding what place they were (e.g. in a shopping mall), about what they were doing and with whom, whether they used any alcohol or drugs at that time, carried weapons, were being truant, entered into any risk situation (e.g. were harassed or witnessed an act of violence), committed a crime or were a victim of one. All interviews took place in the schools in a private room supplied by the school and under supervision of project staff only. A small number of children declined to take part and were excluded from the study but were not enough to produce any bias in the sample.

In this paper, most of the analysis is based on data for the Wave 1 with children aged 12–13 years old. However, in some cases (visualisation of 2-D and measure of exposure), other waves are also included and are therefore notified in the text.

Children were divided into two groups: *crime adverse* and *crime prone* children. Measures of moral and self-control for crime adverse children are stronger than for crime prone ones, which would hypothetically make crime adverse children less at risk to offend than crime prone ones.

We restricted ourselves to the time spent in risky environments by individuals within the Peterborough urban area since information about the levels of risk in the surrounding villages was not available. This, of course, may have an under-estimated effect on the total scores for individuals who are highly mobile. For more details of the method, see Wikström et al. (2011).

7.4 Visualisation of Individual Activity Patterns

The next section explores methods for visualisation of an individual's activity patterns in space–time using the database of the Peterborough case study. Various segments of the original sample data are used to illustrate these four methods. All geoprocessing is performed using a combination of tools available in ArcView GIS, ArcGIS and the ArcGIS extension 3-D Analyst.

7.4.1 Individual Activity Patterns in 2-D

Lines are used to represent individual movement patterns of individuals over the city and neighbouring villages (Fig. 7.2) from the Peterborough Study database (See electronic version for colour figures). Different colours represent samples of each individual data wave (yellow is wave 1, the youngest group; the oldest group, in green, is wave 4). This particular group has offended at least once. Points represent stations or nodes (e.g. home, schools, shopping) where offenders have

[2] EDs were later replaced by Output Areas (OA).

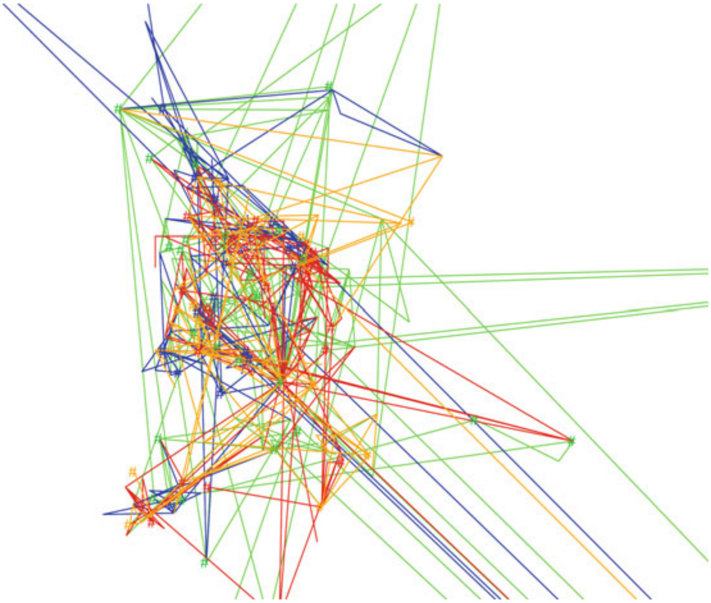


Fig. 7.2 Activity patterns in space. PADS offenders – activity fields – wave 1 = 12–13 years old, wave 2 = 13–14 years old, wave 3 = 14–15 years old, wave 4 = 15–16 years old (See electronic version for colour figures)

declared spending time. In bi-dimensional visualisation techniques, it is not possible to represent the duration of each activity, but such techniques can provide measures of distance between origins to each station but also between different individuals. This visualisation uses the coordinates of each zone's centroids as departure points (*as the crow flies* distance), therefore disregarding geographical barriers in space, such as streets, buildings and other features of the urban landscape.

7.4.2 Individual Activity Patterns in 3-D

For a meaningful representation of individual activity patterns in space–time, the z-variable in this analysis represents the time dimension (24 h of a day) of activities of a sample of 40 individuals from the Peterborough space–time budget database (from wave 1 only, 12–13 years old). Using the *z*-value, an activity for each individual was first mapped as a point entity using its geographic location (the coordinates of each zone's centroids) and activity start time in ArcGIS 9.0.[3] In order

[3] This procedure can be performed with any other GIS software, such as MapInfo, under 'create points' tool, or ArcView 3.x, by 'add point theme'.

