Multistop-based measurements of accessibility in a GIS environment

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Research Article

Multistop-based measurements of accessibility in a GIS environment†

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Abstract. The opportunities available at a demand location are usually measured as the costs of reaching a specified critical number of facilities from that location. This method does not however, account for multistop trips nor for differences in the diversity of supply at the level of individual facilities. In this paper we introduce an alternative measurement method that overcomes these shortcomings. In this method the probability of successfully visiting a specific facility is assumed to be a function of the diversity of supply provided. Trip routes are constructed that have an acceptable probability of success. Then, the expected costs of travelling the optimum route are determined as an indicator of spatial opportunities. The proposed method has been implemented in a GIS environment, using typical GIS data and GIS tools for spatial analysis and display. The results of a case study indicate that the new method, compared to current methods, may lead to different evaluations of the level of opportunities at demand locations.

1. Introduction

An ever recurring question in applied facility planning concerns the accessibility of service provisions to their target markets, This reflects an interest in knowing the degree of differential access to service establishments and the effects that urban planning proposals may have on increasing or alleviating existing disequilibria.

GIS technology holds many promises for the practice of spatial planning and is increasingly used by both commercial and governmental planning agencies (Dale 1991, Somers 1991, Ottens 1990). Researchers and planners from different disciplines however have stressed that the present generation of GIS packages offers limited possibilities for spatial analysis (see Openshaw 1990). The integration of tools for spatial analysis within GIS has been proposed by several authors as a promising direction for future research (see Goodchild 1992). When integrated with decision support tools, GIS technology can provide a framework for spatial decision making (e.g., Carver 1991, Fedra and Reitsma 1990).

Particularly, indicators of accessibility fit well in a GIS environment, since the locational and thematic data required for calculating these indicators are already available in a typical GIS database. Furthermore, standard GIS tools for spatial analysis can be used to compute component functions. For example, routines for

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network analysis can be used to calculate distances across a road network. Finally, GIS allows the results of the analysis to be represented cartographically. In this article we introduce a method of measuring accessibility which, as an integral part of a GIS, improves the usefulness of GIS for supporting location planning and decision making.

1.1. *Literature review*

Various methods of measuring accessibility have been developed in spatial planning, applied geography and transportation research. Here we will not give a comprehensive review (see Jones 1981), but discuss only a grouping of measures to place our method in a broader context.

We distinguish three basic groups of commonly used accessibility measures. First, we mention measures of travel costs that consumers minimally have to make to satisfy their demands, such as, the measure of distances to nearest supply points. This category can be interpreted as accessibility in a narrower sense, since it operationalizes the generally used concept of accessibility as the ease with which any facility can be reached from a specific location. Next, we distinguish measures of the opportunities available to specific demand locations, while accounting for travel costs. As an example, we mention the sum of weighted facilities using a negative distance function as a weight. These measures indicate the level of service provision and we will use the term 'indicators of spatial opportunities' to refer to this approach. Finally, we distinguish more complex measures that summarize travel costs and attractiveness of supply in a subjective value, for example the surplus, net benefit or utility consumers gain from facilities. This category can be interpreted as measures of consumer welfare.

In this paper we focus on the measurement of spatial opportunities. Within this category a further distinction can be made between (1) measures which depend for their final specification on observed travel behaviour of consumers and (2) measures which are exclusively based on properties of the supply side of the system (Breheney 1978). Behaviour dependent measures include parameters, such as the distance decay effect, which are estimated based on observed choices or preferences of consumers. Behaviour independent measures, on the other hand, do not include parameters that reflect consumer behaviour. Breheney (1978) has advocated the use of this group of methods arguing that they are conceptually sound, easy to interpret and free of measurement biases. Furthermore, the data required for calculating these measures are easy to obtain and, typically, readily available in any GIS. Therefore, these measures, particularly, fit well in a GIS environment. This paper is concerned with these behaviour independent measures of spatial opportunities.

1.2. *Shortcomings of current measures of spatial opportunities*

Breheney (1978) has demonstrated how behaviour independent measures can be summarized in a single integrated system of indicators. The indicators work from a common data set which includes the cumulative number of opportunities of a certain type within successive cost bands radiating from a demand location. Given these data, three types of indicators can be calculated: (1) the number of opportunities available at a demand location within a critical level of travel costs (distance or time); (2) the cost band from a demand location that captures a critical number of opportunities, and (3) the number of consumers having access to a critical number of opportunities within a critical level of costs. Essentially, these indicators represent in different ways the relationship between opportunity and travel costs.

