A Comparison Of GIS-based Supply and Demand Models To Determining Optimal Access To Health Care Facilities

Dr. Ibrahim Obaid Alshwesh(*)
Department of Geography, Qassim University

Abstract

Different health planning applications can be utilised to resolve different types of supply and demand questions. This research compares the results from four commonly available supply and demand models when applied to the same supply and demand question: representing the Minimise Impedance (MI *P*-median Model), the Minimise Facility (MF), the Maximal Covering (MC) and the Maximise Attendance (MA) models. The aim is to provide an in depth understanding of the spatial planning implications associated with the assumptions embedded in each of the models, and thereby to provide a greater insight into the appropriateness of specific approaches to quantifying and optimising public health facility locations and access to them.

The results demonstrates that despite different assumptions underpinning the MI *p*-median and MC models, the two models provided similar results in terms of facilities and demand selection. The MF model identified a different set of facility locations because it identifies the lowest number of services necessary to serve all the demand points within the distance specified. The MA model produced different results to

(*) Assistant Professor of Geographical Information Systems, Department of Geography, Qassim University, Al Qassim, KSA.

the MI *p*-median, MC and MF models in terms of facilities and demand selection when applied across a small number of facilities. Three models produced different 33 facility selections depending on the three distances used.

Supply and demand are used to optimise facility locations by minimising the total demand weighted distance. This research has shown that different models will produce different results. Understanding and verification of these differences are important generating evidence in support of health care planning.

1. Introduction

Supply and Demand Models can be used to determine the optimal location of health care facilities (supply) in relation to some distribution of (demand). A typical approach determines optimality by evaluating the geographic distribution of demand in relation to potential supply locations. There are many different these models but generally they seek to minimise some weighted distance (e.g. population weighted distance or patient weighted distance) to supply locations. The differences between models relate to how they search through possible solutions and how potential solutions are evaluated. Additionally, different health planning applications seek to answer different kinds of supply and demand questions.

This research compares the results of four commonly available supply and demand models applied to the same supply and demand question. These models are:

1) The MI p-median model is a longstanding location-allocation model which seeks to minimise the total weighted distance aggregated over all of the supply and demand locations (Hakimi, 1964 and Teitz and Bart, 1968).
2) The MF model seeks to minimise the number of facilities that cover or serve all demand within a certain distance or travel time (Schilling et al., 1993).
3) The MC model aims to maximise coverage for the number of possible demand points within a certain distance or travel time (Church and ReVelle, 1974; ReVelle and Hogan, 1989; Spaulding and Cromley, 2007 and Murawski and Church, 2009).
4) The MA model aims to maximise the attendance of the demand within the distances used and travel time. The demand weight for each demand point is partially allocated in those areas that are close to the majority of demand (Holmes et al., 1972).

The different models have their own particular statistical and mathematical bases, which are associated with different assumptions. These in turn will result in different solutions being suggested by each of the models when applied to the same supply and demand problem. These models produce different solutions to accessibility questions in terms of how they minimise the total weighted distance, determine the minimum or lowest number of facilities needed to serve the largest number of possible demands and aggregate weighted demand in areas close to the main areas in which demand is concentrated.

This paper describes and compares of the results of applying the 4 models to a hypothetical problem of identifying the optimal number and location of General Practitioners (GPs) in Leicester, a city in the English Midlands, given the same set of demands and supply locations. The aim is to provide a deeper understanding of the spatial planning implications of the assumptions embedded in each of the models, and thereby to provide greater insight into the appropriateness of specific approaches for quantifying and optimising public health facility locations and access to them. The paper proceeds as follows: Section 2 reviews the health geographics and spatial planning literature, providing the scientific background to this research. Section 3 outlines the models. The case study, data and pre-processing are detailed in Section 4. Section 5 presents the results and Section 6 discusses the results in light of the models before some conclusions are drawn in Section 7.

2. Background

2.1 Geographic Information Systems (GIS) and health planning

GIS can readily be integrated into public health and health planning (Cromley and McLafferty, 2002). Some studies have shown the role played by GIS in health facilities planning; for example within the UK National Health Service health planning context (Higgs and Gould, 2001). Other studies have shown the beneficial role of GIS in community health assessment when applied to assess health problems and develop solutions (Scotch et al., 2006), to test social, economic and physical status of an environment and its impact (Basara and Yuan, 2008) and to support decision making in the public health sector (Joyce, 2009).

The capacity to link the spatial dimensions of supply and demand in a GIS has resulted in a number of specific health-related planning analyses. For example, to plan for primary health care facilities based on a census area and the location of services (Bullen et al., 1996), to create service areas by using GIS for hospitals in Switzerland (Klauss et al., 2005) and to assess population health needs (Barnard and Hu, 2005).

2.2 Use of distances and GIS in relation to public health access

Distance is a key factor affecting facility access. Accessibility is affected negatively as distance increases between supply and demand (Dessouky et al., 2007). The analysis of facility distance in a GIS is common public health accessibility studies. Measuring access according to network distances and travel time are the most commonly employed methods. Some approaches use scales for describing access levels based on travel time and travel distance to the nearest local medical services (Parker and Campbell, 1998). Other studies have used a cost path analysis in GIS to measure the minimum distance and time taken to access the nearest public hospitals (Brabyn and Skelly, 2002), and to measure travel time and accessibility when using private or public transport to

GPs in East Anglia (Lovett et al., 2002). Whilst these methods have provided satisfactory results some studies have suggested that these methods ignore potential supply providers who are located within short distances (Guagliardo, 2004). A related study to the network distances and travel time provided a discussion of distances and travel time and investigates the relationship between the need for health care facilities and the distances involved in accessing them (Jordan et al., 2004). Additional, studies have been conducted using information the patients' data and population survey to measure the travel time in GIS to compare estimates with real time access by car for patients attending clinics at 8 hospitals (Haynes et al., 2006). Other study provided evidence that the travel time or distances measured in GIS was related to the times perceived as typical by local residents (Fone et al., 2006).

The uses of catchment area methods are also employed in GIS to measure public health access. Some studies used catchment area analysis in GIS to calculate travel distances to renal replacement therapy in England (Martin et al., 1998). Another study offered an assessment of the spatial differences between access to primary care in a floating catchment area (Luo and Wang, 2003). A floating catchment area was used in another study to identify the areas currently suffering from a shortage of physicians (Luo, 2004). The two step floating catchment area method is an extension of floating catchment area methods applied in many studies to measure access to public health (Wang and Lou, 2005). Whilst two step floating catchment area methods have provided satisfactory results to measure access to health facilities, some studies have suggested that in cases of a large catchment should be undertaken with caution because the distance and size of the catchment area effects the accuracy of results (McGrail and Humphreys, 2009). Recently a three step floating catchment area has been used to reduce overestimations of the demand for health care access (Wan et al., 2012). Other methods that have been used to measure access to health services for example some studies used three aggregation methods with four types of distances to compare results describing accessibility to health services (Apparicio et al., 2008). Another study has used the AccessMod tool to analyse geographic coverage and physical accessibility to health services (Ray and Ebrner, 2008).

2.3 The use of GIS to model supply and demand in health planning

The use of GIS to resolve supply and demand problems in health geography has become widespread (Teixeira et al., 2008). These approaches are frequently based on distance under the assumption that accessibility decreases with increasing distance (Gu et al., 2010). Supply and demand models have been used by many researches to minimise the total weighted distance aggregated across all supply and demand locations (Teitz and Bart, 1968; Schilling et al., 1993; Spaulding and Cromley, 2007 and Daskin and Stern, 1981). *P*-median set coverage models and heuristic solutions are examples of approaches used to solve the problems of identifying optimal facilities locations by reducing the total distance or time between supply and demand (Church and Murray, 2009). The *p*-median model in health geography is frequently applied to determine the location of emergency medical services and other health facilities because it is believed to provide better solutions than other supply and demand models (Hodgson, 1988 and Comber et al., 2011). It has also been used to establish a number of supply and demand models (Serra and Marianov, 1999). However, other studies have suggested that the *p*-median model may be less appropriate in some situations, because it does not realistically address the reality of health responses which may have a hierarchical nature (Hodgson, 1988).

