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The usefulness of measuring spatial opportunity structures for tracking down offenders: A theoretical analysis of geographic offender profiling using simulation studies

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Abstract
Geographic offender profiling (GOP) is an investigative activity aimed at locating an offender's residence on the basis of where he or she commits offences. Current tools that assist in GOP assume that spatial opportunity structures for crime are uniform: they assume that potential targets are evenly distributed in space, and that potential targets are equally attractive everywhere. In addition, they assume that travel distance is the only criterion that offenders consider when choosing a crime site. This paper demonstrates that, with the help of an extended target selection model, GOP tools could be improved if they measured and utilized spatial variation in criminal opportunity structures. The results of a computer simulation study illustrate this finding.

Introduction

Geographic offender profiling (GOP) is an investigative activity. It is aimed at deducing where an unknown offender lives from what is known about his or her spatial behaviour and selection of crime sites. It has also been referred to as geographic prioritization (Rossmo, 2000) to emphasize that although its results could help the police determine where to concentrate their investigations, it will generally not lead them to the offender's doorstep.

In addition to the professional experiences and judgements of police detectives, a comprehensive body of scholarly work, theoretical as well as empirical, is available to support GOP. In the works of Paul and Patricia Brantingham (Brantingham & Brantingham, 1975, 1978, 1981a,b, 1984, 1993a,b, 2003) a rich conceptual framework is developed that describes how potential offenders search for targets in their environment, how their choices are influenced by the spatial distribution of potential targets and the areas they traverse during routine activities, and how they evaluate potential targets and areas as being suitable and attractive. The theoretical work of the Brantinghams and that of many others (e.g. Boggs, 1965; Brown & Altman, 1981; Clarke & Cornish, 1995; Elffers, 2004; Rengert, 1980, 1981, 2004) is complemented by even larger numbers of empirical studies on spatial crime patterns, offender mobility and criminal target choice. For example, many studies

have shown that most offenders commit their offences close to their homes (Baldwin & Bottoms, 1976: 78–98; Capone & Nichols, 1975; Gabor & Gottheil, 1984; Hesseling, 1992; LeBeau, 1987; Phillips, 1980; Ratcliffe, 2003; Snook, 2004; Turner, 1969; Van Koppen & Jansen, 1998; Wiles & Costello, 2000), that the journey may involve a directional component (Constanzo, Halperin, & Gale, 1996; Godwin, 2001), that the average distance travelled varies across types of offences (Baldwin & Bottoms, 1976; Boggs, 1965; Capone & Nichols, 1976; Gabor & Gottheil, 1984; Hesseling, 1992; Pettiway, 1982; Rhodes & Conly, 1981) and across types of offenders (Baldwin & Bottoms, 1976; Canter & Larkin, 1993; Gabor & Gottheil, 1984; Phillips, 1980; Snook, 2004; Van Koppen & Jansen, 1998; Wiles & Costello, 2000).

Furthermore, the finding that larger travel distances to crime sites are associated with higher (potential) profits of robbery (Capone & Nichols, 1975; Van Koppen & Jansen, 1998) and burglary (Snook, 2004) suggests that offenders make trade-offs between distance and other aspects of target attractiveness. Indeed, ethnographic research involving interviews with offenders has demonstrated that most offenders do evaluate the attractiveness of potential targets and situations not only in terms of distance, but also in terms of accessibility, prospective profits and risks of detection (Bennett & Wright, 1984; Nee & Taylor, 2000; Rengert & Wasilchick, 2000; Taylor & Nee, 1988; Wright & Decker, 1997; Wright & Logie, 1988; Wright, Logie, & Decker, 1995).

If these theories and research outcomes are to be of any use in tracking down unknown offenders, police officers need tools that translate theoretical notions and empirical findings into practical guidelines. Such tools have started to become available in recent years. Specialized computer programs like *Rigel* (Rossmo, 2000) and *Dragnet* (Canter, Coffey, Huntley, & Missen, 2000) have been developed to assist the police in GOP. Using as input the geographical coordinates of the crime sites of serial offenders, these GOP tools utilize the criminological concept of *distance decay* to produce *spatial prioritization maps*. *Distance decay* is the phenomenon that the frequency of offending decreases with the distance from the offender's home. Thus, it indicates that most crime is committed relatively close to the offender's home, while few crimes occur at large distances. *Spatial prioritization maps* are maps that show which areas in a city or region have the highest estimated likelihood of containing the offender's residence. These maps can serve as starting points for police investigations.

The starting point for the present article is the observation that because of an exclusive focus on the distance decay concept, the available knowledge on spatial target selection of offenders is under-utilized in software tools for geographic profiling. The aim of the article is to bridge part of this gap between theory and practice by showing that in addition to the use of the *distance decay* concept, the use of the concept of *opportunity structure* could substantially enhance the effectiveness of GOP tools. In particular, it will be argued that the accuracy of GOP tools could be improved if the *locations of potential targets* and other aspects of the *attractiveness of potential targets* were measured and utilized.