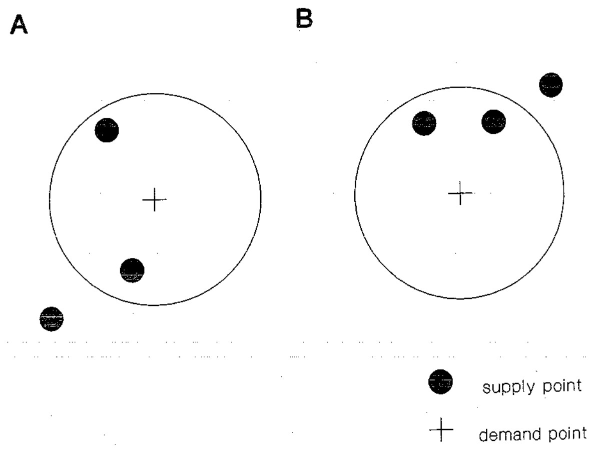

Figure 1. A fictive example to illustrate the effect of spatial structure on accessibility.

An important shortcoming of these indicators is their simplistic underlying assumption about how people travel. Only home-based trips to destinations are considered, while chaining together destinations into trip tours is ignored (Ben Akiva and Lerman 1979). When trip-chaining behaviour is assumed not only demand–supply distances, but also distances between supply locations are relevant. In that case the costs for reaching a certain number of opportunities decrease when supply points are geographically concentrated. This point is illustrated by the two facility systems shown in figure 1. The number of opportunities within the specified cost band in A and B is the same. Consequently, current measures would not differentiate between those two configurations, whereas in fact the consumer in B benefits to a higher degree from combining both facilities in a single trip than the consumer in A. Empirical studies have shown that consumers frequently make multistop trips. O'Kelly (1983) refers to several studies where considerable percentages, ranging from approximately 30 to 50 per cent, of total urban travel appeared to be multistop travel. The multistop trips often involve more than one purpose. However, even within multipurpose trips, single purpose trip chains occur. So, people indeed display a tendency to make multistop trips also for single purposes. A measure of accessibility should, therefore, be sensitive to the spatial structure of supply.

Another drawback of current measures concerns their insensitivity to differences in opportunities at the level of individual supply points. Opportunity levels increase when, *ceteris paribus*, the variety of services at supply points increases. An adequate measure of accessibility must incorporate this factor.

Finally, there is a problem involved in determining the appropriate critical level of opportunities in order to measure travel costs or, reversely, in determining the appropriate critical level of costs in order to measure the level of opportunities. Objective criteria for setting the levels of these parameters are lacking, while they seriously affect measurement results (Breheney 1978).

In this paper we introduce an approach to measuring spatial opportunities that overcomes the drawbacks of current approaches outlined above. In this approach facilities are characterized by a probability of meeting a given demand. This probability of success is assumed to be a function of the variety of provided supply. Then trip routes are constructed that have an acceptable probability of success. The expected amount of travelling of the optimum trip route is then determined as an indicator of spatial opportunities. This measure is sensitive to both the amount of supply in individual destinations and the distances between destinations. Note that there is only one purpose involved in the kind of multistop trips that are of concern here. Trips are chained not to combine different purposes but to achieve a single purpose.

The paper is organized as follows. First, in § 2, we present the assumptions, specification and implementation of the proposed method. To investigate the appropriateness of the proposed method we analyse an existing facility system, and discuss the results in § 3. The comparison with alternative methods is emphasized. Finally, in § 4 we discuss the merits and limitations of the new method.

2. The multistop measure of spatial opportunities

2.1. *Assumptions*

We consider a specific consumer location and a number of available spatially distributed opportunities for satisfying a given demand for goods or services. Each opportunity is characterized by a certain probability that the supply offered matches the given demand. This so called probability of success is supposed to be a function of the variety of supply. For example, the probability of successfully satisfying a demand for clothing in a shopping centre may be estimated based on the total floor space or number of types of clothing stores in that centre. We assume that trip chaining occurs when a purchase fails at a destination. In that case, the trip is continued to another destination where the demanded type of service is supplied. If the purchase also fails at the second destination, then the trip is again lengthened. This chaining of trips continues until the intended purchase is realized. We assume that the probability of success at a next destination does not depend on the supply at former stops of the trip. However, the probability of success at a location which has been visited during the same trip is assumed to be zero. Finally, the assumption is made that the probability of success associated with a certain supply point is independent of whether or not purchases during former trips to that location were successful.