A number of studies have described different applications of the *p*-median model, its operation and its assumptions. The LSCP seeks to minimise the number of facilities needed to cover all demands within a certain distance or timeframe (Schilling et al., 1993). Optimising the geographical coverage of facilities using such models have been described by a number of researchers. A GIS-based geographic coverage method was proposed to measure the accessibility of services related to a methadone treatment programme in Hong Kong (Pang and Lee, 2008). The LSCP has also been used to determine locations where potential supply sites are not defined a priori (Straitiff and Cromley, 2010). In contrast the MCLP seeks to cover the largest possible area of demand, based on a certain distance or journey time between demand and facility locations, allowing for the maximum population to be covered within the area identified (Church and ReVelle, 1974). A number of recent studies have demonstrated the capabilities of GIS in supporting supply and demand problem by examining and evaluating the spatial distribution and accessibility of services (Murawski and Church, 2009 and Mitropoulos et al., 2006). Further research has used a maximal cover-class solution to evaluate accessibility and capture all the demand criteria associated with hospitals (Messina et al., 2006). In addition, a modification of MCLP was used to maximise coverage for emergency services (Indriasari et al., 2010). The MA model seeks to capture the largest number of points of demand within a certain distance or timeframe (Holmes et al., 1972). This represents an extension to coverage problems. Some research has compared different supply and demand models in the context of spatial planning for fire station locations in Kuwait (Algharib, 2011). The results showed that the demand coverage results of the MI *p*-median, MF and MC models were better than those for the MA model because the demand selections from the MA model were less for the other models.

2.4 Summary of the points arising from other research

1) The *P*-median model reduces the total distance or time between supply and demand (ReVelle and Swain 1970), and has been extensively used in health geography for determining the location of emergency medical services (Serra and Marianov, 1999 and Comber et al., 2011). The model is considered to generate better solutions than other supply and demand models, because it enables the

user to analyse and minimise some weighted distance, over aggregated supply and demand (Hakimi, 1964; Teitz and Bart, 1968 and ReVelle and Swain 1970). In addition, as distance is a key factor affecting accessibility to facilities locations, the *p*-median model allocates demand to the nearest supply point while minimising the total distance or time.

2) The *P*-median model and all extensions of this model are founded on the assumption that optimal accessibility to locations can be achieved by minimising the total distance between the supply and demand. However, there are cases in which the use of the *p*-median model may be less appropriate, because the model does not realistically suit those health systems that have a hierarchical nature (Hodgson, 1988). In addition some studies have suggested that there is a critical distance in terms of travel time, beyond which a dramatic reduction is experienced in the use of service facilities (Rahman and Smith, 2000), in this case the *p*-median model may lead to solutions that are not acceptable from the standpoint of service.
3) The LSCP is based on the assumption that the number of facilities needed to cover all demands within a certain distance or time should be minimised (Schilling et al., 1993; Daskin and Stern, 2009; Church and Murray, 2009; Straitiff and Cromley, 2010 and Toregas et al., 1971). The main disadvantage of the use of LSCP is that it does not allow for the possibility that at the time the

call for an ambulance arrives the server may be busy (Marianov and ReVelle, 1994). In this case some extensions, such as probabilistic LSCP, have been suggested to overcome the main disadvantage of LSCP by giving a local estimate of the busy fraction, within the scope of geographic coverage around a node (ReVelle and Hogan, 1989).

4) The MCLP seeks to cover the largest possible demand area according to a certain distance or journey time between the supply and demand points (Church and ReVelle, 1974 and Hogan and ReVelle, 1986). This model is considered to be appropriate when there are a small number of suppliers, and there is a need to cover maximal demand in an area (Gu et al., 2010 and Messina et al., 2006). The assumptions of MCLP are different from those of LSCP. In terms of facilities selections, the MCLP does not minimise the number of facilities needed to serve all the demand points over a certain distance or time, such as was the case with LSCP. However MCLP provides solutions to cover the largest possible area of demand according to certain distance requirements or time lapse between supply and demand. The MCLP is more appropriate than LSCP when resources are limited (Church and Murray, 2009). This is because the MCLP is appropriate when there is a small number of suppliers and a need to cover the largest possible area of demand with supply.

5) The MA model seeks to capture the largest number of points of demand whilst simultaneously minimising the average distance for all the demand points which are serviced by one or more facility within a certain distance or timeframe (Holmes et al., 1972). The assumptions upon which this model is founded have been formulated based upon other supply and demand problems, such as the *p*-median model, in terms of minimising average or all distance and coverage problems. The MA model tends to maximise attendance to the facilities that are located close to the majority of the demand (Algharib, 2011). This model addresses the important aspects relating to the relationship between demand and the supply, such as maximising attendance and minimising distances within a certain distance or allotted period of time.

3. Models

In this section the four models are formally described:

3.1 MI *p*-median model

The MI *p*-median model seeks to minimise some weighted distance, aggregated over supply and demand. The objective of this model was written in some studies (Teitz and Bart, 1968 and Cromley and McLafferty, 2002) as follows:

Objective function of this model is to:

$$\text{Minimize } Z = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \qquad (1)$$

It is faced with the following restraints:
A facility has to be allotted with a separate demand site
$x_{ij} \leq x_{jj}$ for all (i, j)
An open facility must be allotted a demand

$$\sum_{j \in J} x_{ij} = 1 \text{ for all } i \quad (2)$$

Only the p facilities are to be located

$$\sum_{j \in J} x_{jj} = p \text{ for all } j \quad (3)$$

(All the communities assigned to them equal the number of facilities to be located).
Total demand from a separate demand site $x_{ij} = (0, 1)$ for all (i, j)
is allotted to only one facility.
When:
Z = objective function.
I = all the demand areas where the nodes on network along the subscript *i* are an index signifying a specific demand area.
J = the collection of candidate facility sites when frequently the nodes on network along with the subscript *j* are an index that signifies a particular facility site.
a_i = the amount of people present at the demand site *i*.
d_{ij} = denotes the distance or time in terms of the travel cost and separates place *i* from candidate facility site *j* facility.

x_{ij} = equal to 1 when demand at place i is allotted to a facility opened at site j, or equal to 0 when the demand at place i is not allotted to that site.
p = the amount of facilities that need to be located.

The aim of the MI p-median model is to provide solutions of reduce the total distance between supply (GPs) and demand points (the centroid points in the output areas) that fall within the distances used in this paper. This model will then select the GP locations that are chosen as solutions when measuring the accessibility to demand within the distances entered.

3.2 MF model of LSCP

The MF model seeks to determine the minimum or lowest number of facilities needed to serve all the demand points within a certain distance or time (Schilling et al., 1993). It was written in some studies (Schilling et al., 1993 and Cromley and McLafferty, 2002) as follows:
Objective function of this model is to:

$$\text{Minimize } Z = \sum_{j \in J} x_j \qquad (4)$$

Range of an individual demand site has to be either the critical service distance else the time of at least one open facility site.

$$\sum_{j \in N_i} x_j \geq 1 \text{ for all } i \qquad (5)$$

A candidate facility site has to be closed or open $x_j = (0, 1)$ for all j
When:

Z denotes the objective function.

I specify the collection of demand areas which are nodes on a network mostly, plus the subscript i is an index that reports a specific demand area.

J identifies the collection of candidate facilities which are nodes on a network mostly, plus the subscript j is an index that indicates a specific facility site.

x_j takes up the value 1 in a situation when a facility is opened at candidate site j else its value will be 0 with the facility unopened at candidate site j.