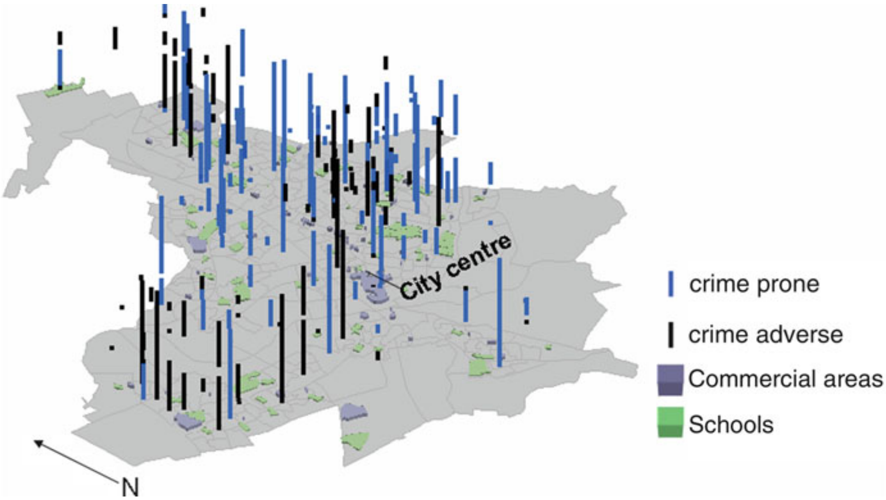


Fig. 7.3 Activity patterns in space–time (See electronic version for colour figures)

to visualise the duration of each activity, the activity points in 3-D were mapped by assigning heights to the *z*-values and were later extruded from their start times by a value equal to the duration of the activity. Activity duration is indicated by the length of the vertical line that represents the span of an activity (for more details, see Kwan 2000: 191). Figure 7.3 shows the result of using this method for all activities performed by crime prone individuals (grey vertical lines) and crime adverse individuals (black vertical lines) during a week by hour. The locations of commercial areas and schools were set as a background for individuals' activity patterns by adding layers of geographic information to a 3-D scene (See electronic version for colour figures).

The widely spread pattern of activities for both crime adverse (classified according to a scale of questions on moral and self-control) and crime prone individuals is indicated by the fact that both groups spent most of their time either at home or at school on weekdays. At this age (12–13 years old), children are mobile but normally do not travel very far from home (e.g. 46% go to school in the same zone in which they live), generating an activity pattern that is often affected by the location of their home and school. They are also clustered in time: weekdays are often spent at home (from 10 p.m. to 7 a.m.), at school (from 9 a.m. to 3 p.m.) or elsewhere (from 3 p.m. to 6 p.m. or from 7 p.m. to 10 p.m.). This representation illustrates how much time is spent in each location by each individual, but very little can be said about differences within individuals of the same group. This is because individuals belonging to the same group and spending similar amounts of time in the same zone end up being misrepresented by the same vertical line (remember: they are all mapped using the coordinates of each zone's centroids). Another limitation with this representation is that it does not follow the individual paths by connecting places over time. No information is visually readable in a 3-D representation about time/locations between places (e.g. the exact time/location an individual leaves home and goes to school and then returns and the path he or she used). As suggested by Gahegan (1999), the orientation of the user in a visualised scene also becomes a limiting factor since it may change the way the scene looks like. The visualisation of common patterns of activities by groups is difficult to ascertain visually since it is difficult to disentangle them in space. Moreover, paths are not home standardised (see Kwan 2000: 197), which means that an individual living in the south would tend to have a more southern activity pattern than a individual living in north Peterborough. These issues are further discussed in the next subsections.

7.4.3 Individual Mobility as Space–Time Prism

Space–time prisms (or aquariums) produced in GIS are perhaps the most similar form of representation to Hägerstrand's original daily prisms (1970: 13–14). Traditionally, space is represented by a two-dimensional (2-D) plane indicating an individual's location and destination, whilst time is represented by the vertical axis, creating a 3-D box for a specific portion of space–time. Hägerstrand used the space–time path to demonstrate how human spatial activity is often governed by limitations and not by independent decisions by spatially or temporally autonomous individuals. This means, for instance, that an individual cannot be in two places at the same time or travel instantaneously from one location to another – a certain trade-off must be made between space and time. According to Kwan (2000), until recently one of the main difficulties of implementing space–time aquariums was the need to convert the activity data into '3-Dable' formats, which has been greatly reduced by the incorporation of 3-D capabilities into GIS packages.

The activities of an individual from wave 1 on a Monday were mapped using the coordinates of each zone's centroids. The coordinates were generated initially in 2-D and then converted to 3-D shape files together with three other background layers (lines connecting places, time scale and the zone map). These layers were added to the 3-D scene, as illustrated in Fig. 7.4 (See electronic version for colour figures). The use of colour codes for distinguishing different types of places (stations) provides the analyst with an indication of differences in geography of movement that did not exist in the previous 3-D visualisation. Another advantage is that angles of lines connecting places give the sense of direction of the path, whilst the time scale (an indication of duration of each activity) reveals features that were missing in the previous 3-D scene.

Although the use of individual data mapped at very detailed level (e.g. street address) has considerable potential for development of person-specific, activity-based methods at fine scales, it still has a few potential limitations. The use of multiple paths at once in a space–time prism can be visually challenging since it is very difficult to disentangle one path from another and may lead to risk of privacy violation (Kwan 2000). By focusing on detailed features, the technique fails to provide a comprehensive picture of patterns of groups of individuals.