Given the location of supply points and the attached probability of success, it is possible to construct for each demand point chains of trips that have a high (nearly unity) probability of success. From this set of chains the optimum multistop trip, that is the chain with the lowest expected travel costs, can be selected. The costs of this optimum trip indicate the spatial opportunities available at the demand location concerned.

We emphasize that this method must not be interpreted as a model of travel behaviour of consumers. The ideal trips are constructed not to reflect actual behaviour, but to indicate the least possible costs as an indicator of spatial opportunities.

2.2. *Specification*

The costs of the optimum trip from a consumer location is used as a measure of spatial opportunities. In order to establish the optimum route for each consumer location we allocate trip stops to supply points in such a way that the expected travel costs are at a minimum:

$$a_{ij}=\begin{cases}1, & \text{if } C_{ij}<C_{ik}, \quad \forall k\neq j \quad j,k\in N_i\\ 0, & \text{otherwise}\end{cases} \tag{1}$$

N_i is the set of optional next destinations at the current location i. N_i includes the home location ($i=0$) and all supply points reachable within a specified level of travel costs away from i, called the Scope parameter. C_{ij} are the expected travel costs assigned to a trip from i to the next destination j (that is the first destination when i is the home location). C_{ij} is formally defined as:

$$C_{ij} = d_{ij} + p_j d_{j0} + (1 - p_j) \sum_k a_{jk} C_{jk} \tag{2}$$

where:

d_{ij} are the costs of travelling from i to j (d_{j0} = costs of travelling from j to the home location);

p_j is the probability of success at destination j.

In words, the expected travel costs of a trip from i to j equal the costs of travelling to j (d_{ij}) plus the costs of travelling back home when the purchase at j has succeeded ($p_j d_{j0}$) plus the expected travel costs of a trip from j to the allocated next destination when the purchase at j has failed ($(1 - p_j) \Sigma a_{jk} C_{jk}$). Note that the expected travel costs are defined recursively: to determine the expected costs of a trip to the first destination, the expected costs of (continuing) the trip to the next destination must be known, and so on. Also the a-variables are defined recursively: the allocation of the first trip stop depends on the allocation of the next stop, and so on.

The allocation pattern that results from this recursive rule may differ from the allocation to nearest destinations. Differences may occur when other facilities are better accessible from a more distant destination (c.f., Kitamura 1984). Another possible reason for bypassing the nearest supply point is that a more distant facility may increase the probability of success to such a degree that the expected costs of visiting that facility (and continuing the trip thereafter) are lower.

The home location is part of the set of optional destinations at every location. The home location is, however, not an attractive option, because the probability of success is zero at that location ($p_0 = 0$, since there are no facilities at home). The same holds for destinations which have been visited before in the same trip, because the probability of success at these locations has become zero.

The probability of success of a (multistop) trip starting from i is found by the recursive equation (3)

$$P_i = p_i + (1 - p_i) \sum_j a_{ij} P_j \tag{3}$$

In words: the probability of success of a trip starting at i equals the probability of success in i plus the probability of success of (continuing) the trip starting at the next destination when the visit to i fails.

The following example serves to explain the recursive nature of equations (2) and (3). We assume that the set of a-variables, that is the allocation pattern, is already known (table 1).

This matrix describes a trip from 0 (the home location) to 1 and from there to 3 and next to 2 etc.. The expected costs of this trip are found by using equation (2):

$$C_{01} = d_{01} + p_1 d_{10} + (1 - p_1) \sum a_{1k} C_{1k} \tag{4a}$$

Substitution of the a-variables results in:

$$C_{01} = d_{01} + p_1 d_{10} + (1 - p_1) C_{13} \tag{4b}$$

The same formula, equation (2), is used to find C_{13}:

$$C_{01} = d_{01} + p_1 d_{10} + (1 - p_1)\{d_{13} + p_3 d_{30} + (1 - p_3) C_{32}\} \tag{4c}$$

Table 1. The a_{ij}-variables of the example worked in the text.