N_i points out the collection of facilities when the distance between demand site i and candidate facility site j is less than the critical distance or time or $d_{ij} \leq s$.

d_{ij} refers to the distance present among the demand site i and the candidate facility site j.

s is the symbol of important service response time or the distance.

The aim of the MF model is to select the minimum number of GPs that are necessary to serve the demand locations, or that allow accessibility solutions to describe the demands within the distances used. This is done by reducing the distance and identifying the minimum number of GPs present within the distances entered.

3.3 MC model of MCLP

The MC model seeks to cover the largest possible demand according to a certain distance or journey time between populations and facilities (Church and ReVelle, 1974; ReVelle and Hogan, 1989b; Spaulding and Cromley, 2007 and Murawski and Church, 2009). The objective of MCLP was written in some studies (Church and ReVelle, 1974 and Murawski and Church, 2009) as follows:

$$\text{Minimize } Z = \sum_{i \in I} a_i y_i \tag{6}$$

$$\sum_{j \in N_i} x_j + y_i \geq 1 \text{ for all } i \in I \tag{7}$$

$$\sum_{j \in J} x_j = p \tag{8}$$

$$x_j = (0, 1) \text{ for all } j \in J$$
$$y_i = (0, 1) \text{ for all } i \in I$$

When:

I = denotes the set of demand nodes.

J = happens to be the collection of the facility sites.

s = signifies the distance; when it is past the demand point it is thought to be uncovered.

(You can select a value of S as per your choice for each demand point).

d_{ij} = specifies the shortest distance amid the node *I* and the node *j*.

x_j = 1 when the facility is assigned to the site *j*

0 when the facility is not assigned to the site *j*

$N_i = \{ j \in J \,|d_{ij} \leq S \}$

a_i = specifies the population which is to be serviced at the demand node *I*.

y_i= 1 when demand is fulfilled at the site *i*

0 if it's not fulfilled

p = refers to the total facilities that are to be located.

The aim of the use of the MC model is to serve the greatest demand for each GP within the distances specified and also to reduce the total distances between GPs and demand. This model will select those GPs that are chosen according to accessibility solutions by demand based on the extent of the largest volume of demand used within the distance.

3.4 MA model

The MA model seeks to capture the largest number of points of demand, whilst minimising the average distance for all the demand points serviced by one or more facilities within a certain distance or time. The objective of the MA model was written in Holmes *et al.*, 1972 as follows:

$$Z = \sum_{i=0}^{n} \sum_{j=0}^{n} a_i \left(s - d_{ij}\right) x_{ij} \tag{9}$$

When:

Suppose that the demand or need exists in the *i*th areal unit, then $i = 1, 2\ldots n$ is usually symbolised as the total amount of people.

Suppose: d_{ij}, j=1, 2... n, specifies the distance amid the areal units i and j, an appropriate metric is required to measure it.

S signifies the threshold distance.

The variables used to make choices are as follows:

(When, the variables are n^2 in number)
$x_{ij} = 0$ in a case when the areal unit *i* is not attended by a facility in j.
$0 < d_{ij} \leq 1$ when areal unit *i* is attended by a facility in *j*.

The aim of using the MA model is to capture the largest amount of demand for each GP within the distances used. At the same time reducing the total distances between the GPs and the demand point. This model will identify the GPs which most likely represent accessibility solutions to suit the demand, and are also close to the majority of that demand.

4. Methods

This research seeks to determine the optimal locations for GPs by maximising their geographic accessibility for a demand based on population counts of the under five years and over 65 years people in Leicester based on the four supply and demand models detailed above.

4.1 The Case Study

The case study that has been chosen for the application of supply and demand models to determine accessibility to potential healthcare facility locations such as GP service provision in the city of Leicester, UK. Two population groups were selected and combined to represent demand: young children (under five years) and elderly people (over 65 years) in Leicester. The population of Leicester numbered 279,923 people distributed across 890 census Output Areas (OAs).

There were 19,087 children under five years old, representing approximately 7% of the total population and 37,803 people over the age of 65 years old, representing about 14% of the total population. This analysis merged population counts of the under five years and over 65 years into a single set of hypothetical demands (see Figure 1). The supply facilities are General Practitioner (GP) locations, of which there were 75 in Leicester. There are some duplicate facilities at the same location of the 75 potential GP facilities, about 6 were at locations with 2 or more GPs.

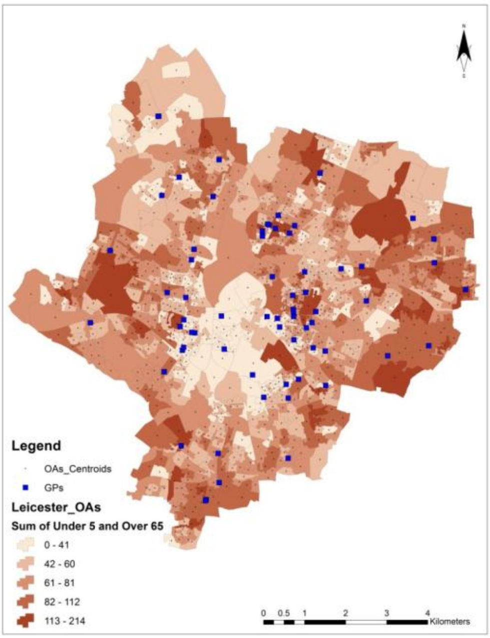


Figure 1. The demand density in Leicester and 75 potential GP locations.

*Data Source: The total number of GPs in Leicester city was obtained from the Leicester City Primary Care Trust (2012). The total number of GPs in Leicestershire was approximately 186, calculated according to the total number of GPs in the UK.

4.2 Data and preprocessing

The road network dataset, GPs locations and census OAs were provided by the UK National Academic Data Centre (EDINA). The population data was obtained from [Casweb 2011, UK Data Service Census Support) available from: [http://casweb.mimas.ac.uk/]. An initial analysis was performed to determine the network distance between each demand point (OA centroids) and each potential supply point (GP locations), resulting in a .matrix of distances between each supply and each demand point. The demand surfaces were derived from the population of young under five years and over 65 years at each OAs centroid, which were used to weight the distances.