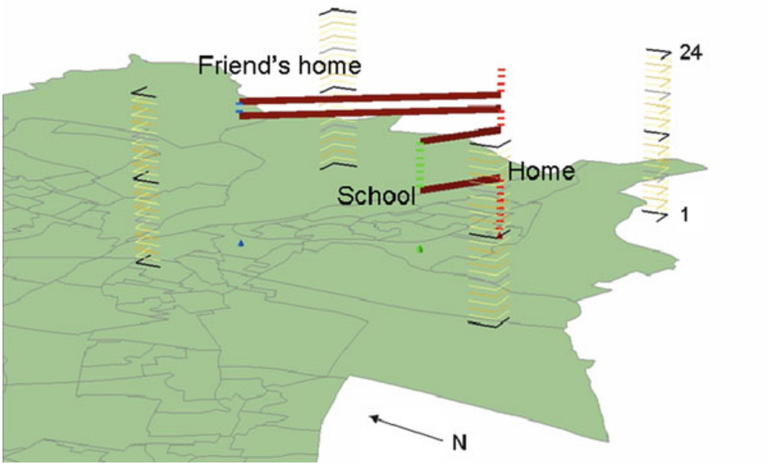


Fig. 7.4 Space–time prism with space–time path of an adolescent on a Monday (See electronic version for colour figures)

7.4.4 Individual Activity as Density Surfaces

The identification of common spatial patterns of movements of two groups of individuals was explored using the kernel home range technique. This kernel method has been chosen since it has extensively been tested for estimation of animal movements in biology studies (e.g. Worton 1989; Ferguson et al. 1999). There are other techniques that could be tested here instead, such as the confidence ellipses, minimum convex polygon home range (see Hooge and Eichenlaub 2000; Schönfoelder and Axhausen 2003) or tools for analysing clustering in time and in space, such as Knox and Mantel indices and the Correlated Walk Analysis.[4]

The data come from two sets of individuals living in the district of North Werrington, Peterborough. The activities of crime adverse and crime prone individuals were mapped using the coordinates of each zone's centroids. Places visited by the individuals outside the study area were excluded from the analysis (all crime prone individuals spent at least 1 h a week outside Peterborough, whilst among the crime adverse individuals, only three did). A preselection of coordinates using a script in ArcView was necessary since most movements were cyclical (e.g. home–school–home) and redundant from a spatial point of view, generating a large set of multi-points. This procedure has not, however, reduced the number of places (or 'stations') that the individuals passed during the week (16 for crime adverse individuals and 25 for crime prone). The activity space of an individual is described in terms of a probabilistic model. Using default parameters, a fixed *kernel home range utilisation distribution* (the name given to the distribution of an animal's position in the plane, Worton 1989) as grid coverage was calculated for each group of individuals using the Animal Movement extension (Hooge and Eichenlaub 2000)

[4] These techniques are implemented in CrimeStat 2.0 by Ned Levine & Associates, available at http://www.icpsr.umich.edu/NACJD/crimestat.html#MAPS.

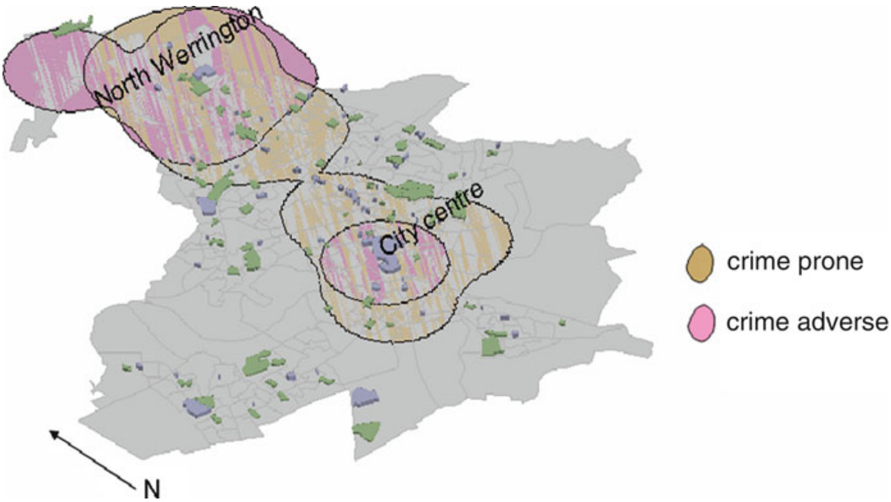


Fig. 7.5 Patterns of weekly activity for two groups of kids living in the district of North Werrington, Peterborough, using kernel home range, with 95% probability polygons (See electronic version for colour figures)

to ArcView. The resulting kernel polygons are similar for the two groups but not exactly the same (Fig. 7.5) (See electronic version for colour figures).