	Destination 0	1	2	3	etc.
Origin 0	0	1	0	0	—
1	0	0	0	1	—
2	0	0	0	0	—
3	0	0	1	0	—
etc.	—	—	—	—	—

Again, we use equation (2) to find C_{32} and so on. The result is:

$$C_{01}=d_{01}+p_1d_{10}+(1-p_1)\{d_{13}+p_3d_{30}+(1-p_3)\{d_{32}+p_2d_{20}+(1-p_2)\{\ldots\}\}\} \quad (4\,d)$$

This can be written as:

$$\begin{aligned} C_{01}=d_{01}&+p_1d_{10} && (5\,a)\\ &+(1-p_1)(d_{13}+p_3d_{30}) && (5\,b)\\ &+(1-p_1)(1-p_3)(d_{32}+p_2d_{20}) && (5\,c)\\ &+(1-p_1)(1-p_3)(1-p_2)(\ldots) && (5\,d)\\ &+\ldots \end{aligned}$$

The equation expresses that costs assigned to a trip from 0 to 1 equal the costs of travelling from 0 to 1 including travelling back home when the purchase succeeds (a) plus the costs associated to a trip from 1 to 3 when the purchase in 1 fails (b) plus the costs of a trip from 3 to 2 when the purchase in 1 and 3 fails (c) plus the costs of a trip from 2 to the next destination when the purchase in 1, 3 and 2 fails (d), etc.

Next, the probability of success from the example trip is found by using equation (3):

$$P_0=p_0+(1-p_0)\{p_1+(1-p_1)\{p_3+(1-p_3)\{p_2+(1-p_2)\{\ldots\}\}\}\} \quad (6)$$

This can be rewritten as:

$$\begin{aligned} P_0=p_0&\\ &+(1-p_0)p_1\\ &+(1-p_0)(1-p_1)p_3\\ &+(1-p_0)(1-p_1)(1-p_3)p_2\\ &+(1-p_0)(1-p_1)(1-p_3)(1-p_2)(\ldots)\\ &+\ldots \end{aligned} \quad (7)$$

As long as the successive probabilities, p_0, p_1, p_3, p_2 etc., are higher than zero, P_0 approaches to unity. This means that it becomes more and more likely that a trip succeeds with every successive continuation to a next destination.

In order to calculate the expected costs of a trip, we must define a criterion for terminating the recursion (the chaining of trips). We stop the recursion the moment P_i exceeds the specified level of probability that is supposed to be a sufficient approximation of unity (e.g., $P^{lim}=0{\cdot}95$). This means that the allocation to next destinations is stopped, when the trip, developed so far, is very likely to be successful. However, it may occur at a certain moment of choice that there are no optional next destinations with a probability higher than zero. In that case, the home location will be selected as the next destination (the home location is the most attractive option, because $d_{00}=0$). The allocation of the home location is the second way of terminating a trip (stopping the recursion). Terminating a trip in this way implies that it is impossible to construct a trip with a satisfactory probability of success. This may occur when either the level of supply in the study area is too low or the specified scope that defines the set of optional destinations is too restrictive. Trips that fail to reach the specified level of probability cannot be compared to each other or to successful trips.

We conclude that by using equations (1), (2) and (3) the optimum trip chain from each demand location can be determined. Next, the expected costs of successful trips can be compared to evaluate the relative level of opportunities at demand locations.

2.3. *Implementation*

In order to calculate scores on the measure outlined above, we have developed a computer program, named ALTINDIC (an ALTernative INDICator of spatial opportunities). A depth-first algorithm is used to determine the optimum trip from a specific (consumer) location, as follows. A (arbitrary) trip is built up from the home location by repeatedly selecting a destination from the set of options reachable from the current location, until the stop condition is met ($P_i > P^{lim}$ or $a_{j0}=1$). At that point the process tracks back to the former destination from which all alternative ways of continuing the trip are investigated (in the same way). The continuation with the lowest expected costs is selected. These costs are assigned to the current location and the process tracks back to the former stop. From this point the foregoing procedure is repeated. These recursive steps of investigating alternative continuations, selecting the best option and going back to the former stop are repeated until the home location is reached. Following this recursive procedure, all possible trip chains are investigated and the chain with the lowest costs is selected. The efficiency of the process can be improved by remembering the lowest costs that have been established and rejecting routes examined as soon as they exceed those costs. Then, the expected computational costs can be further reduced by using a heuristic, such as selecting the nearest destination, to establish the initial route (and thus the initial lowest costs).