The line of argument is as follows. First, the basic principles of how GOP tools work are outlined. Then two straightforward and concrete examples are presented. They illustrate at a basic level how GOP tools could be improved if the locations of potential targets and other aspects of their attractiveness were measured and utilized. Subsequently it is explained how that can be realized by turning around the spatial target selection model of Bernasco and Nieuwbeerta (2005). Finally, the set-up and outcomes of a simple simulation study are addressed. It is concluded that for the purpose of GOP, the measurement and use of spatial

opportunity structures is effective, and that it is comparatively most effective in situations where criminal opportunities are strongly clustered in space.

GOP tools

A range of methods – all using a series of crime site locations as their input – can be employed to support predictions on where an offender's residence is located. The most sophisticated contemporary GOP methods are implemented as computer programs, like *Rigel* (Rossmo, 2000), *Dragnet* (Canter et al., 2000) and *CrimeStat II* (Levine, 2002).[1] Using mathematical calculations on the coordinates of a series of crime sites, these GOP tools yield a probability density function on a flat surface, called "jeopardy surface" (Rossmo, 2000), or "prioritized search map" (Canter et al., 2000). These maps look like coloured altitude maps, but instead of altitude the colours represent for every point or small grid cell on the map how likely it is to be the offender's home or anchor point, given the locations of a series of offences ascribed to him or her.

General principles of GOP tools

How do these tools work? Stripped of details, all GOP tools are based on the same idea. They all make use of the phenomenon that by their choice of a crime site, offenders reveal something about the place from where they started their journey to crime. One of the most robust findings in criminology is the concept of *distance decay*, the finding that the frequency of offending decreases with the distance from the offender's home (see the references in the Introduction). GOP tools reverse this logic, by arguing that the likelihood of a particular location being the offender's residence reduces as the distance from that location to the crime site increases. Thus, the best place to find an offender's residence is close to the crime site. GOP normally involves the application of this rule not to a single offence, but to a series of similar offences perpetrated by the same offender. Thus, the challenge is to assess for each location in an area whether it is a likely starting point for the journey to crime to *all* crime sites in a series. According to Rossmo (2000), minimum number of five crimes are necessary for the prediction to be accurate enough for practical purposes, but the principle itself can be applied just as well to a single crime or to a small series.

   By way of illustration, Figure 1 shows how such a prediction is produced. To simplify matters, the figure shows a one-dimensional space, in which the horizontal axis represents a street where offences have been committed at crime sites a, b and c. First, the curves A, B and C are drawn around the crime sites. For every address in the street, they represent the likelihood of the offender living at the address. The curves show that the offender's most probable address is always the crime site itself, and that the probability gradually reduces from that point out in both directions. The exact shape of the curves may be based on previous research, or on theoretical arguments, and is not restricted to monotonically decreasing functions but could also involve a non-decreasing "buffer zone" around the crime site (Canter et al., 2000; Rossmo, 2000) or could follow a piecewise constant function (Van Koppen & De Keijser, 1997).

   Curve S is the one-dimensional variant of the "jeopardy surface" or "prioritized search map". It represents the combined likelihood of curves A, B and C, i.e. the product of the separate three probabilities. It is the address likelihood function of an offender who has committed all three offences. In terms of prioritization, curve S would direct police investigations first to the area between and around a and b, and then to the area around c.
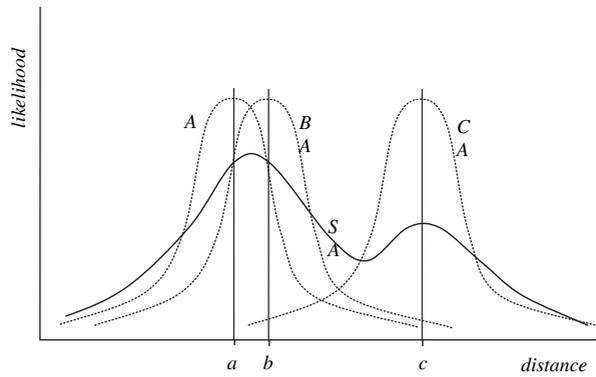
Figure 1. Principle of geographic offender profiling (one-dimensional).

Accuracy assessment

In order to assess the value of a GOP tool, a relationship must be drawn between where the offender really lives and the tool's calculated probability distribution. The *search cost index* (Canter et al., 2000) is an appropriate means to this end. The search cost index is so named because it can be interpreted as the percentage of space that on average must be searched in order to locate the offender, if the prioritization of a particular GOP tool is followed. The search cost index is calculated by first dividing the space (in our example in Figure 1, the street) into a large number of smaller units. The average probability density (curve *S*) of each unit is then determined. Units are then sorted on the basis of diminishing probability, and finally a calculation is made to identify what percentage of space (the street) must be searched in this sequence in order to find the place where the offender actually lives. Since a completely random search procedure on average requires half of the space to be searched before the offender is located, a successful GOP tool should on average produce a search cost index lower than 50%.

Why are opportunity structures important?