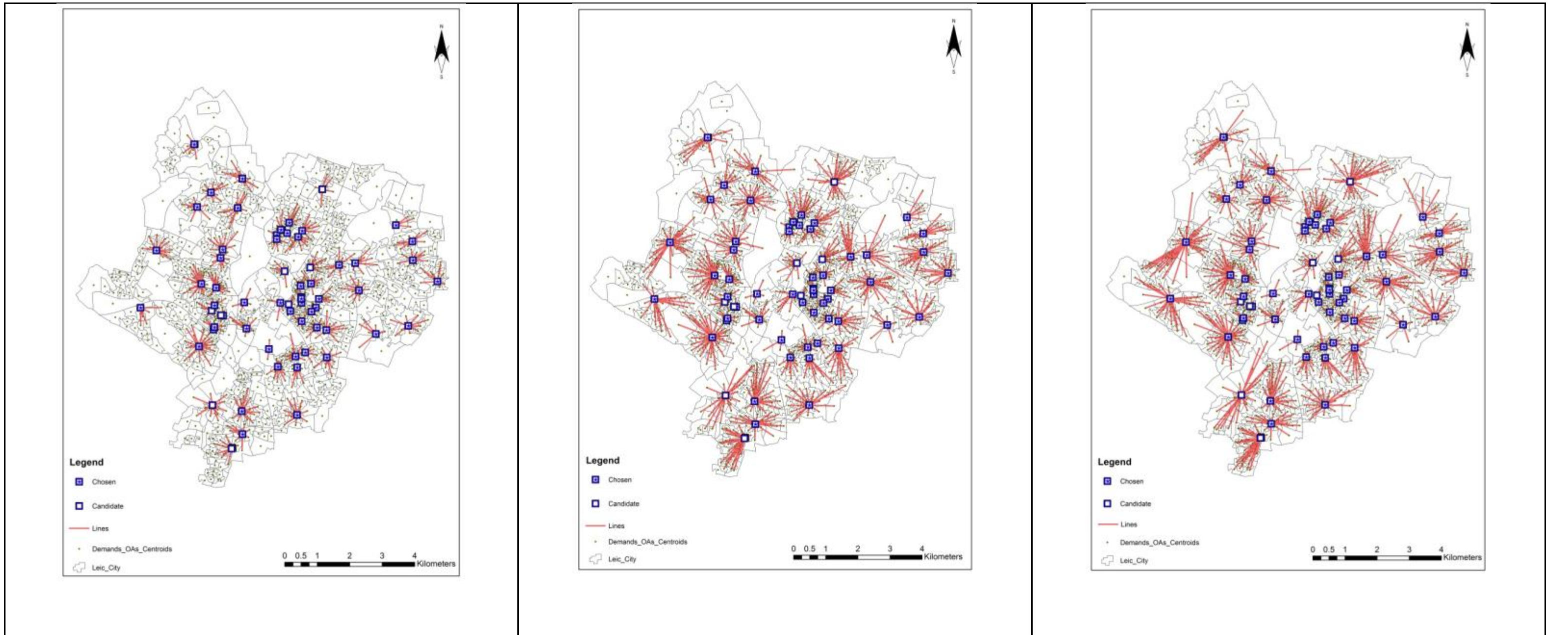
In the absence of criteria determining the optimal distance between the beneficiaries and the healthcare facilities, specifically the GPs, this work applied several example scenarios to determine the distances and accessibility to GPs. The distances that were chosen were 800 metres, 1,600 metres and 2,400 metres and were between the centroid points for the OAs and those closest to GPs via the road network.

5. Results

Four supply and demand models were applied, in order to determine optimal GP locations in support of accessibility a sets of demands derived from the under five and over 65 population, using three specified distances. The following terms are used to describe the results:

- **Distances:** different specified distance limits in metres between supply and demand points.
- **Chosen** facility: selection of a facility as being within the accessibility solution subset and within the distances used.
- **Candidate** facility: a facility that was not chosen and may contribute to accessibility solutions within the distances used.
- **Lines:** these indicate the demand locations covered by the selection of supply points.
- **Covered**: the demand points that fall within the distances used.
- **Uncovered**: the demand points falling beyond the distances used.

An initial analysis has been applied to determine the number of GPs that will be selected as being in the best locations, using the MI *p*-median, MC and MA models. The results of this analysis revealed that 66 GPs were chosen from amongst the 75 in the Leicester area to serve the population's needs over the three distances (see Figure 2). In this case, this study aimed to choose the best 33 GPs, representing half of the 66 GPs chosen to provide a deeper understanding of the spatial planning implications of the assumptions embedded in each of the models. The MF model was applied to all 75 GPs in Leicester.

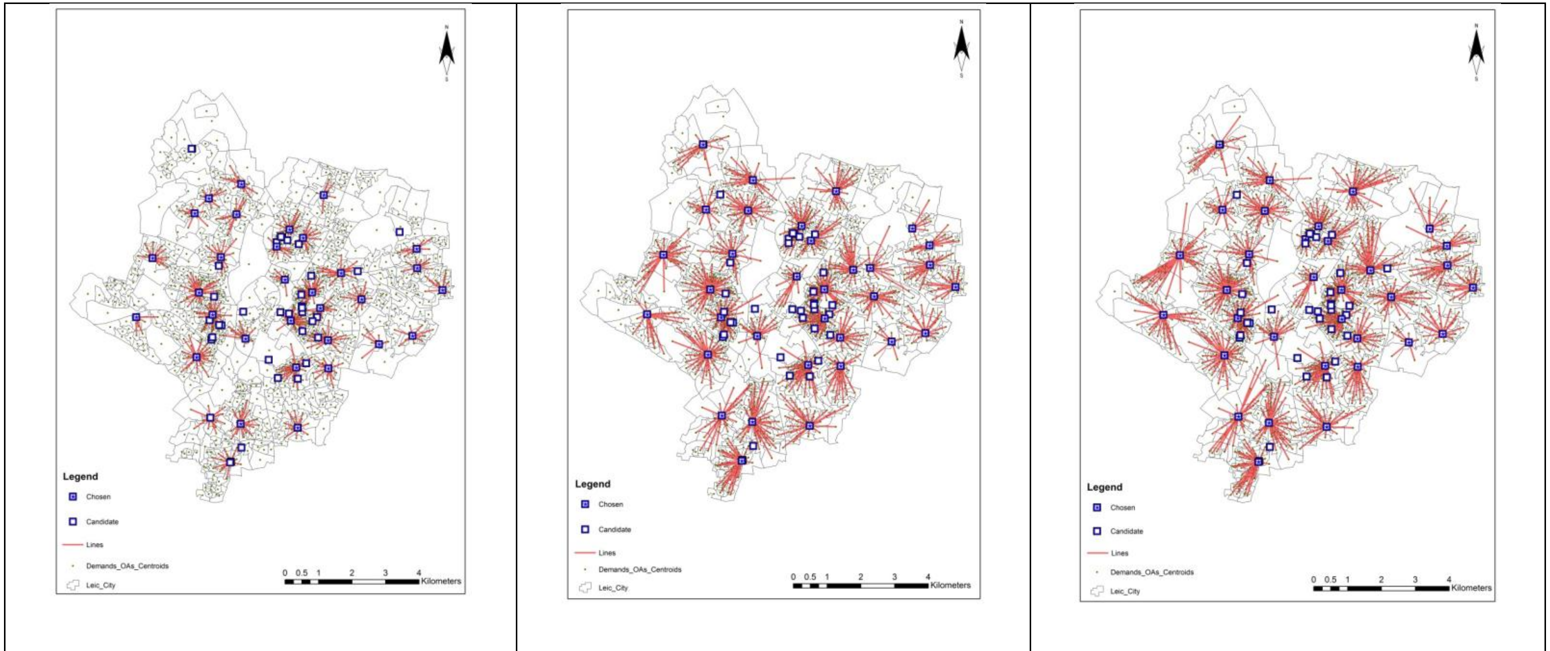


a) b) c)

Figure 2. The results of applying the MI *p*-median, MC and MA models using threshold distances between GP and demand locations of a) 800 metres b) 1,600 metres and c) 2,400 metres. The lines indicate the demand locations that are covered by the selection of supply points.

5.1 MI *p*-median model

The MI *p*-median model was parameterised to select the best 33 GP locations from the 75 to serve the demand, within the three distances of 800 metres, 1,600 metres and 2,400 metres (see Figure 3). The 33 GP locations selected for this model represent the accessibility solutions intended to minimise the distances between the supply and demand points. Obviously there are some differences in the numbers of GP locations selected; the 33 locations that were selected to serve all the demand needs over 800 metres are different when the distance is increased to 1,600 metres and 2,400 metres. The differences in locations selected were clear between the 800 metre and 1,600 metre distances; in contrast, there was one different location selected between the 1,600m and 2,400m distances (see Figure 3 b and c). It can be noted that all the locations selected were distributed evenly to cover all the demand needs depending on the distance used. The candidate locations not chosen were located close to the other GPs over the three distances.



a)	b)	c)

Figure 3. The results of applying the MI *p*-median model using threshold distances between GP and demand locations of a) 800 metres b) 16,00 metres and c) 2,400 metres. The lines indicate the demand locations that are covered by the selection of supply points.

