ACCESSIBILITY AND THE ALLOCATION OF CLINIC RESOURCES TO OPTIMIZE BLOOD DONOR YIELD

A CASE STUDY OF THE HAMILTON CMA

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ABSTRACT

Blood in Canada is donated by a volunteer base that is increasingly challenged, through a combination of demographic aging and immigration, to meet the needs of the health sector. Canadian Blood Services, the agency with the mandate to manage blood products in Canada with the exception of Quebec, is therefore actively involved in the development of programs to help increase the number of donors, to improve the retention of existing donors, and to increase the frequency of donation of repeat donors. An important factor that influences blood donation is the accessibility to clinics. Accessibility to clinics is determined by the location of clinics, the resources allocated to each clinic in terms of number of beds and hours of operation, and the distribution of the population in the areas serviced by the clinics. The objective of this research is to investigate, given a set of fixed sites for clinic locations and population characteristics, the potential for increasing the donor yield as a function of accessibility. A case study is presented of the Hamilton Census Metropolitan Area, in Canada. Using donor and clinic data provided by Canadian Blood Services, and census information, an objective function is derived by estimating a generalized linear model of donations. The objective function is maximized globally using Genetic Algorithm techniques, subject to total resources available for clinic operations. The results suggest that an optimized allocation of resources to clinic sites has the potential to increase the donor yield by approximately 50% of the current donor base.

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Chapter 1 Introduction

1.1 Rationale

Blood transfusion is a non-optional activity that is an essential requirement in health services for the treatment of many life-threatening illnesses and conditions. Ensuring safe blood transfusion and an adequate supply of blood products is a concern in jurisdictions all around the world – and Canada is no exception (Saberton et al., 2009). Blood in Canada is donated by volunteers and the supply of blood, while still sufficient, is increasingly challenged by demographic trends such as an aging and a large immigrant population. Indeed, at the sub-national level, there are projections to indicate potential future issues to meet the needs of the health sector (Drackley et al., 2012). Canadian Blood Services, the agency with the mandate to manage blood products in Canada with the exception of Quebec, is therefore actively involved in the development of programs to help increase the number of donors, to improve the retention of existing donors, and to increase the frequency of donation of repeat donors. Demographic patterns are changing in Canada and to keep pace with this changing demand of blood it is indispensable to maintain the safety and sufficiency of the blood supply. Efforts to ensure the efficacy and effectiveness of blood donation programs require a better understanding of the factors that influence both supply and demand of blood products, from a geographical and demographic perspective. The aim of this study is to investigate the supply of blood, by focusing on the role of clinic accessibility in affecting the number of donors. A key aspect of the study is the effort to identify optimal accessibility landscapes, which could potentially yield gains in the number of donors.

1.2 Research Challenge

Extensive research has been completed regarding blood transfusion in Canada and all of them are heavily concentrated on donor behaviour (Boulware et al., 2002; Cimaroli et al., 2012; Drackley, 2010; Hollingsworth and Wildman, 2004; James and Matthews, 1996; Murphy et al., 2009; Pol et al., 2000; Veldhuizen et al., 2009). As the Canadian blood supply is entirely based on voluntary donations, the factors that influence donor turnout must be understood properly. Previously, Saberton et al. (2009) investigated the demographic and geographic factors that influence donor turnout rates in Census Metropolitan Areas (CMAs) in Canada, with the exception of Quebec. In his study, younger age people, immigrants, English-speaking ability, having higher education and greater accessibility to clinic are the major factors which he found as influential for blood donation. In addition, there was evidence of considerable variation between Metropolitan Areas, not only in donor turnout rates, but also in terms of the effect of accessibility and other variables such as income.

The present research follows the work of Saberton et al. (2009), by focusing on one Metropolitan Area, namely the Hamilton CMA. In this study, geo-referenced data are used in order to understand the spatial variation of donation factors. A concern when conducting modeling of spatial data is the presence of residual spatial autocorrelation, which represents a violation of a key independence assumption (Griffith, 2004). Following the study of Saberton et al. (2009), this issue is dealt with by means of an eigenvector based spatial filtering technique (Saberton et al., 2009). It has already been shown that accessibility to clinics is a factor that influences blood donation (Saberton et al. 2009). A new model for Hamilton will provide coefficient estimates specific to this city. Furthermore, accessibility to clinics is defined in terms of the location of clinics, the resources (number of beds and hours of operation) allocated to each clinic, and the distribution of the population in the areas serviced by the clinics. A logical question is whether resources can be allocated in such a way that the estimated number of donors can be increased. In other words, an intriguing question is whether optimal accessibility landscapes can be designed. The idea of optimal accessibility landscapes has been proposed and used in the context of commuting to work (Horner, 2008), but it has not before been applied in the context of accessibility to health services. There are at least three ways in which the accessibility landscape can be modified in the case of blood clinics: 1) by changing the location of the clinics while keeping the resources fixed; 2) by maintaining the location of clinics fixed while reallocating the resources assigned to each clinic; or 3) by relocating clinics while also reallocating resources. The focus of this study is on the reallocation of resources among a number of fixed clinic locations.