The previous section has shown that GOP tools are fairly straightforward reverse applications of the concept of distance decay. They could be improved, at least conceptually, if they would use another concept from criminology: *opportunity structure*. All current GOP tools assume that opportunity structures do not vary across space. In the words of Levine:

> "A final problem is that opportunities for committing crimes – the attractiveness of locations, are never measured. That is, there is no enumeration of the opportunities that would exist for an offender nor is there an attempt to measure the strength of this attraction. (...) a more complete theory of journey to crime behaviour would have to incorporate some measure of opportunities, (...)" (Levine, 2002: 353)

In the context of a geographic analysis, the concept of a criminal opportunity structure can be refined, by distinguishing two aspects. The first aspect is the *distribution of potential targets over space*. To measure it, all potential targets for a specific type of crime must be identified and their locations be established. The second dimension is the *distribution of target attractiveness over space*. To measure it, not only the locations of potential targets must be

established, but also other aspects of their attractiveness to criminals in terms of being "good targets" for a specific type of crime. Traditional GOP tools assume that both aspects do not display any spatial variation.

Spatial variation in locations of potential targets

The first assumption underlying GOP tools is that potential targets are uniformly distributed in space, i.e. that they are situated at regular distances from each other without any clustering. This assumption makes it superfluous to actually measure criminal opportunity, and therefore GOP tools focus exclusively on actual targets instead of on potential targets. Thus, the locations of potential targets are not measured because they are assumed to be all around.

Figure 2 illustrates a conceptual problem inherent in this approach. It shows a map with two identical potential targets, T_1 and T_2. These could be, for instance, two branches of a commercial bank. The cross in T_2 indicates that an unknown bank robber has chosen T_2 as a target. Thus, he robbed T_2, but he left T_1 alone. The logic of current GOP tools dictates that only actual targets are relevant, which means, in this case, only T_2. According to these tools, the two locations R_1 and R_2 are equally likely to be the offender's residence, as they are situated at equal distances from bank T_2. If, however, the presence of the non-selected but identical target bank T_1 is taken into consideration, R_2 seems more likely than R_1 to be the offender's residence. After all, if R_1 were his residence, why would he choose T_1 instead of the identical but more distant T_2? T_2 is the closest branch to an offender living in R_2, and is therefore the more obvious target on the basis of the distance decay principle. This illustration demonstrates intuitively that GOP could benefit from taking account the locations of all the potential targets rather then only those of actual targets.

Spatial variation in target attractiveness

The second assumption underlying current GOP tools is that all criminal targets are the same, except for their geographic location. If, however, there are other differences between targets in the degree to which they are attractive to offenders and if this characteristic is not evenly distributed over space, this variation too may help locate unknown offenders. To illustrate this point, Figure 3 represents an area with 25 criminal targets. These could be, for instance, 25 different stores. In order to distinguish the consequences of this second assumption clearly from the first discussed above, in Figure 3 the distribution of potential targets is completely uniform: the 25 targets are evenly located across the area, at equal distances from each other. In Figure 3, however, it is assumed that potential targets not only differ in terms of their locations, but that they also differ on another characteristic that defines their attractiveness to criminals. For the sake of the argument, let us assume a dichotomous attractiveness variable: the shaded potential targets in the north-west are more attractive than those in the south-east, for example because the north-west contains the more upmarket shopping streets.
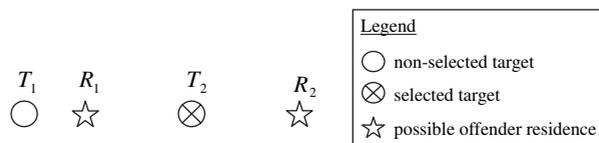

Figure 2. Relevance of non-selected targets in geographic offender profiling.
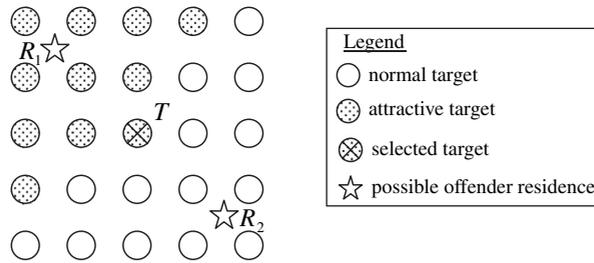
Figure 3. Relevance of target attractiveness in geographic offender profiling.

An unknown offender has burgled T, a jewellery store, but none of the remaining 24 stores that are potential targets. Since current GOP tools do not measure differences in other aspects of potential target attractiveness besides distance, locations R_1 and R_2 are seen as equally likely residences for the offender. After all, they are located an equal distance away from the store selected. However, if non-spatial differences in attractiveness are taken into account, if given a certain distance offenders prefer the most attractive target, and if given a certain level of attractiveness they prefer the closest target, R_2 is more likely to be the offender's residence than R_1. If R_1 were the offender's residence location, he would surely have selected an attractive store closer to home. Store T is the closest attractive target to an offender living in R_2. This illustration demonstrates the value of considering non-spatial differences in targets' attractiveness in GOP.

Spatial target selection as a generalization of distance decay

As pointed out, traditional GOP tools are based on a reversal of the distance decay function. The distance decay function is used as a behavioural model, according to which the likelihood of an offender selecting a particular location for committing a crime depends on the distance from that location to his home address. This could be considered a rather restrictive description of offenders' choice of crime site. A more flexible model would at least measure the presence of potential targets and take into account that besides distance offenders must take other characteristics of potential targets into consideration, such as the expected yield of the offence, and the risk of being apprehended and arrested.