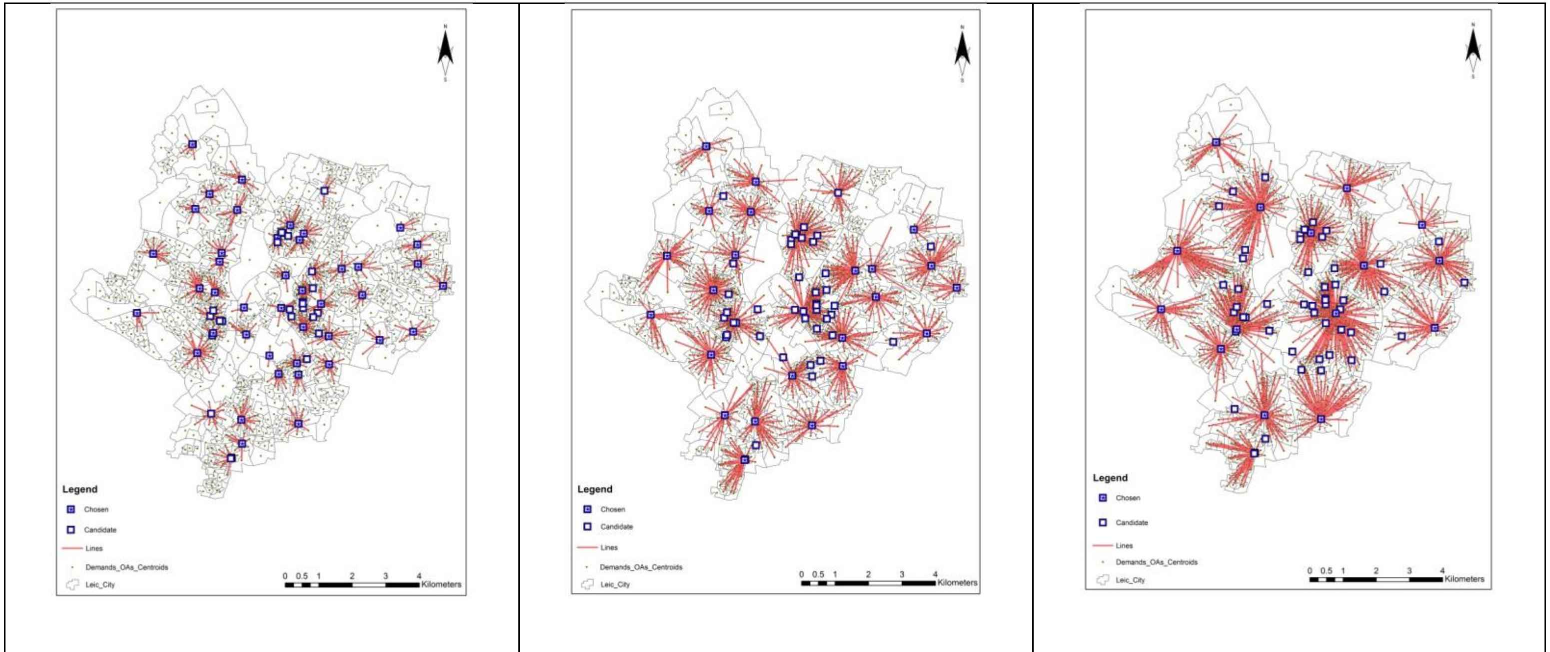
In terms of demand selection the MI *p*-median model provided different results, depending upon the distances used (see Table 1). For example, the number of demands covered by GP locations in Leicester was 33233 within 800 metres, representing approximately 58% of the demand population. The number of demands covered by GPs in Leicester was 53983 when the distance is extended to 1,600 metres and 56436 when the distance was further increased to 2,400 metres, representing coverage of more than 95% and 99% of the demand respectively.

Table 1. Results of demand covered by the MI *p*-median model

Distances	Demand covered
800 metres	33,233
1,600 metres	53,983
2,400 metres	56,436

5.2 MF model

The MF model provided different results in terms of facilities selection in the three examples given: 800 metres, 1,600 metres and 2,400 metres (see Figure 4). This model selected 47 GPs within the distance of 800 metres, 27 GPs within the 1,600 metres distribution and 16 GPs within a 2,400 metre boundary to serve demand needs. The 47, 27 and 16 GP locations selected in this model represent the accessibility solutions based on demand needs when the MF model was minimised to describe the number of GPs necessary to serve demand within the specified distances. The MF model was adapted to minimise the number of GPs located in the middle of the city.



a)	b)	c)

Figure 4. The locations selected by the MF model using distances between demand and supply locations of a) 800 metres, b) 1,600 metres and c) 2,400 metres. The lines indicate the demands that are covered by the different solutions.

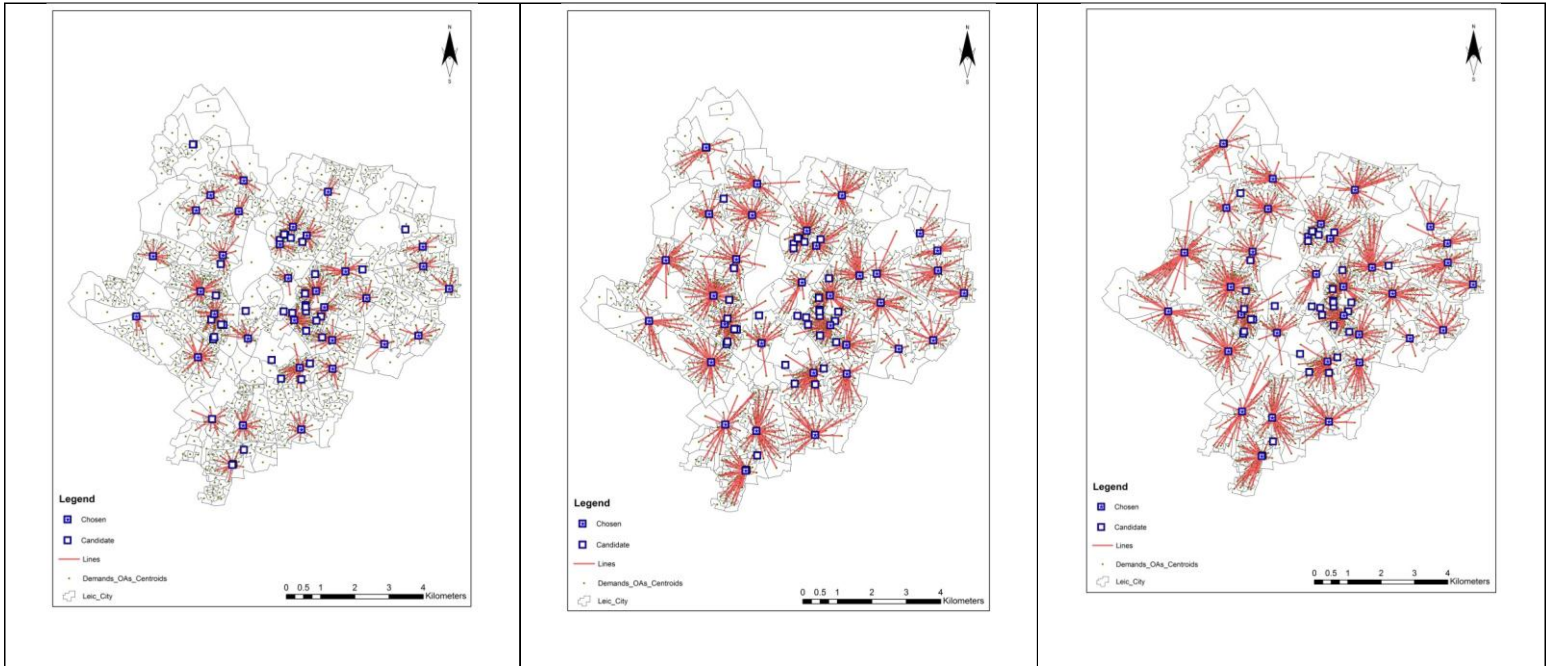
In terms of demand selection the MF model provided similar results to MI *p*-median model, based on the 1,600m and 2,400m distances used (see Table 2). However, the MF model covered 35737 demands with 47 GPs within 800 metres, 53983 demands with 27 GPs at 1,600 metres and 56436 demands with 16 GPs when the distance is set at 2,400 metres. These results show that this model provides accessibility solutions for demand but with a minimum number of GPs.