The program receives data related to the supply side, demand side and distances (or times) of travelling. With regard to the supply side, the location of each supply point and the associated probability of success is specified. The data related to the demand side include the location and the size of populations at demand points. Travel costs are defined by a matrix that relates demand to supply points and a matrix that relates supply points to each other. Furthermore, the user sets the scope (radius) and the probability threshold (the stop condition). Given these imput data and parameter settings, ALTINDIC calculates for each demand location: (1) the minimal expected travel costs; (2) the optimum trip chain and (3) the probability of success of the trip (this probability is higher than the threshold, unless the trip ends at the home location).

ALTINDIC is integrated as a procedure in the GIS package TRANSCAD (Caliper 1992). In TRANSCAD, a procedure is a stand alone DOS program that operates on the TRANSCAD database. A command language is available to pass on information or parameters to the procedure. The results of a procedure may be imported to the central database, where general GIS tools can be used for data management and display functions.

ALTINDIC can be used to analyse the spatial opportunities at the level of location plans, study areas, or demand locations. Therefore, the program may be a useful GIS procedure for location planning.

3. The application of the method: a case study

To be useful as a measurement tool, the multistop method (the MS method) must be robust for reasonable variations in the specification of the probability threshold and the function used for calculating probabilities of success. Furthermore, the method must be sufficiently sensitive to differences in the spatial structure of supply, that is the method must lead to different measurement results compared to the alternative method of measuring cost bands that capture a specified number of facilities. To investigate these properties, we have applied the MS and the cost-band method to the shopping system of the city Maastricht, The Netherlands, using ALTINDIC.

3.1. *Description of the case*

Maastricht is a municipality of medium size with approximately 117 000 inhabitants. The area is subdivided into 41 residential zones which correspond to neighbourhoods. The centroids of these zones are considered the demand locations. The supply of consumer goods is concentrated in 30 spatially distributed shopping centres. Information on the location and attributes of the residential and shopping zones and the connecting road network are stored in TRANSCAD. A TRANSCAD procedure for determining shortest routes on a network is used to calculate distances between locations.

The probability of success of purchasing g at location j is calculated as a function of K indicators of supply, X, using equation (8)

$$p_j^g = \begin{cases} 0, & \text{if } g \text{ is not supplied in } j \\ \exp\left(\sum_k \alpha_k^g X_{kj}^{*g}\right), & \text{otherwise} \end{cases} \tag{8}$$

X_{kj}^g is the score of g-type shops in centre j on the kth indicator for g-type supply. The X-factors (indicators) are normalized to a scale ranging from zero to unity as follows:

$$X_{kj}^{*g} = \frac{X_{k\max}^g - X_{kj}^g}{X_{k\max}^g - X_{k\min}^g} \tag{9}$$

Where $X_{k\min}^g$ and $X_{k\max}^g$ are the minimal and maximal level of the kth indicator. The probability of success is assumed to be an exponential function of (a measure of) supply resulting in a S-shaped relationship. As a consequence of using normalized supply factors, a maximum supply level corresponds to the maximum probability level of unity. The weights, α_k^g, are set to negative values, so that the function values range between infinitely small and unity. The relative level of the weights reflects the relative importance of the factors, whereas the absolute levels determine the slope of the curve (high absolute levels result in a steep curve).

In this case study we have considered the factors floorspace, F, and number of shop types, N, as indicators of the variety of supply. Consequently, the general equation (8) is specified as:

$$p_j^g = \begin{cases} 0, & \text{if } g \text{ is not supplied in } j \\ \exp\left(\alpha_1^g F_j^{*g} + \alpha_2^g N_j^{*g}\right), & \text{otherwise} \end{cases} \tag{10}$$

Three sectors (types) of supply have been analysed. From high to low density of shops, these are the food, clothing and footwear sector.

3.2. *Results*

The length of optimum trip chains depends, among other factors, on the specified probability threshold. When the threshold is set to 0·95, the typical trip involves three to four destinations. Table 2 summarizes the scores of demand locations on both the MS method and the current method of measuring costs bands respectively. In the cost-band method four levels of opportunities were considered, 1, 2, 3 and 4 facilities (centres supplying g), resulting in four sets of scores. Note that the 1-facility variant corresponds to the accessibility measure of nearest centre travel costs.