Spatial target selection model

In a recent paper, Bernasco and Nieuwbeerta (2005) introduced a spatial target selection model that could be seen as a generalization of the behavioural model that underpins the distance decay function. It includes the concept of distance decay, but it also includes the concept of spatial opportunity structure. The model, actually a straightforward application of McFadden's (1973) discrete choice model to criminal target choice, is based on the explicit enumeration of potential targets or crime sites, and it allows a simultaneous assessment of the influence of distance and other aspects of attractiveness indicators of potential targets. It can also be reversed for the purpose of geographical offender profiling.

The model's starting point is that an offender must select one of a set of potential targets. The model inputs are characteristics of potential targets and (possibly) characteristics of the offender, the model output is the prediction which of the potential targets will be chosen. It is assumed that the offender is able to assess all potential targets and to draw comparisons between them. The net expected yield of target j for offender i is seen as a

weighted sum of distance and other aspects of target attractiveness, represented by the following formula:

$$U_{ij} = \alpha D_{ij} + \beta A_j + \varepsilon_{ij} \qquad (1)$$

D_{ij} in the formula is the distance between the residence of offender i and target j. A_j represents the attractiveness of target j, for instance in terms of the anticipated yield and the degree of risk. Symbols α and β are empirically estimated parameters indicating the relative importance of distance and an arbitrary other measure of attractiveness. The term ε_{ij} is a random error term for the unmeasured aspects that affect the choice outcome. The probability of offender i choosing target j is given by the following formula, designated the conditional logit model:

$$\Pr(Y_i = j) = \frac{e^{\alpha D_{ij} + \beta A_j}}{\displaystyle\sum_{j \in J} e^{\alpha D_{ij} + \beta A_j}} \qquad (2)$$

where $\mathcal{J}$ represents the set of potential targets.

Reversal of the spatial target selection model

Bernasco and Nieuwbeerta (2005) applied the model with the purpose of testing hypotheses. Their question was whether the most likely value of α is indeed negative (indicating distance decay) and that of β positive (indicating that criminal attractiveness indeed leads to attractive targets being preferred), given the characteristics of potential targets, the distances between offender residences and potential targets, and the actual choices made.

In the application of the model to GOP, the question is which location is most likely to be the offender's residence, given the characteristics of the potential targets, the distances between potential residences and potential targets, the actual selections made, and the "true" values of α and β. This application of the model to geographical profiling is a generalization of traditional distance decay models, because it portrays spatial target selection as based on more criteria than distance alone. For that reason it relaxes the *assumptions* of evenly spaced target distributions and evenly spaced distributions of target attractiveness, and replaces them with *measurements* of the locations of potential targets and other aspects of their attractiveness.

Like traditional GOP tools, the first phase in the reversed spatial target selection model is a calibration phase, which involves establishing the values of α and β, either on the basis of theoretical considerations or by estimating them – using data on solved crimes – with the spatial target selection model, i.e. the conditional logit model of equation (2).

Once the values of α and β are known, once potential targets have been established and once their attractiveness is measured, equation (2) is used to calculate a "probability map" of the likelihood of offender residence, and this map can be tested on its accuracy with the search cost index. Thus, the whole procedure itself is similar to the procedures followed by the GOP tools previously developed (Canter et al., 2000; Levine, 2002; Rossmo, 2000), except that that the calculations in the model proposed here involve measurements of the locations of potential targets and of other aspects of their criminal attractiveness, while those in the traditional GOP tools involve only the measurements of locations of actual targets.

Simulation study

To gain insight in the potential value of incorporating the measurement of criminal opportunity structures in GOP tools, a computer simulation study was carried out.[2] This simulates the spatial selection behaviour of offenders who commit crimes according to a specific model, and it subsequently compares the accuracy of three alternative GOP tools under varying conditions of spatial clustering of potential targets and spatial clustering of target attractiveness.

Three alternative GOP tools

The simulation study compares the accuracy of three alternative GOP tools. The three tools differ with respect to the specific assumptions they make, and consequently with respect to the information they utilize (and require to be measured). The first tool (A) is based on the assumptions common to traditional GOP tools: it assumes that potential targets are uniformly distributed in space, and it assumes that all potential targets are equally attractive. As a consequence, it uses information on the locations of actual targets only. The second tool (B) also assumes that all targets are identical, but it does not assume that potential targets are uniformly distributed in space. This tool measures the locations of all potential targets, including targets actually chosen, to make its predictions. The third tool (C) neither assumes that targets follow a spatially uniform distribution, nor does it assume that all potential targets are equally attractive. It measures the locations as well as the non-spatial attractiveness of all potential targets, and thus uses both sets of information in the prediction.[3]

Six target configurations

In order to compare the three methods, the simulation creates a virtual world. In this study, the world is a square island, divided into 100 cells with coordinates (0,0) to (9,9). A concrete example could be an urbanized island comprising 100 neighbourhoods. Each neighbourhood can contain one of the 25 potential targets, and each potential target is either attractive (13 potential targets with value 10) or unattractive (12 potential targets with value 0), irrespective its location on the grid. Thus, attractiveness is a dichotomous variable.