The overlapping lines over North Werrington and surroundings indicate a local social interaction pattern determined by the location of individuals' home, school and local commercial centre. They overlap also over the city centre, but for crime prone individuals, the polygon spreads towards North Werrington, flagging for the existence of 'other stations' between neighbourhood and centre for this group. On the other hand, and less interestingly, this overlapping pattern could be at least in part the result of using polygon's centroids (which provides a rough estimation of where individuals are in place that week) instead of the exact coordinates of places (e.g. home, school, shops). Although the output provides a good estimate of a group's activity space, it ignores the connections between separated activity spaces over an urban landscape. More importantly in these results is the fact that they show that crime prone individuals tend to have a segregated pattern of mobility than those expressed by crime adverse ones (low propensity to offend). Despite living in the same part of the town, the concentrated mobility pattern of individuals may be an indication of the impact of limited economic resources on their lifestyles and daily mobility.

7.5 Risky Environments, Individual Activity Patterns and Offending

When do risky environments lead to offending? To answer this question, we need information about an individual's propensity and exposure to a criminogenic environment/setting – both will lead to an individual's decision to commit

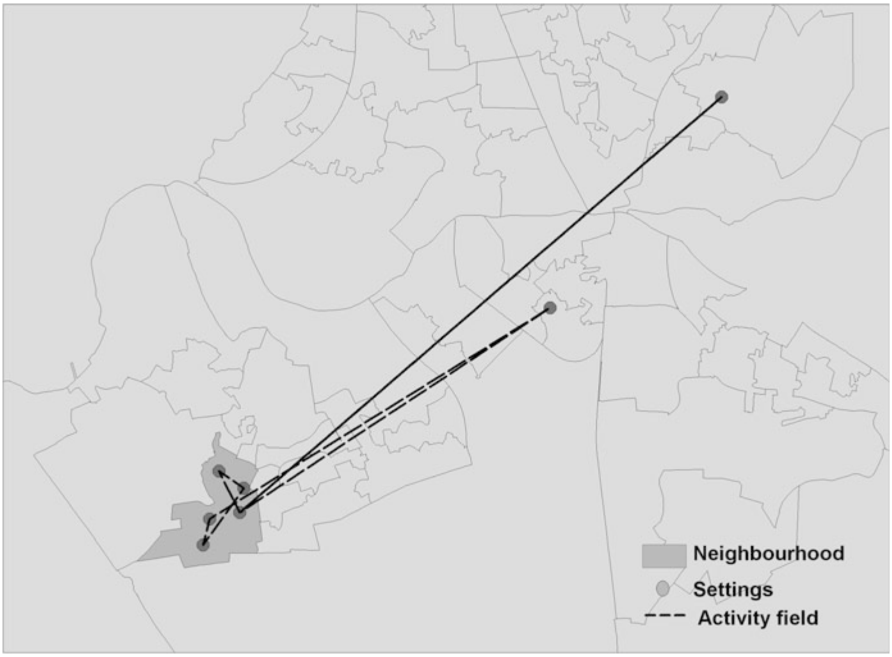


Fig. 7.6 Settings, activity field and neighbourhood context

(or not) the offence. Wikström (2005, 2006) proposes a theoretical framework that combines the interplay of mechanisms linking individual characteristics, settings and lifestyles over time (Fig. 7.6).

If the *environment* is all that is external to an individual, a setting may be conceptualised as part of the environment that the individual (at any given moment) can access with his or her senses (e.g. home, school). An *activity field* may be defined as the configuration of settings in which the individual takes part at a given period (e.g. daily, weekly, monthly). An activity field needs space to occur – what we may call *activity space*: the configuration of the environment which an individual is using for his/her activities (see Golledge and Stimson 1997 for an overview). An *activity field* may be spatially localised – a couple of hundred metres from home, or dispersed, consisting of home, school, shopping malls and peers' homes in a relatively distant neighbourhood. The *individual's environment* can thus be defined as the cumulative characteristics of the settings that constitute the individual's nodes of activity field and the environmental contexts (e.g. a neighbourhood at a given time).

Individuals differ in their individual propensities to crime, in their time spent in behaviour settings and in their environmental contexts. We briefly describe the procedures involved in these three measures:

1. *Individual risk*
   Individual risks are calculated based on scales of an individual's morals and self-control. For more details, see Wikström and Loeber (2004); Wikström (2005, 2006).

Table 7.1 Setting measure: risky socialisation, activity and places

Socio-psychological	Number of awaken hours spent in risky place and with peers and unsupervised activities (awaken varying by individual), from Monday to Sunday
Risky socialisation	Defined as variable WHOM = peers, 1 male peer, 1 female peer, 2 or more male peers, 2 or more female peers, mixed male and female peers
Risky activities	Defined as variable ACTIVITY = talking face to face, hanging around
Risky places	Defined as variable PLACE = streets, street corners, parks/recreation, car park lots