Absolute scores are often not very useful for spatial decision making. Evaluations and decisions are mostly based on the ranking of demand locations rather than exact positions on a measurement scale. For example, the decision maker may wish to identify the 10 per cent worst-off residential zones to decide where to locate additional facilities (Van der Heijden *et al.* 1984). Therefore, in the following we will consider rank scores rather than absolute scores. (Note that this implies a stricter test on the performance of the method, because differences in rank scores imply differences in absolute scores but the reverse may not be true.)

How sensitive is the MS method to variations in the specification of the function for calculating probabilities of success? To assess this sensitivity, we have analysed the food sector using four different sets of probabilities, which were obtained by varying the weights α_1^g and α_2^g of equation (10). Both the weights relative to each other and the absolute level of the weights are varied. The effects of varying the function specifications on the distribution of probabilities across supply points are shown in table 3. An increase in the absolute value of both weights results in an increase in the variation of probability and vice versa. The degree to which the measurement results depend on the

Table 2. The mean and standard deviation of the expected minimal travel costs (MS, $p^{\text{lim}}=0{\cdot}95$, $\alpha_1^g=-0{\cdot}35$, $\alpha_2^g=-0{\cdot}35$) and the cost bands capturing 1, 2, 3 and 4 facilities.

	Food		Clothing		Footwear	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
MS	11·39	6·28	20·89	13·72	22·85	17·67
1 fac	3·32	2·80	7·63	7·14	8·51	8·90
2 fac	7·44	3·35	11·54	6·13	13·07	8·14
3 fac	10·66	5·11	15·12	7·59	15·85	7·95
4 fac	12·71	5·87	17·34	7·33	18·1	7·79

Table 3. The mean and standard deviation of probabilities of success for both normal and extreme values.

	Normal	(1)	(2)	(3)	(4)
	$\alpha_1^g=-0{\cdot}35$ $\alpha_2^g=-0{\cdot}35$	$\alpha_1^g=0$ $\alpha_2^g=-0{\cdot}70$	$\alpha_1^g=-0{\cdot}70$ $\alpha_2^g=0$	$\alpha_1^g=-0{\cdot}26$ $\alpha_2^g=-0{\cdot}26$	$\alpha_1^g=-0{\cdot}46$ $\alpha_2^g=-0{\cdot}46$
Mean	0·68	0·71	0·74	0·75	0·61
Std. Dev.	0·14	0·14	0·13	0·11	0·17

Table 4. Kendall's rank correlation coefficients for different sets of probabilitities of success.

	Normal	(1)	(2)	(3)	(4)
Normal	1				
(1)	0·91	1			
(2)	0·85	0·95	1		
(3)	0·87	0·90	0·90	1	
(4)	0·90	0·80	0·73	0·77	1

Table 5. Kendall's rank correlation coefficients for various threshold probability levels.

	$p^{\mathrm{lim}}=0{\cdot}900$	$p^{\mathrm{lim}}=0{\cdot}925$	$p^{\mathrm{lim}}=0{\cdot}950$	$p^{\mathrm{lim}}=0{\cdot}975$
$p^{\mathrm{lim}}=0{\cdot}900$	1			
$p^{\mathrm{lim}}=0{\cdot}925$	0·98	1		
$p^{\mathrm{lim}}=0{\cdot}950$	0·96	0·97	1	
$p^{\mathrm{lim}}=0{\cdot}975$	0·95	0·96	0·98	1

set of probabilities used is indicated by the rank correlation coefficients in table 4. The degree of agreement between results varies between 73 and 95 per cent. That is to say, after subtracting inconsistent pairs 73 to 95 per cent of all possible pairs of demand locations have the same rank ordering when the results based on different probability sets are compared.

The minimal expected costs of a successful trip depend on the threshold probability (the stop condition) specified by the user. How sensitive is the MS method for variations in this parameter? Table 5 shows the rank correlation coefficients between the results that are obtained when the threshold probability is varied between 0·900 and 0·975. The degree of agreement between results ranges between 95 and 98 per cent.