The *target configuration* varies according to the spatial distribution of opportunity and according to the spatial distribution of target attractiveness. As depicted in Figure 4, three levels of spatial clustering of opportunity are distinguished (uniform, weakly clustered and strongly clustered) and for each of these, two levels of spatial clustering of target attractiveness are distinguished (uniform and clustered). Of the resulting six target configurations, only configuration 1 conforms completely to the assumptions underlying traditional GOP tools: potential targets themselves and their attractiveness are evenly spaced across all cells (or neighbourhoods).

Set-up of the simulation

In the virtual world of the simulation study, offenders select targets on the basis of the spatial target selection model in equation (1). Thus, the outcome of their evaluation of a potential target depends on the distance to the potential target, on the attractiveness of the potential target and on a chance factor. In choosing a target, all offenders behave identically but they do not necessarily choose the same target (because they do not live in the same

Legend
⊗ attractive target
○ normal target

uniform attractiveness   clustered attractiveness

configuration 1   **configuration 4**

uniform targets

configuration 2   **configuration 5**

weakly clustered targets

configuration 3   **configuration 6**
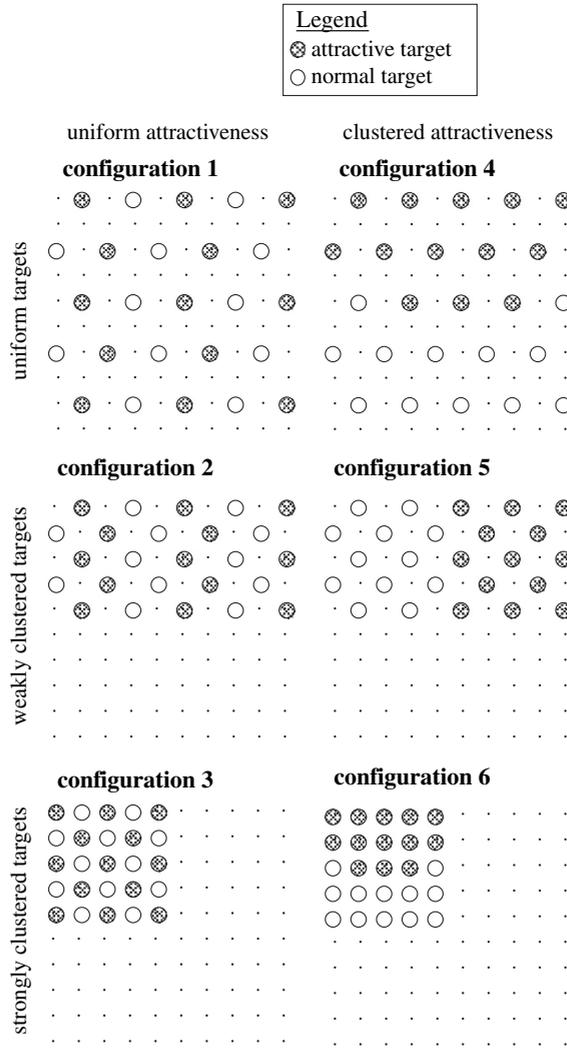
strongly clustered targets

Figure 4. Target configurations by spatial clustering of targets and target attractiveness.

place and because of the chance factor involved). The values chosen are -6 for α and 3 for β. Aside from the fact that α must be negative if offenders are subject to distance decay and that β must be positive if the attractiveness of targets is relevant, no special considerations dictated the choice of these values. Given the distribution of the distance and attractiveness measures to be discussed below, these entries produce a behavioural model in which the determined part of equation (1) is "realistic" in proportion to the value of the probabilistic random term ε_{ij}.

The number of offenders and their spatial distribution is fixed: each cell contains one offender, so the simulation always involves 100 offenders, and each offender commits exactly five crimes.

The target selection process is simulated for each of the six target configurations and for each offender, by calculating equation (1) (including the random term ε_{ij}). Whichever target produces the highest value for U_{ij} is marked as being selected. The random error

term ensures that this need not be the same target for each of the five offences committed by an offender.

To sum up, the preceding procedure yields a dataset of 75 000 records ($6 \times 100 \times 5 \times 25 =$ target configurations $\times$ offenders $\times$ crimes per offender $\times$ potential targets) that represent the "empirical data" in the simulation. It is only after these data are generated that the GOP tools A, B and C actually come into play to analyse the data.

Using a random half of the offender population in the constructed data, the parameter(s) of the target selection function for methods A, B and C are estimated with the equations listed in Footnote 3. Using the estimated parameters, all three tools generate a prioritization list of the 100 island cells for each crime series of the other half of the offender population. To evaluate the effectiveness of each tool, the search cost index is used: it is assessed how many of the 100 cells must be searched before the offender is found, if the prioritization of the tool is followed.

In order to reduce the risk of chance fluctuations causing distortion, 50 simulations were held for each target configuration, and the averages and standard deviations of the search cost indices over the 50 simulation runs were calculated.