2. *Risk setting*
   A risk setting for criminal involvement for an individual has been defined as a setting in which the individual spends time in a public place, unsupervised (i.e. no significant adults present) together with peers and engaging in a non-structured activity. We tried a combination of several variables (Table 7.1). This example illustrates one of the risk setting measures used in the analysis. For every hour the individual spends time in a certain setting, they receive 1 risk point, and for all other hours, they receive 0 risk point. The final setting score is a result of the individual's exposure to all these risky settings (excluding sleeping hours).
3. *Environmental risk*
   Environmental risk is composed of summed hours of exposure of both risky setting and overall neighbourhood risky contexts (e.g. high-crime areas). This gives a weekly environmental risk score for the individual based on the risk characteristics of the settings in which the individual has taken part. We describe below in detail how the measures of environmental risk were generated using the Peterborough space–time budget database for Wave 1, police official statistics, small-area community survey, socio-economic statistics available at the municipality city council and land-use digital data from Digimap.[5]

Environmental risk factors are place-related variables created to indicate how much time (waking hours) an individual spends in risky environments. The initial step was to create a weighted-based map that captures areas with *high risk*. The second step was to determine to what extent individuals were exposed to these risky environments over the period of a week, attach these values to each individual and finally to assess whether or not this might have an effect on their involvement with crime. Spreadsheets and desktop mapping systems were used to generate environmental risk factors by small unit areas (Fig. 7.7):

1. *Central and commercial areas* – The location of the centre and the commercial areas was obtained from the Peterborough Municipal Council by zone. They are important indicators of people's convergence in space over time. The centre includes the central business districts, whilst the commercial areas indicate all local commercial centres. Dummy variables were created having 1 for centre/commercial area, 0 otherwise.

[5] http://edina.ac.uk/digimap/

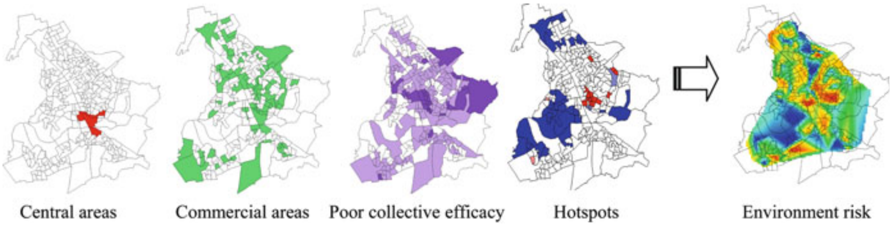


Fig. 7.7 Calculating exposure measure: an example (See electronic version for colour figures)

2. *Deprived areas* – The 1998 Index of Local Deprivation was incorporated into the data set as an indicator of poverty and exclusion. The classification was produced by the Department of the Environment, Transport and the Regions and obtained from Peterborough Municipal Council at zone level. The deprivation index included indicators that covered the following dimensions: economic, health, educational indicators, environment, crime and housing. Only the positive values were mapped, which means that only those areas in Peterborough that have some degree of deprivation compared with the England average were added to the data set as a dummy variable (1 for any degree of deprivation, 0 otherwise).
3. *Areas with clusters of violence and property damage* – High-crime areas are often known as risky environments since individuals are more exposed to criminogenic conditions that they would otherwise be – we believe that exposure to this particular environment would affect an individual's propensity to offend. The methodology at this stage involved first, mapping the offence data; second, attaching offence data to a spatial framework; third, calculating standardised offence ratios on this spatial framework; and finally, detecting clusters of offences using a spatial statistical technique and offence data at x,y coordinates from the Cambridgeshire Constabulary. Since violence and property damage are proven to be typical individual-related offences, we created the indicator based only on these crimes. Using SQL functions[6] in a desktop mapping system, the offence point data set was aggregated and later attached to zones. A standardised offence ratio (SOR) for violence and damage was calculated. A cluster detection technique was applied to the SOR data to select only hotspots of violence and damage. Clusters of high values were detected using a local Getis–Ord statistic of spatial concentration $G(i)^*$ (Getis and Ord 1992) available in GeoDa.[7] Areas with positive and significant z-values indicated spatial clustering of high SOR and were therefore classified as a hotspot (1 for hotspot, 0 otherwise).

As illustrated in Fig. 7.8, individuals living in the same area differ in the amount time spent in risky environments (See electronic version for colour figures). Dots represent all places visited by two individuals living in west district of Peterborough

[6] SQL – Structured Query Language, a language used by relational databases to query, update and manage data.