To what degree do the results of the MS method differ from the results of alternative methods? First, we have compared the MS method to the current method of measuring the cost band that captures a specified critical number of facilities. Again, four critical levels of opportunities (1, 2, 3 and 4 facilities) were considered. Second, we have compared the MS method with the results that are obtained when singlestop trips are assumed. The singlestop alternative includes making different one-destination trips from the home location until the threshold level of probability is reached. The expected costs of the optimum set of trips is a measure of spatial opportunities. This singlestop alternative is derived as a special case of the MS method, namely by setting the Scope parameter to zero. Finally, we have compared the MS scores to scores that result when the probability of success at all supply locations is set to the same level (0·70). The comparison with the singlestop and the 'equal probabilities' alternative yields insight into the separate effects of differences in supply size across facilities and in the spatial structure of supply points on the measurement results. The tables 6, 7 and 8 show the degree of agreement between the methods when they are applied to the food, clothing and footwear sector respectively. (We leave the '1-facility' level in the cost-band method out of consideration, since this measure is not comparable to the MS method, which typically involves more than one supply point.) The degree of agreement between the MS method and the cost-band method varies from 51 to 56 per cent in case of the food sector, from 67 to 71 per cent in the clothing sector and from 71 to 75 per cent in the footwear sector. The degree of agreement of the MS method with the singlestop

Table 6. Kendall's rank correlation coefficients for the MS, the singlestop (Sstop), the 'equal probability' (EQ) and the cost-band method, for the *food sector.*

	Mstop	Sstop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0·92	1					
EQ	0·63	0·53	1				
1 fac	0·48	0·41	0·78	1			
2 fac	0·56	0·56	0·50	0·22	1		
3 fac	0·51	0·52	0·40	0·15	0·69	1	
4 fac	0·52	0·51	0·42	0·16	0·64	0·83	1

Table 7. Kendall's rank correlation coefficients for the *clothing sector.*

	Mstop	Sstop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0·91	1					
EQ	0·70	0·61	1				
1 fac	0·60	0·52	0·90	1			
2 fac	0·71	0·70	0·64	0·52	1		
3 fac	0·67	0·70	0·55	0·43	0·74	1	
4 fac	0·69	0·69	0·55	0·44	0·68	0·84	1

Table 8. Kendall's rank correlation coefficients for the *footwear sector.*

	Mstop	Sstop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0·94	1					
EQ	0·75	0·71	1				
1 fac	0·68	0·62	0·90	1			
2 fac	0·71	0·72	0·62	0·51	1		
3 fac	0·75	0·77	0·65	0·55	0·76	1	
4 fac	0·74	0·75	0·59	0·48	0·75	0·96	1

alternative range between 91 and 94 per cent. When compared to the 'equal probability' method, we find figures between 63 and 75 per cent.

Further, it is interesting to compare the sets of scores that are obtained when the critical level of opportunities are set to different numbers of facilities in the cost-band method. In case of the food sector we find correspondence rates ranging from 64 to 83 per cent, in the clothing sector 68 to 84 per cent and in the footwear sector 75 to 96 per cent.

3.3. *Interpretation of the results*

The relatively high standard deviations of the scores (table 2) indicate that the MS method strongly differentiates between demand locations. The MS method appears to be rather sensitive to differences in the applied set of probabilities of success (table 4). This means that the results of the method depend to a small degree on the specification of the function used to calculate probabilities. On the other hand, the method is not sensitive to variations in the chosen probability threshold within a reasonable range (table 5).

Compared to the cost-band method, the MS method leads to considerable shifts in the ranking of demand locations. This is particularly true in the case of the food sector, where agreement rates of approximately 50 per cent are found (table 6). But even in the sector where the highest degrees of agreement are found, that is footwear, the shifts in rank scores are significant ($r = [0{\cdot}71, 0{\cdot}75]$, table 8). Therefore, the choice of using the MS method rather than the cost-band alternative, at least in the case of Maastricht, does have consequences for the evaluation of spatial opportunities at demand locations, irrespective of the type of shops considered.

To explain how differences between measurement results may arise, consider the pairs of shopping situations of figures 2 and 3. The pairs are analysed using both the cost-band and the MS method. In both pairs the MS method gives rise to a different ranking of the shopping situations, because of its sensitivity to the spatial structure of supply (figure 2) and differences in supply size across centres (figure 3).

Only slightly higher levels of agreement are found *within* the cost-band method when different critical numbers of facilities (2, 3 or 4) are chosen. This finding means

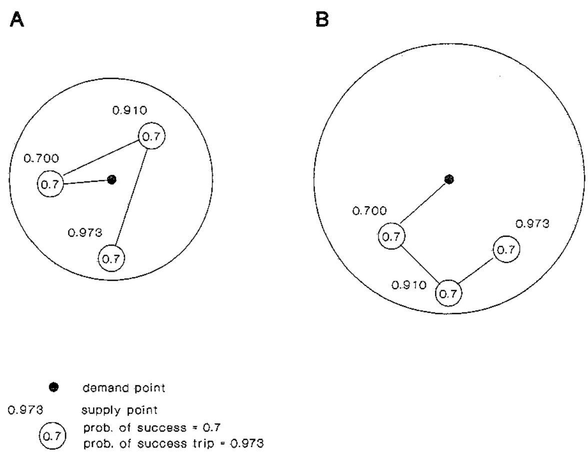

Figure 2. A fictive example to illustrate the effect of *multistop trips*: the cost-band and MS method give different rankings of costs: $A \langle B$ and $A \rangle B$ respectively.