Results

Table I summarizes the results of the simulation study. For each target configuration, the average search cost index of tools A, B and C is reported, as well as their standard deviations.

Before comparing the effectiveness of the three tools, it is important to consider that the overall effectiveness of geographic profiling reduces, no matter which method is used, as targets become more clustered in the space and as the criminal attractiveness of targets becomes more clustered. The average search cost index of the three methods in configuration 1, in which both targets and target attractiveness are uniformly spread, is 12. In configuration 6, with the highest degree of clustering, the average index is 41. This finding emphasizes that the effectiveness of GOP is necessarily limited when there is a strong clustering in space of potential targets and of target attractiveness. In exceptional cases of target clustering, for example art thieves targeting a specific Picasso painting, there

Table I. Results from the simulation. Means and standard deviations (in parentheses) of the search cost indices for tool A (distance only), tool B (distance and locations of potential targets) and tool C (distance, location of potential targets and target attractiveness).

	Uniform attractiveness	Clustered attractiveness
Uniform targets	Configuration 1	Configuration 4
tool A	12 (1)	32 (2)
tool B	12 (1)	30 (2)
tool C	12 (1)	18 (2)
Weakly clustered targets	Configuration 2	Configuration 5
tool A	34 (1)	43 (1)
tool B	18 (2)	39 (2)
tool C	18 (2)	25 (2)
Strongly clustered targets	Configuration 3	Configuration 6
tool A	46 (1)	48 (1)
tool B	28 (3)	43 (3)
tool C	28 (3)	33 (2)

is a single target located at a single venue, and the location of the crime can then tell us little or nothing about the offender's anchor point. For this reason, the only valid comparison of the accuracy of tools A, B and C is within the same target configuration.

We first compare the effectiveness of GOP tools A and B. Both tools utilize distance decay, but only tool B measures the spatial distribution of targets. In configurations with uniform target attractiveness (configurations 1, 2 and 3), tool B performs better than tool A as the level of target clustering increases from configuration 1 (where both tools are equally effective) to configuration 3 (where tool B is almost twice as effective as tool A). This illustrates that the advantage of tool B over tool A is in its measurement of the distribution of potential targets.

Tool B is only slightly more effective than tool A in configurations with clustered target attractiveness (configurations 4, 5 and 6) Thus, measuring and utilizing the locations of all potential targets in GOP tools appears to be useful only of there is not too much spatial variation in attractiveness.

Next we compare the effectiveness of tools B and C. Both tools utilize distance decay and measure the spatial distribution of potential targets, but only C measures the spatial variation in target attractiveness. It turns out that B and C are equally effective in configurations with a uniform distribution of target attractiveness (1, 2 and 3), and that tool C is more effective than tool B in target configurations where attractive targets are clustered (4, 5 and 6). This finding nicely underlines that the advantage of tool C over tool B is precisely its measurement and utilization of spatial variation in target attractiveness.

Overall, the results show that tool C is more effective than tool A in all configurations except for configuration 1. The absence of any effectiveness differences in configuration 1 is not surprising. In fact, it exactly confirms to the expectation, because the distinction between the three tools lies precisely in the assumption of evenly spaced opportunity structures. If the assumption is completely fulfilled, as in configuration 1, there is no need to measure them and utilize them in the prediction.

Although the simulation set-up allows for an analysis of variance to test the effects of target clustering (three levels), attractiveness clustering (two levels), and tool (three levels) on the search costs, we will not present such an analysis here. This is because we are dealing here with synthetic data that are generated by computer simulations of spatial behaviour under artificial conditions of spatial clustering. Therefore, it is difficult to say anything about how the effect sizes relate to phenomena (GOP search costs, criminal opportunities, criminal attractiveness and indeed distance as well) in the real world. In addition, for simulation outcomes statistical tests of significance do not have the usual interpretation of Type I error probabilities.

In the absence of an analysis of variance, note that the search cost variation within the conditions is much smaller than the variation between the experimental conditions, as all the standard deviations of the search costs in Table I are very small compared to the differences between the means.

Discussion

This paper has demonstrated that GOP tools that measure spatial variation in criminal opportunity and utilize it in their prioritization, like the reversed spatial target selection model, could be more effective than traditional GOP tools that utilize the distance decay concept only. The improvement in prioritization would be particularly evident in circumstances of strong spatial clustering, and spatial clustering is widespread in the real

world. Car parks, shopping malls, and business centres are examples of potential targets being strongly clustered in space, and the spatial separation between deprived and affluent neighbourhoods provides an example of spatially clustered attractiveness of potential targets.

Traditional GOP tools do not measure and utilize the clustering of opportunity, although obviously in practice the police will often take into account some aspects of the geographic backcloth when they prioritize areas. For example, they will typically overlay the outcomes of the GOP tools – the "jeopardy surfaces" or "prioritized search maps" – onto topographical maps to identify likely areas of offender residence, geographic barriers and possibly other relevant geographic information that could inform the search for the offender. However, that part of the investigation is not formalized and is not informed by an explicit theoretical model of spatial target selection.