Table 2. Results of demand covered by the MF model

Distances	Demand covered
800 metres	35,737
1,600 metres	53,983
2,400 metres	56,436

5.3 MC model

The MC model was parameterised to select 33 GP locations from the initial 75, to serve the population’s needs using the specified set of distances (see Figure 5). The results show that the 33 GP locations selected in this model are similar to the locations selected by the MI *p*-median model, providing accessibility solutions between supply and demand points. In fact, the similarity in the results of the MC and MI *p*-median models was due to the similar assumptions of the two models in terms of minimising the total weighted distances between GPs and demand. However this should differ in terms of the demand selections. Because the MC model should select the GPs with extent of the largest volume of demand for each distances used.



a)	b)	c)

Figure 5. The results of the MC model using distances between supply and demand locations of a) 800 metres b) 1,600 metres and c) 2,400 metres. The lines show the allocation of demands to supply locations.

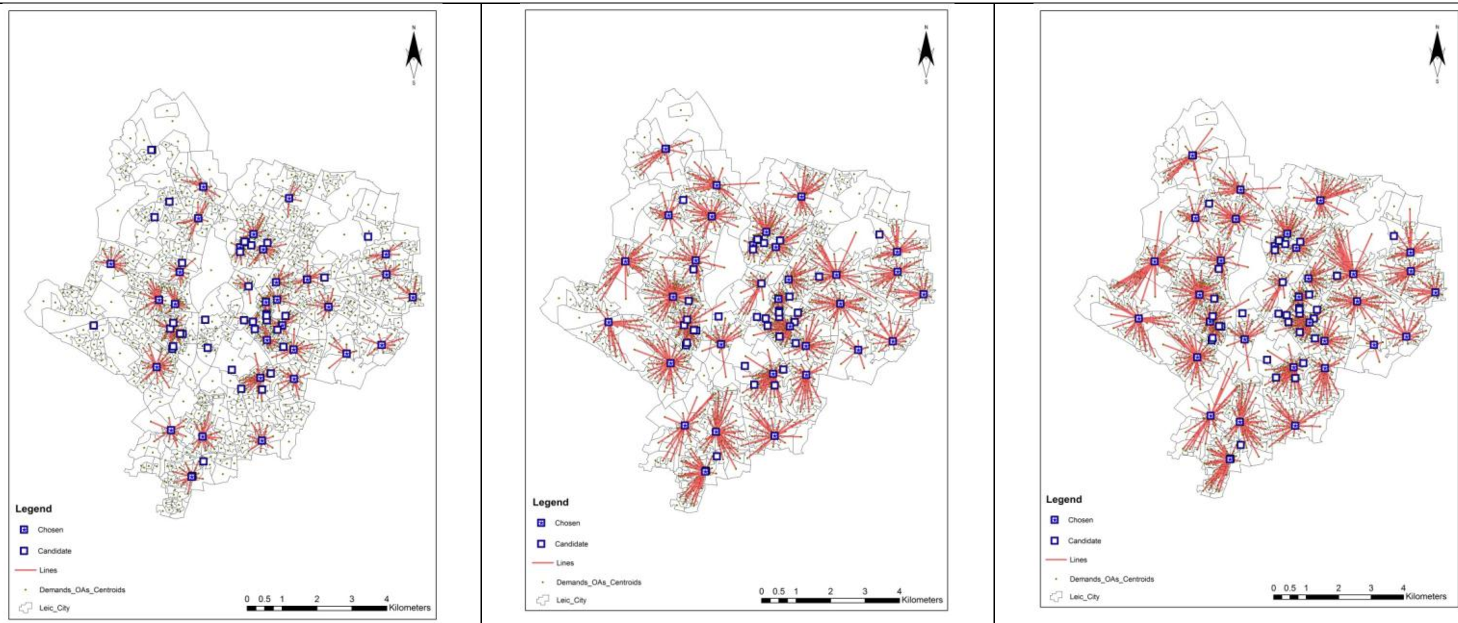
In terms of demand selection, the MC model provided different results depending upon the distances used. The results collected were similar to the demand selections from the MI *p*-median model (see Tables 1 and 3). For example, the number of demand points covered by GPs in Leicester was 33,233 within 800 metres, representing approximately 58% of the demand surface. In addition, the number of demand points covered by GP locations was 53,983 when the distance was set to 1,600 metres and 56,436 when the distance was 2,400 metres, representing more than 95% and 99% of the demand respectively. The similar results between the MC model and the MI *p*-median model, in terms of facilities and demand selections, can also be found in other work (Algharib, 2011). However, it can be argued that the large number of GPs and short distances between them may have affected the operating capacity of the MC model in terms of demand selection in this case study.

Table 3. Results of demand covered by the MC model

Distances	Demand covered
800 metres	33,233
1,600 metres	53,983
2,400 metres	56,436

5.4 MA model

The MA model was parameterised to select, from the initial 75 GP locations, the best 33 to serve the population's needs using the specified set of distances (see Figure 6). The results show that the 33 GP locations selected in this model were different depending on the three distances used: 800 metres, 1,600 metres and 2,400 metres (see Figure 6 a, b and c). There were clear differences in locations selected between the 800 and 1,600 metre distances; in contrast, there were minor differences between the 1,600 and 2,400 metre distances used. The 33 GP locations selected for this model are the accessibility solutions intended to minimise the distances travelled and maximise attendance at those facilities that are close to the majority of demand points (Algharib, 2011). These results are different to the results of the MI *p*-median and MC models in terms of facilities and demand selections. These differences will be described in more detail in the discussion section below.



a)	b)	c)

Figure 6. The results of the MA model using distances between supply and demand locations of a) 800 metres b) 1,600 metres and c) 2,400 metres. The lines show the allocation of demands to supply locations.

In terms of demand selection the MA model provided different results, depending upon the distances used (see Table 4). The results of the demand selections from the MA model were less than the demand selections from the MI *p*-median, MC and MF models within the distances used (see Figure 7). The reason for this result was due to the adoption of the MA model to allocate a ratio from the demand weight for each demand point, and this ratio will decrease when the distance is increased between supply and demand points.