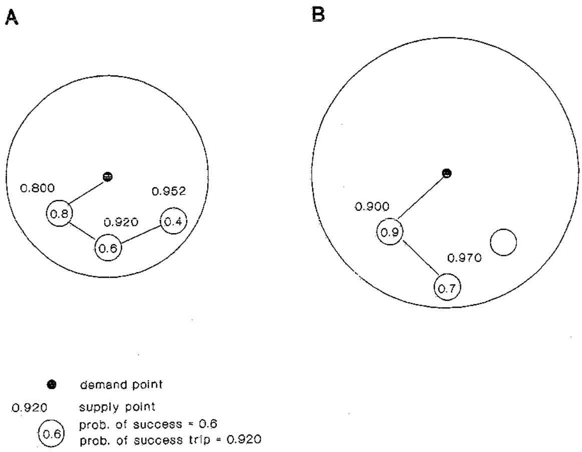

Figure 3. A fictive example to illustrate the effect of *differential supply size*: the cost-band and MS method give different rankings of costs: $A \langle B$ and $A \rangle B$ respectively.

that the cost-band method includes arbitrary elements if objective criteria for determining the critical number of facilities are lacking.

The assumption of multistop trips appears to have only a small effect on the measurement results. This follows from the high rates of correspondence between MS and singlestop results ($r = [0{\cdot}91, 0{\cdot}94]$). The differentiation of probabilities of success, on the other hand, has a stronger impact on the results as indicated by the agreement rates between the MS and 'equal probability' measures ($r = [0{\cdot}63, 0{\cdot}75]$). We conclude, therefore, that differences between demand locations are mainly caused by differences in variety of supply at the level of supply points and to a lesser extent by differences in distances between supply points. However, since it does have effect, albeit small, it is worthwhile to include trip chaining into the analysis.

4. Evaluation of the method

In this paper a new method for the measurement of accessibility defined in terms of spatial opportunities is introduced. The method is meant to be a refinement of the current method of measuring the number of opportunities within various levels of travel costs. In contrast to these existing methods, the MS method accounts for distances between supply locations and the variety of supply at these locations, assuming multistop rather than singlestop travel behaviour. The results of a case study show that the MS method may lead to different evaluations of opportunities at the level of demand locations. Furthermore, the results of the MS method appear to be practically independent of the chosen critical level of supply (the probability threshold). The alternative method, in contrast, appears to be highly sensitive to the chosen critical number of facilities. This is a serious drawback, since there are no objective criteria available for determining the level of this parameter (Breheney 1978).

The MS method is slightly sensitive to variations in probabilities of success assigned to facilities. This means that measurement results may be somewhat distorted if these probabilities do not accurately reflect the variety of supply of facilities. In order to obtain good estimates, the function for calculating probabilities of success can be specified based on observed consumer behaviour. General modelling techniques can be used to select appropriate independent factors (indicators of the variety of supply) and to determine appropriate levels of the function parameters.

The MS method is applicable to all types of goods or services where the probability of meeting a specific demand depends on the diversity or size of supply. Generally, this is the case if purchase decisions are based on comparing alternative outlets. In an applied context, the method has the advantage that the data for calculating the measure are easy to obtain and, furthermore, that the results have a clear interpretation.

It should be noted that the MS method does not account for the implications of multipurpose trips on spatial opportunities. However, if multipurpose trips are assumed, then the travel costs that have to be made to reach a certain level of opportunities do depend on distances between supply points of different types. Another method developed by Arentze *et al.* (1992) accounts for multipurpose trips. If these two methods are used in combination, the accessibility of any spatial facility system can be measured from different, complementary perspectives.

The method should be seen as an extension of standard GIS functionality, since it is based on typical GIS data structures and it uses GIS network analysis tools to generate distance data. The results obtained can be displayed by means of GIS visualization tools.

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