Extensions of the reversed spatial target selection model

The paper has also shown that the reversed spatial target selection model is able to handle the increased complexity that is involved in measuring and utilizing spatial opportunity structures. In fact, the model is flexible and offers many other ways of adopting knowledge about criminals' spatial selection behaviour. Some will be briefly discussed here.

Firstly, target selection may be based on multiple criteria of attractiveness, if it appears that criminals use multiple criteria. Examples of criteria that offenders could use are the access to escape routes, the physical accessibility of the target and the visibility of the target location to passers-by. If such characteristics of potential targets can be measured, they can be inserted in the target selection equation (1) and their associated parameters can be estimated with the spatial target selection (conditional logit) model, using as input a set of solved cases of similar types of offences where the home address of the offender and the locations of the committed offences are known. The process of estimating baseline parameters for a specific type of crime on the basis of solved cases is called "calibration" in GOP tools. The estimated parameters could then by used in the reversed model, and aid to the accuracy of the GOP tool.

A second elaboration relates to the form of the distance decay function. While the presented example uses a monotonically decreasing function, non-monotonic distance effects can easily be modelled with the spatial target selection model. An example of this is the earlier mentioned possibility of a distance decay function with a buffer zone around the offender's base location (Canter et al., 2000; Rossmo, 2000). The addition of a quadratic distance term to equation (1) is sufficient to enable such a non-monotone form of distance decay in the spatial selection model. Alternatively, the piecewise-constant distance decay function suggested by Van Koppen and De Keijser (1997) can be implemented by replacing the continuous distance term with a dichotomous one (for example, whether the distance is greater than 1 mile).

Further, the reversed spatial target selection model enables the sequence in which crimes have been committed to be used in the GOP. This may be important if patterns of location selection vary systematically during the series of crimes. Canter and Larkin (1993) and Warren et al. (1998) found that serial rapists live closer to their first offence than to subsequent offences, and Rossmo (2000: 181–184) demonstrated that serial killers' crime trip distance tends to increase during the series, i.e. during the course of the series they tend to commit the next crime further from home than the previous one. Such findings could be incorporated into the spatial target selection model by including a sequence number variable for each offence in the series, and assess its interaction with the distance. The effect

on the prioritization algorithm would be that initial offences in the series receive a larger "weight" in the outcome than the ones that occurred later, reflecting that the first offences tend to be more informative regarding the identification of the home of the offender.

A fourth and final extension could be the inclusion of individual characteristics of unknown offenders in the GOP tool. This could potentially be of great value, because the meaning and salience of the characteristics that define criminal attractiveness ("yield", "risk", and even "distance") may greatly differ between different types of offenders. For example, Bernasco and Nieuwbeerta (2005) find that the ethnic heterogeneity of a potential target neighbourhood is a more important selection criterion for non-native burglars than for native burglars. In addition, Bernasco and Nieuwbeerta suggest that distance restricts criminal mobility more for juvenile offender than for adults, probably because juveniles have less means of transportation available than adults. Similarly, the image of what "good targets" are will also depend on issues of time, for example whether the offender is urgently in need of money or drugs. Although GOP is about tracking down *unknown* offenders, the option to incorporate offender characteristics in GOP could be useful, since certain characteristics of unknown offenders are often revealed by crime scene evidence, by victims or witness statements or other clues.

Costs and caveats

Despite its potential for GOP, some reservations also exist with regard to the measurement and utilization of spatial variation in the distribution of potential targets and spatial variation in target attractiveness.

The first is whether its value is worth its cost. Even if a more effective prioritization were produced than with other tools, the improvement must be related to the investment it requires. For traditional GOP tools, it suffices to collect the coordinates of locations of a linked series of crimes, i.e. of the *coordinates of actual targets*. The approach proposed in this paper, on the other hand, is much more demanding. Its minimum requirement is a list of *coordinates of all potential targets*. To function optimally it would further require a set of attractiveness measures, i.e. the *characteristics of all potential targets* that are relevant to criminals. The collection of this information could be very costly and time-consuming, because such data are often not readily available. Furthermore, traditional GOP tools only use a simple theoretical concept (distance decay) for tracking down offenders of all types of crime, although the shape of the distance decay function can vary between crime types. The approach proposed in this paper, however, uses a concept (opportunity structure) that is very different for different types of crime types. For example, opportunities for commercial robbery could be spatially concentrated in downtown commercial areas and the relevant attractiveness measures could include type of commerce, opening hours, estimated cash flow, and number of employees. Opportunities for residential burglary, however, could be concentrated in (suburban) residential areas, and relevant measures are likely to include the ease of entering and leaving the property, and the presence of residents and neighbours. Consequently, the approach proposed here is rather ambitious, as it requires us to think about opportunity structures for many different types of crime, and to estimate for each type of crime separately – on the basis of solved cases – the effects of attractiveness measures that offenders use to select targets.