Table 4. Results of demand covered by the MA model

Distances	Demand covered
800 metres	12,863
1,600 metres	29,488
2,400 metres	38,151

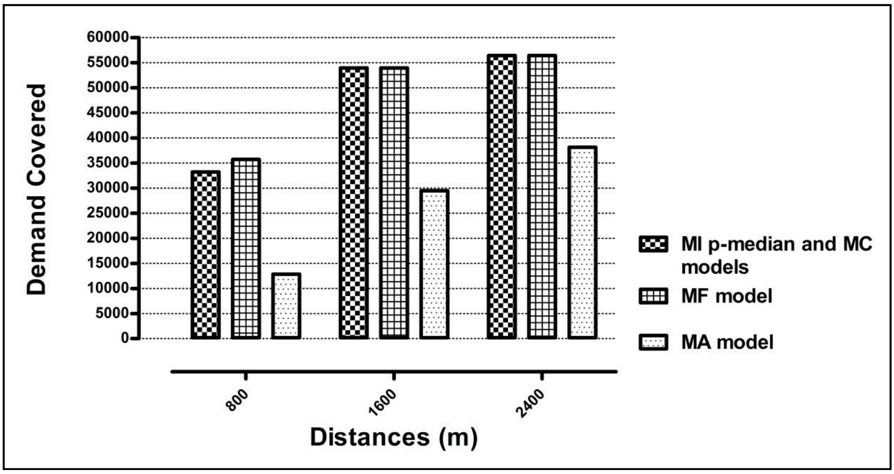


Figure 7. Results of demand coverage from the four supply and demand models

6. Discussion

One of the key issues arising from the increasing use of supply and demand models and their ease of implementation is how to determine which model to use for any given supply and demand problem. This includes how best to provide information to assist public health users in their selection of models. ArcGIS now includes a number of models such as the models used in this work and other models. Different models produce different results when applied to the same problem. Four supply and demand models were applied to the same data in order to compare their results and to provide a deeper understanding of the spatial planning implications of their use. The results showed the following:

1) That the MI *p*-median model minimised the total weighted distances between the GPs and demand, it selected the best set of 33 locations from a total number of 75 that best served serve the demand with the distances measured.
2) That the MF model determined the minimum or lowest number of facilities needed to serve all demand points within the distances specified 47 locations at 800 metres, 27 locations at 1,600 metres and 16 at 2,400 metres.
3) That the MC model produced the same results as the MI *p*-median model in terms of minimising the total weighted distances between the GPs and demand points.
4) That the MA model selected 33 locations that maximised the demand for each facility.

5) That the four models produced different facility selections depending on the three distances used.

The operations and objectives found the MI *p*-median model to produce similar results to those obtained by many authors involved in determining applications for GIS in health related areas (Serra and Marianov, 1999 and Comber et al., 2011). However, the MI *p*-median model does not deal realistically with health response systems that incorporate a hierarchy; for example, in the case of triage (Hodgson, 1988). In addition, this model does not take into account the fact that it may lead to solutions that are unacceptable from the standpoint of services (Rahman and Smith, 2000) when using this model to analyse one type of facility separated into different levels. On this basis, those planning the distribution of healthcare services should also take into account the fact that this method might minimise the distance between a set of points of demand, which may cause them to exceed the capacity of a facility in practice.

The results from the MF model demonstrate that this model selects the minimum number for supply simultaneously with being allocated the same demand weight as was selected with the MI *p*-median model and the MC model within the distances used. This suggests the MF model can help to streamline costs by providing a method that optimally selects facility locations and number. However, there is an associated disadvantage, in that it does not consider the possibility that the server may be busy (Marianov and ReVelle, 1994). Moreover, it can be argued that the MF model may be inappropriate for use in areas suffering from higher population densities where the number of medical staff and services and facilities may be inadequate to cover all the demand points identified within the distance used.

The MC model seeks to cover the largest possible demand according to the distances between the GPs and the points of demand (Church and ReVelle, 1974; Gu et al., 2010; Messina et al., 2006 and Hogan and ReVelle, 1986). The aim informing the use of the MC model was for each GP to serve the greatest demand. However, the results of this work demonstrate similar results between the MI *p*-median model and the MC model in terms of facilities and demand selection in the case study, as was also found in other work (Algharib, 2011). Minimising the distance between users and GP locations was the main goal for the MI *p*-median model. In contrast, the MC model should select those GPs able to serve the largest volume of demand within the distances used. It can be argued that the large number of GPs and short distances between them may have affected the operating capacity of the MC model in terms of demand selection in this case study. Also, it may need to be applied at a very large number of demand points, which may have helped this model to allocate the largest possible demand within the distances used.

The MA model seeks to capture the largest number of points of demand, whilst simultaneously minimising the average distance for all the demand points serviced by one or more facility within a certain distance or timeframe (Holmes et al., 1972). The assumptions of the MA model have been formulated according to a number of supply and demand models, such as the *p*-median model (ReVelle and Swain, 1970); in terms of minimising the averages or the distances between the supply and demand points, and the LSCP (Toregas et al., 1971). The interaction between the facilities and demand in the MA model tend towards maximising attendance at those facilities that are close to the majority of the demand points (Algharib, 2011). The MA model produced different location selections to the MI *p*-median, MF and MC models in terms of facilities and demand selections. This was due to the assumptions and objective of this model, which sought to select the best facility locations close to the majority of the demand points (Algharib, 2011). In terms of demand coverage, the MA model produced different results to the other three supply and demand models in this case study. The difference between the MA model, as compared to the MI *p*-median, MC and MF models related to the process of linking demand weight to the facilities and was due to the aforesaid assumption of the need to maximise attendance. The study noted that the MA model allocated a reduced size of demand compared to the other three models in terms of demand selection and facilities, while the demand uncovered by this model exceeded that obtained by the other models over the distances used. The reason for this result was due to the adoption of the MA model to allocate a ratio from the demand weight for each demand point, and this ratio will decrease when the distance is increased between supply and demand points. Thus, it can be argued that it is inappropriate to use the MA model in the health planning process when the level of demand is distributed evenly within the city. However, in cases where there is a higher density of demand in certain locations within the city, the MA model may in fact give better results than the other three models.

The differences between the different coverage models are associated with their different assumptions. Future analyses will focus on the accessibility and spatial variations among populations in various case studies, taken from different countries with different spatial and demographic contexts, and using demand surfaces constructed in different ways.

7. Conclusion

Four supply and demand models were applied in order to detecting the appropriateness of the approaches used for quantifying and optimising public health facility locations and the access to them. These are commonly found in recent GIS software. They were used to analyse accessibility for the two population groups to GP services in Leicester, combining the data into a single set of demands. This paper demonstrated the effects of the different assumptions between the models.

The MI *p*-median model and MC model of MCLP generated similar results in terms of facilities and demand selection. In contrast, the MF model of LSCP, yielded different results from the previous models because it sought to identify the lowest number of services needed to serve all the demand points within the distances used. The MA model produced different results to the MI *p*-median, MC and MF models in terms of facilities and demand selection when applied on the same supply and demand problem. Analysis of the assumptions based on the models and the results of the case study explains the differences between these models when determining the facilities and demand selection.

- **References**

1. Algharib, S. M. (2011) **Distance and coverage: an assessment of location-allocation models for fire stations in Kuwait City, Kuwait.** PhD thesis, Kent State University.
2. Apparicio, P., Abdelmajid, M., Riva, M. and Shearmur, R. (2008) **Comparing alternative approaches to measuring the geographical accessibility of urban health services: distance types and aggregation-error issues.** *International Journal of Health Geographics*, **7**:7 doi:10.1186/1476-072X-7-7.
3. Barnard, D. and Hu, W. (2005) **The Population Health Approach: health GIS as a bridge from theory to practice.** *International Journal of Health Geographics 4*, **23**, doi:10.1186/1476-072X-4-23.
4. Basara, H. and Yuan, M. (2008) **Community health assessment using self-organizing maps and geographic information systems.** *International Journal of Health Geographics 7*, **67**, doi:10.1186/1476-072X-7-67.
5. Brabyn, L. and Skelly, C. (2002) **Modeling population access to New Zealand public hospitals.** *International Journal of Health Geographics*, **1**:3.