[7] Software available at http://geodacenter.asu.edu/

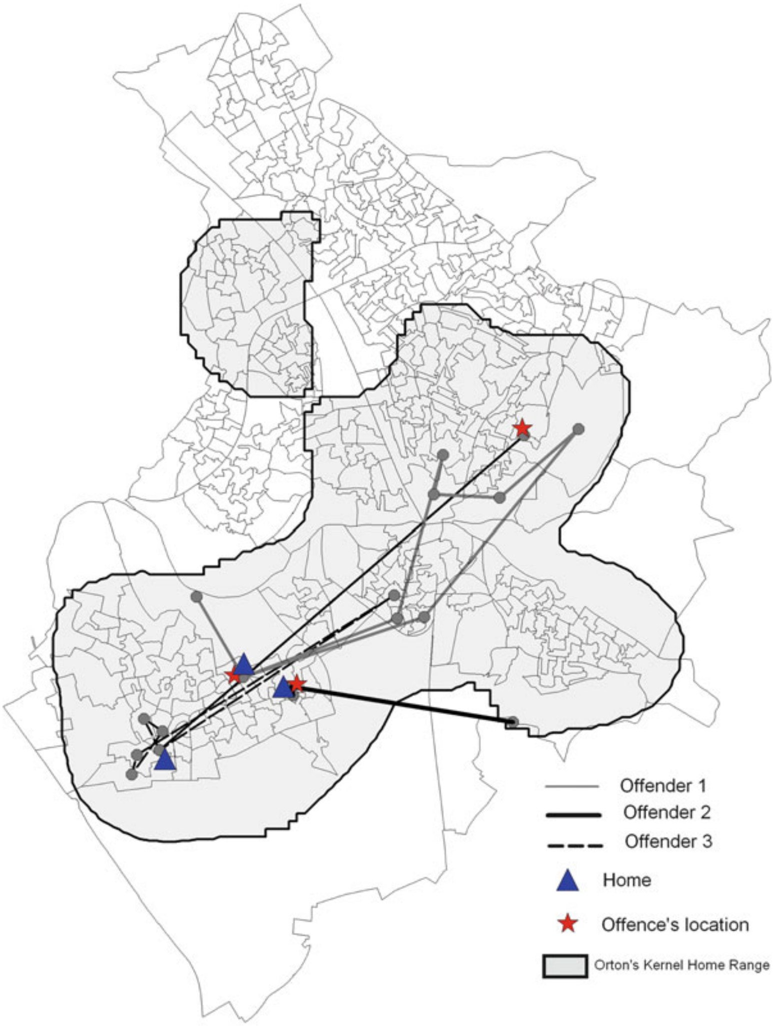


Fig. 7.8 Tracking activity pattern for three kids living in West district, Peterborough (See electronic version for colour figures)

during the whole week. Lines illustrate individual paths during the weekend by hour, whilst black stars are indicative of offences committed by one of the individuals. The weekend was chosen since it does not have the same time–space *constraints* as weekdays, in which most individuals follow cyclical patterns of activities (e.g. home, school, home).

Each hour spent in central and commercial areas, deprived areas or hotspots of violence and vandalism was added up by individual, generating a gross measure of level of exposure to risky environments by day and week. This measure was then analysed individually (as shown in Fig. 7.8) or aggregated by group of individual risk (crime adverse and crime prone), place of residence, levels of deprivation and land use. Although levels of exposition to risky environments tend to differ between groups (e.g. crime prone individuals in comparison to crime adverse individuals), there were cases in which the difference was not statistically significant to state any causal relationship because of the sample size by group. Also, dividing groups by individual risk did not avoid cyclical convergent patterns of activities (all adolescents spend at least 5 h a day at school, for instance). We therefore split the database into *time-windows* to capture times when individuals would diverge in their activity patterns, such as after-school hours and weekends.

Individual characteristics interact with risky environments and help to explain close to 28% of offending of individuals of the sample (self-reported offences). These findings flag for a differentiated effect of environment on individuals over time but also indicate that the spatial scale that environmental risk measured is important to capture the environmental effect on the individual. The effect of environment on individuals' behaviour has also been confirmed with later data waves using similar methodology,[8] as reported in, for example, Wikström et al. (2010: 75). The authors show that 'individuals with different crime propensities exhibit some interesting differences in their activity fields. Those with a high crime propensity tend to spend much more of their time awake at locations other than their home and school (output) areas. Those with the lowest crime propensity spend 21% of their time in locations outside their home and school areas, while the corresponding figure for those with the highest crime propensity is considerably higher (33%). Spending time outside one's home and school areas is likely to involve a higher risk of being exposed to criminogenic settings.

Data on offenders from the five waves show that the large majority of offences are committed elsewhere than home neighbourhood (21 best friends' neighbourhood, 17 commercial centre and 42% elsewhere) but follow their routine activity patterns (Wikström et al. 2010). These findings provide evidence for the need to consider an individual's exposure to different environments to better predict offending and the geography of crime. These results also lend weight to both Brantingham and Brantingham's theory of *offenders' space awareness* and *routine activity* by Cohen and Felson (1979) since offending tends to happen in places in which offenders spend time and perform their daily activities.

In the next section, the remaining challenges in measuring environmental risk using GIS in criminological context are further discussed.

7.5.1 Remaining Challenges in Measuring Environmental Risk

Measuring exposure to environment in an area such as Peterborough (i.e. relatively small by UK standards and highly monocentric) imposes a series of limitations.

[8] In the subsequent analysis, time spent in neighbourhood with poor collective efficacy was also part of the measure of environmental risk.