The second reservation concerns the fact that many types of crime can occur just about anywhere. For example, for the crime of residential burglary the list of potential targets is virtually endless. This fact presents theoretical as well as practical challenges to the discrete spatial choice model. It poses theoretical difficulties because the model assumes that

offenders compare all potential targets, while most human beings are incapable of comparing more than a few alternatives within a reasonable span of time. It poses practical difficulties because of the quantity of target data to be collected and the time-consuming nature of estimating the model parameters. A solution to both problems could be the aggregation of individual targets and places to larger units, for example housing blocks, street segments or entire neighbourhoods. This would solve some of the practical burden of data collection, and can be legitimized theoretically by the conceptualization of criminal target search as a spatially structured, sequential and hierarchical decision process (Brantingham & Brantingham, 1978; Brown & Altman, 1981; Cornish & Clarke, 1986). By performing some spatial aggregation GOP tools would identify larger spatial units as potential targets and would measure target attractiveness in terms of features of these units, thereby possibly saving substantial data collection and processing costs without losing much predictive precision.

The third reservation concerns the mobility of targets. The targets of crimes like murder, rape, robbery and car theft are mobile, they move around all the time. In the traditional approach to GOP this does not present an analytical problem, however, because the only point that matters is where the crime took place. But if we want to measure the opportunity structure for car theft, robbery or other crimes with moving targets, we are confronted with the fact that potential targets do not have fixed positions in space, so that the opportunity structure changes over time constantly. It may be quite different at different times of the day and on different days of the week, and thus may be very difficult to measure.

A fourth reservation concerns the observation from the previous subsection that many criteria of spatial target selection are offender specific. Although in theory this could be taken into account by making the spatial target selection model dependent on a number of offender characteristics, in practice this is often impossible. Through victim and witness statements the police may have some traces or descriptions of violent offenders, but they often do not have them of unknown thieves, burglars, arsonists, and other offenders who commit covert offences. Thus, unless we do have a clue on some characteristics of the offender, we will not be able to use those characteristics in the construction of the geographic profile.

General GOP caveats

Some reservations regarding geographical offender profiling are independent of the tools used for its purpose. For example, the suggested improvements do not offer a solution for the problem of how to decide whether a series of crimes is the work of one offender. Common assumptions that remain largely unchallenged in all GOP tools, including the one proposed here, is that there is a single offender (rather than a group) involved, and that he or she has no more than one single anchor point during the whole series of offences (rather than changes of address during the series, or multiple simultaneous anchor points, e.g. home, work, gym, parents' home).

In addition, it is true of all GOP tools that their effectiveness depends on the validity of the underlying behavioural model. The spatial target selection model of Bernasco and Nieuwbeerta (2005) is a transfer of an economic model of choice to criminology, and as such is based on the assumption that offenders choose their targets using a cost–benefit analysis of alternative targets. Perhaps this model only applies to a select group of offenders who may be considered to be planning criminals, while the target selection process is carried out differently by offenders who act more impulsively (Elffers, 2004).

A more fundamental question is whether spatial prioritization tools actually perform better than human evaluators who use simple heuristic rules. Using test subjects with no knowledge of GOP, Snook, Canter, and Bennell (2002) presented maps showing targets selected by offenders and asked subjects to indicate the offender's likely residence. He compared their results with those produced by a computer program (*Dragnet*) and with the offenders' actual residence locations, and concluded that human judges with no special training are just as proficient at geographical profiling as computer programs specially designed for the purpose.

In this respect it may be worthwhile to note that Figures 2 and 3 have been presented informally on several occasions to various people who had no knowledge of GOP, and that without additional information or hints, almost everyone thought that the offender "is more likely to live in R_2 than R_1". This anecdotal evidence suggests that the concepts of distance decay and spatial opportunity structure are part of the heuristic rules that people automatically apply when they interpret these and similar figures. This could mean that the opportunity structure concept would be a natural candidate to be integrated in tools that assist the police in tracking down offenders. Nevertheless, the plea in this paper to include spatial opportunity structure in GOP tools should be taken for what it is: a theoretical analysis. The proof of the pudding will be in the eating. Only empirical validations of GOP tools can assess whether they offer a useful complement to the experience and intuition of real-life detectives.

Notes

1 *CrimeStat II* is not a standalone GOP tool, but a general purpose program for the analysis of spatial crime data. Geographic profiling algorithms are implemented in the journey-to-crime estimation subroutine. The output must be imported into a GIS system for the construction of a prioritization surface.

2 The simulation was carried with the statistical program *STATA* (StataCorp, 2003). The source code of the simulation program is available upon request from the author.

3 All three methods are implemented in a conditional logit model. Tool A uses the equation:

$$\Pr(Y_i = j) = e^{\alpha D_{ij}} \left/ \sum_{j \in O} e^{\alpha D_{ij}} \right.$$

in which O represents the set of all 100 locations and therefore comprises both locations where potential targets actually exist and locations where they do not. Tool B uses the equation

$$\Pr(Y_i = j) = e^{\alpha D_{ij}} \left/ \sum_{j \in J} e^{\alpha D_{ij}} \right.$$

in which $\mathcal{J}$ is the set of 25 potential targets. Tool C uses

$$\Pr(Y_i = j) = e^{\alpha D_{ij} + \beta A_j} \left/ \sum_{j \in J} e^{\alpha D_{ij} + \beta A_j} \right.,$$

which is equation (2) in the main text.

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