6. Bullen, N., Moon, G. and Jones, K. (1996) **Defining localities for health planning: a GIS approach.** *Social Science and Medicine 42*, **6**:801-816.
7. Caseweb, (2011) UK Data Service Census Support, UK, available from: [http://casweb.mimas.ac.uk/].
8. Church, R. and Murray, A. (2009) *Business Site Selection, Location Analysis and GIS*. New Jersey: John Wiley & Sons.
9. Church, R. and ReVelle, C. (1974) **The maximal covering location problem.** *Papers of the Regional Science Association*, **32**:101-118.
10. Comber, A., Sasaki, S., Suzuki, H. and Brunsdon, C. (2011) **A modified grouping genetic algorithm to select ambulance site locations.** *International Journal of Geographical Information Science 25*, **5**:807-823.
11. Cromley, E. and McLafferty, S. (2002) *GIS and Public Health*. New York: Guilford Press; 2002.
12. Daskin, M.S and Stern, E.H. (1981) **A hierarchical objective set covering model for emergency medical service vehicle deployment.** *Transportation Science,* **15**:137-152.
13. Dessouky, M., Hongzhong, J. and Fernando, O. (2007) **A modeling framework for facility location of medical services for large-scale emergencies.** *IIE Transactions*, **39**:1-41.
14. Fone, D., Christie, S. and Lester, N. (2006) **Comparison of perceived and modelled geographical access to accident and emergency departments: a cross-sectional analysis from the Caerphilly Health and Social Needs Study.**

International Journal of Health Geographics, **5**:16, doi:10.1186/1476-072X-5-16.

15. Gu, W., Wang, X. and McGregor, E. (2010) **Optimization of preventive health care facility locations.** *International Journal of Health Geographics*, **9**:17.
16. Guagliardo, M. (2004) **Spatial accessibility of primary care: concepts, methods and challenges.** *International Journal of Health Geographics*, **3**:3.
17. Hakimi, S. (1964) **Optimum locations of switching centres and the absolute centres and medians of a graph.** *Operations Research*, **12**:450-459.
18. Haynes, R., Jones, A., Sauerzapf, V. and Zhao, H. (2006) **Validation of travel times to hospital estimated by GIS.** *International Journal of Health Geographics*, **5**:40, doi: 10.1186/1476–072X-5–40.
19. Higgs, G. and Gould, M. (2001) **Is there a role for GIS in the 'new NHS'?** *Health & Place* 2001, **7**:247-259.
20. Hodgson, G.M. (1988) *Economics and Institutions: A Manifesto for a Modern Institutional Economics*. Cambridge and Philadelphia: Polity Press and University of Pennsylvania Press;.
21. Hogan, K. and ReVelle, C. (1986) **Concepts and applications of backup coverage.** *Management Science*, **32**:1434-1444.
22. Holmes, J., Williams, F. and Brown, L. (1972) **Facility location under a maximum travel restriction: an example using day care facilities.** *Geographical Analysis 4*, **3**:258-266.

23. Indriasari, V., Mahmud, A., Ahmad, N. and Shariff, A. (2010) **Maximal service area problem for optimal siting of emergency facilities.** *International Journal of Geographical Information Science 24* 2010, **2**:213-230.
24. Jordan, H., Roderick, P., Martin, D. and Barnett, S. (2004) **Distance, rurality and the need for care: access to health services in South West England.** *International Journal of Health Geographics*, **3**:21, doi:10.1186/1476-072X-3-21.
25. Joyce, K. (2009) **To me it’s just another tool to help understand the evidence: public health decision-makers’ perceptions of the value of geographical information systems (GIS).** *Health & Place*, **15**:831-840.
26. Klauss, G., Staub, L., Widmer, M. and Busato, A. (2005) **Hospital service areas - a new tool for health care planning in Switzerland.** *BMC Health Services Research5*, **33**, doi:10.1186/1472-6963-5-33.
27. Luo, W. (2004) **Using a GIS-based floating catchment method to assess areas with shortage of physicians**. Health & Place, 10:1-11.
28. Luo, W. and Wang, F. (2003) **Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region.** *Environment and Planning B: Planning and Design 30*, **6**:865-884.
29. Marianov, V. and ReVelle, C. (1994) **The queuing probabilistic location set covering problem and some extensions.** *Socio-Economic Planning Sciences 28*, **3**:167-178.

30. Martin, D., Roderick, P., Diamond, I., Clements, S. and Stone, N. (1998) **Geographical aspects of the uptake of renal replacement therapy in England.** *International Journal Popular Geographer*, **4**:227-242.
31. McGrail, M. and Humphreys, J. (2009) **Measuring spatial accessibility to primary care in rural areas: improving the effectiveness of the two-step floating catchment area method.** *Applied Geography*, **29**:533-541.
32. Messina, J., Shortridge, A., Groop, R., Varnakovida, P. and Finn, M. (2006) **Evaluating Michigan's community hospital access: spatial methods for decision support.** *International Journal of Health Geographics*, **5**:42, doi:10.1186/1476-072X-5-42.
33. Mitropoulos, P., Mitropoulos, I., Giannikos, I. and Sissouras, A. (2006) **A biobjective model for the locational planning of hospitals and health centers.** *Health Care and Management Science*, **9**:171-179.
34. Murawski, L. and Church, R. (2009) **Improving accessibility to rural health services: The maximal covering network improvement problem.** *Socio-Economic Planning Sciences*, **43**:102-110.
35. Pang, T.T. and Lee, S.S. (2008) **Measuring the geographic coverage of methadone maintenance programme in Hong Kong by using geographic information system (GIS).** *International Journal of Health Geographics*, **7**:5, doi:10.1186/1476-072X-7-5.
36. Parker, E.B. and Campbell J.L. (1998) **Measuring access to primary medical care: some examples of the use of**

geographical information systems. *Health & Place*, **4**:183-193.

37. Rahman, S. and Smith, D. (2000) **Use of location-allocation models in health service development planning in developing nations.** *European Journal of Operational Research 123*, **3**:437-452.
38. Ray, N. and Ebener, S. (2008) **AccessMod 3.0: computing geographic coverage and accessibility to health care services using anisotropic movement of patients.** *International Journal of Health Geographics*, **7**:63 doi:10.1186/1476-072X-7-63.
39. ReVelle, C. and Hogan, K. (1989): **The maximum reliability location problem and, y-reliable p-center problem: derivatives of the probabilistic location set covering problem.** *Ann. Operations Research*, **18**:155-174.
40. ReVelle, C. and Swain, R. (1993) **Central facilities location.** *Geographic Analysis*, **2**:30-42.
41. Schilling, D., Jayaraman, V. and Barkhi, R. (1993) **A review of covering problems in facility location.** *Location Science*, **1**:25-55.
42. Scotch, M., Parmanto, B., Gadd, C. and Sharma, R. (2006) **Exploring the role of GIS during community health assessment problem solving: experiences of public health professionals.** *International Journal of Health Geographics 5*, **39**, doi:10.1186/1476-072X-5-39.
43. Serra, D. and Marianov, V. (1999) **The P-median problem in a changing network: the case of Barcelona.** *Location Science 6*, **1**:383-394.

44. Spaulding, B.D. and Cromley, R.G. (2007) **Integrating the maximum capture problem into a GIS framework.** *Springer-Verlag*, **9**:267-288.
45. Straitiff, S. and Cromley, R. (2010) **Using GIS and K = 3 central place lattices for efficient solutions to the location set-covering problem in a bounded plane.** *Transactions in GIS 14*, **3**:331-349.
46. Teitz, M.B. and Bart, P. (1968) **Heuristic methods for estimating the generalized vertex median of a weighted graph.** *Journal of the Operational Research Society of America 16*, **5**:955-961.
47. Teixeira, J., Antunes, C. and Antonio, P. (2008) **A hierarchical location model for public facility planning.** *European Journal of Operational Research*, **185**:92-104.
48. Toregas, C., Swain, R., ReVelle, C. and Bergman, L. (1971) **The location of emergency service facilities.** *Operations Research*, **19**:1363-1373.
49. Wan, N., Zou, B. and Sternberg, T. (2012) **A three-step floating catchment area method for analysing spatial access to health services.** *International Journal of Geographical Information Science*, doi:10.1080/13658816.2011.624987.
50. Wang, F. and Luo, W. (2005) **Assessing spatial and non-spatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas.** *Health & Place*, **11**:131-146.