The first refers to the difficulty of disentangling activity fields of crime adverse and crime prone individuals. In Peterborough, most individuals have little problem in reaching most parts of the city just by walking 15–20 min from their homes. The city centre is, for instance, within walking distance of most neighbourhoods. This means that any attempt to differentiate individuals by tracking their time spent in the city centre as an indicator of risk becomes almost inappropriate since most individuals will spend some time each week there. We could expect then that a polycentric, larger city structure would provide a better basis for differentiating individuals' activity fields between crime prone and crime adverse individuals using visualisation techniques.

In terms of data gathering, the complexity of a detailed space–time budget methodology may make it difficult for untrained participants to effectively and consistently record their activities. It is also difficult for participants to locate activities in the desired spatial units. Many resources are needed to effectively code such data, including detailed maps of the study area broken into geocoded spatial units (at a geographic level where one can pinpoint participants' locations precisely, if an exact address is not known), comprehensive lists of streets and other relevant features of the study area (the more detailed the better) and familiarity with the study area and the space–time budget codes (Wikström et al. 2011: 123).

Another type of limitation refers to the lack of variability of different types of socio-economic indicators. For instance, Peterborough has a couple of areas that are among the 10% most deprived in England and only one among the 10% least deprived. This homogeneity towards the extreme poverty scale creates biased indicators of individuals' risk since most parts of the city are regarded as risky environments. One way to minimise these limitations is to define, as has been done in this study, measures of exposure based on a set of combined conditions that includes the individual risk (crime prone/crime adverse), settings (place, e.g. street corners/school), activity (e.g. hanging around/studying, and socialisation, e.g. with peers/with family) and neighbourhood context (e.g. high/low risky environments).

Most of the challenges of creating measures of exposure to the environment discussed below are inherited from the limitations imposed by aggregated level data. The difference, however, is that in the traditional ecological approach of crime, these limitations affect phenomena that are assumed to take place where people live (*the neighbourhood* for which assumptions are made on aggregated individuals' characteristics are linked to statistics at areal unit level), whilst in the space–time approach, they are linked to the process of portraying *risk* dynamically over time and space. Although these remaining challenges are overlapping in nature, we will try here to discuss each of them separately.

One challenge refers to the fact that the measure of environmental risk is based on composites. We assume that deprived areas and centres, commercial and high violent crime areas are regarded as riskier environments than other places in the city. We are aware that these indicators are perhaps too crude to pick up significant differences between individuals, but they are, at the moment, the only available data sources. This implies, for instance, that indicators do not have the same meaning across the city. For instance, in most central districts, commercial areas are still a good indication of meeting places, whilst in wealthy districts, they often look like parking lots (e.g. Werrington), isolated from residential areas. These centres may therefore share little (if any) similarity on their criminogenic conditions to crime. Another example is the indicator of deprivation at area level. This variable provides a good indication of general levels of disadvantage but may fail in classifying the most peripheral areas. The reason is that accessibility to services is a dimension of the index that classifies peripheral areas as deprived just because they have longer distances to basic services, a fact that has very little criminogenic meaning. The calculation of environmental risk may therefore be flawed in certain cases since it combines areas that are genuinely risky with those that are not. A solution to this limitation is to combine general indicators of risk, as performed in this study, with those generated by an individual survey data on social disorganisation, neighbourhood attachment and social cohesion at a very local level.[9] Surveys potentially produce more sensitive measures of risk since they would reflect residents' knowledge and perception of their immediate environment.

Zone shape and size influence how data are gathered and aggregated. The literature in geography has a long tradition of providing evidence on how zone design influences results – the so-called modifiable areal unit problem (MAUP) (e.g. Openshaw 1984; Fotheringham and Wong 1991). The MAUP consists of both a scale and an aggregation problem. The scale problem refers to the variation which can occur when data from one scale are aggregated into more or less areal units (Ratcliffe and McCullagh 1999). When the measure of environmental risk is based on geographical units that are relatively large, it may be masked by a combination of different land uses and activities that occur at a given time and space within that area. Typical examples are Peterborough's zones of local regional centres. As Fig. 7.9 illustrates, the Bretton centre (polygon FB14) contains schools located near shopping malls, potentially combining risky (e.g. being with peers at commercial centre) and non-risky places/activities (e.g. studying at school under adult supervision) into the same unit of analysis. The measure of risk could in these areas be either under- or overestimated simply because the measure by polygon fails to show these variations. One possible solution is to decrease the size of the geographical unit. This may improve the problem, to a certain degree, but does not help in selecting the best set of units to represent the data. Regardless of the scale, choosing a new set of units may imply possible border effect problems when events are misrepresented since the area's boundary splits the phenomenon in two (see, e.g. Griffith 1983). For the specific case of creating measures of exposure, a simpler solution is to determine *time-windows*, as done in this study, to capture differences in individuals' activity patterns in space. *Risk* is then measured based on a set of hours that are potentially risky, such as after-school hours as opposed to school hours, when children are more often engaged in structured supervised activities.

[9] The Peterborough Study incorporated indicators from a community survey in later analysis. Findings are reported in Wikström et al. 2010.

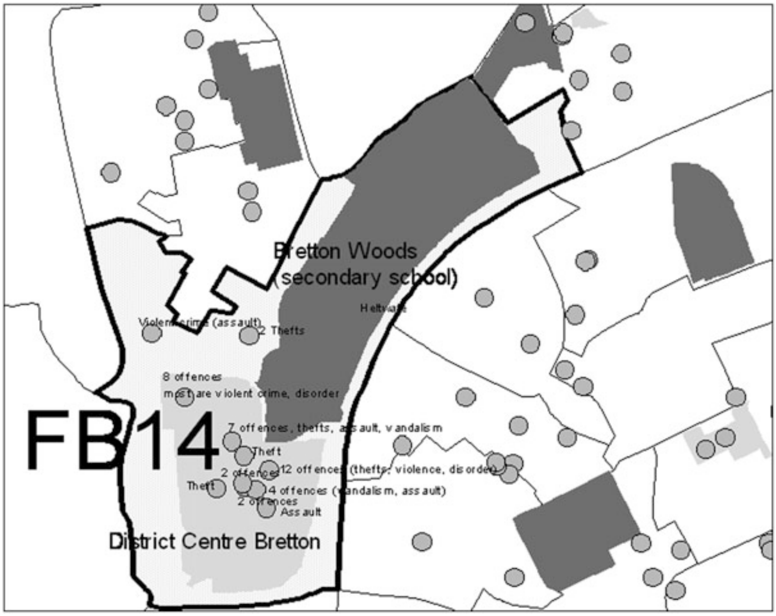


Fig. 7.9 Risky and non-risky settings in the same unit of analysis. *Grey dots* represent the location of offences

7.6 Drawing Conclusions and Looking Ahead

In this chapter, we reported advances of spatial methodologies based on GIS capabilities and space–time budgets to visualise and track individuals over time and space in Peterborough, UK. The novelty of this study is to portray and track social life in different city environments using individuals' activity fields and measures of exposure to environments that go beyond individuals' places of residence. Theories of urban criminology are used as reference to this methodological testing, with particular focus to the main ideas postulated by situational action theory (SAT).

Findings show that space–time data on individual activity patterns can be visualised using standard GIS technology. The simple 3-D time–space view shows how much time is spent in each location by each individual, but very little can be said about differences between individuals of the same group. Space–time prisms, on the other hand, allow the use of colour codes for distinguishing different types of places and an indication of differences in geography of movement that did not exist in the simple 3-D visualisation. However, the use of multiple paths at once in a space–time prism makes the visualisation of common patterns of activities by groups very difficult. One solution is to use probability density estimation techniques, such as the kernel home range, that provide a *spatial summary* of activity patterns over space. One limitation of this type of spatial representation is that it ignores the spatial connection between groups of statistical significant activity patterns. Kernel home polygons showed, for instance, differences between extensions of mobility patterns between groups of individuals with different crime propensity levels. Future studies should take advantage of space–time visualisation techniques to better understand the effect that different urban layouts and landscapes have on individuals' environmental perceptions at certain time-windows, for instance, that may trigger urban fear.

We also suggested ways that GIS can be used to generate measures of environmental exposure, which in combination with individual characteristics and behaviour settings, has the potential to explain differences in levels of offending between groups of individuals. The analysis shows that measures of risky settings at individual level (defined as a combination of risky places, risky activities with risky social contacts), together with environmental exposure, were effective in distinguishing groups' differences in offending. Those with a high crime propensity tend to spend more of their waking hours at locations other than their home and school areas. Among those who offend, crimes are often committed elsewhere than in the area where their homes are located. However, these offences do not happen at random locations in space. They tend to follow offenders' routine activity patterns (e.g. school area, friend's home area). These findings lend weight to both Brantingham and Brantingham's theory of *offenders' space awareness* and *routine activity* by Cohen and Felson (1979) with individual-level data. Some of the remaining challenges of creating environmental exposure measures, as those reported in this chapter, are not related per se to the way data are obtained (in space–time budget) or manipulated (in GIS) but are inherited from the limitations imposed by methods dealing with aggregated level data. The major implication for policy of the methods employed here is their potential to produce results that go beyond individuals' places of residence – which is crucial information for criminology but also for urban planning applications.

Based on international experience so far, one central issue is to further test whether GIS technology, associated with other fine detailed data gathering methods, can be used to model different aspects of social life and human behaviour, including offending. For the first time, we are able to capture snapshots of movement in slices of time of a pulsing city. For planning urban safety, this development potentially impacts on how safety services are guided by the level of detailed data on individuals in time and space and the level of interactivity they may share with agencies and data holders. Better grounds to assess risk of victimisation can help individuals to make dynamic decisions as they move and support police enforcements to be in the right place at right time. The forecast is that a rapid development will occur in the field, particularly using tracking devices, such as GPS and data on mobile data users. Although these devices are useful for tracking individuals over time and space, they are still expensive for large samples, intrusive from a privacy point of view and not yet suitable for recording simultaneously activities and types of socialisation, as space–time budgets are. In this context, it is important to be able to report on the experience of using space–time budget and GIS in the field of criminology, as illustrated in this chapter.

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