Optimizing donor yield is developed as a new dimension in blood donation research. Allocation of blood resources along with calculating accessibility to clinics can be a convenient procedure to increase the number of donors in a given geographical areas. Use of accessibility allocates the donation resources based on population in different geographical area which at the same time enhances donor participation. In addition, it becomes possible to evaluate various scenarios (i.e. alternative accessibility landscapes) in order to assess the potential gains in number of donors against the magnitude of the change required to generate the associated accessibility landscape.

1.3 Research Objective

The specific objectives of this research are as follows:

1) To determine the demographic and socio-economic factors that impact blood donation in the Hamilton CMA.
2) To calculate accessibility to clinics and incorporate it as an explanatory variable to analyse its relationship with blood donation.
3) To evaluate the effect of spatial auto-correlation and over-dispersion and to solve this using an eigenvector based spatial filter and over-dispersion parameter.
4) To investigate, given a set of fixed sites for clinic locations and population characteristics, the potential for increasing the donor yield as a function of accessibility.

1.4 Layout of Chapters

There are four chapters incorporated in this thesis comprising this introductory chapter and all case studies are presented of the Hamilton Census Metropolitan Area, in Canada. The chapters are as follows:

i) Introduction of the thesis

ii) Regression analysis to analyze donor turnout in the Hamilton CMA

iii) Design of optimal accessibility landscapes for the Hamilton CMA

iv) Concluding remarks

In Chapter Two, a log-linear regression model of donor turnout is developed for the Hamilton CMA. Using data aggregated at the level of Dissemination Areas (DAs), the model is intended to identify a suite of significant covariates for donor turnout, including different socio-economic and demographic factors. The model is based on donor and clinic data provided by Canadian Blood Services, as well as census information. As spatial data is used in this research, there is a possibility that residual spatial autocorrelation will be present (Saberton et al., 2009). For this reason a spatial filtering approach based on the eigenvector techniques of Griffith (2004) is used. This spatial filtering approach removes spatial autocorrelation by introducing a synthetic variable to accompany the set of explanatory variables of the model. The synthetic variable is designed in such a way that it absorbs (i.e. filters) residual autocorrelation, leaving well behaved residuals. Moreover, an over-dispersion coefficient is also calculated in order to provide sharper inference of the coefficients of the model (Moniruzzaman and Páez, 2012).

The model developed in Chapter Two becomes an objective function for the optimization approaches employed in Chapter Three. The model, whose independent variable can be translated into number of donors, includes accessibility as a variable. Accessibility in turn is a function of resources allocated to clinics. In this way, resources can be changed in an effort to try to increase the number of donors in the region. There are a number of different techniques to solve an optimization problem of this type. In the present research, the objective function is maximized globally using Genetic Algorithm techniques, subject to total resources available for clinic operations. Genetic Algorithm approaches introduce a degree of randomness in the solution process – which means that variations in optimal landscapes can be observed. Some of the solutions will be local optima, and therefore improvable. However, as will be seen, these solutions also require more limited changes to attain gains in number of donors. A number of scenarios are investigated. The results suggest that an optimized allocation of resources to clinic sites has the potential to increase the donor yield by as much as 52% of the current donor base. Finally, Chapter Four presents a summary of all outcomes and discusses the scope and limitations of the research. This leads to a concluding discussion regarding future research directions concerning blood donation in Canada.

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Chapter 2 Spatial modeling of blood donor turnout in the Hamilton CMA

2.1 Introduction

Donating blood is a relatively simple task that can have important, indeed life-saving implications. Safe blood transfusion is an essential aspect of contemporary medical treatment, in a host of elective and non-elective procedures. No one really knows whether and when they, or a loved one, will need to receive blood transfusions, but the chances are high: according to a recent poll reported by Canadian Blood Services, 52% of Canadians say they or a family member have needed blood or blood products (Canadian Blood Services, 2012). Elsewhere, it has been estimated that one in three people will need a blood transfusion in their lifetime (New York Blood Center, 2003). The safest source of blood products are voluntary donors who are considered the most responsible (World Blood Donor Day, 2010). Though there is a great imbalance in the supply and demand of safe blood all over the world, about 60 percent of global supply of blood being donated by the donors in developed countries (World Blood Donor Day, 2010). In Canada, Canadian Blood Services (CBS) and Héma-Québec are the two non-profit organizations who are responsible for the supply of blood and blood products in the whole country. Canadian Blood Services (CBS) manage the blood supply for all provinces except Quebec, where this responsibility is held by Héma-Québec. The major duties of these two organizations include managing initial enrolment of donors, collection and management of blood, and also advertising to raise the blood supply (Ontario Regional Blood Coordinating Network, 2008). Both of these organizations collect blood using permanent collection sites and mobile donor clinics. In 2010, 43 permanent collection sites and 20,000 mobile donor clinics were operated by CBS. Approximately 423,000 individuals donated blood in 2010 (Canadian Blood Service, 2010).

Although CBS has a large number of donors, their annual collection decreased about 0.5% in the year 2010 than the previous years (Canadian Blood Service, 2010). Furthermore, a study of Godin et al. (2005) showed that among the adult population, only 3% donate blood (Godin et al., 2005). In September 2003 a Donor Research Network Meeting (DRNM) was held by the McMaster Transfusion Research Program (MTRP) where it was found that around 50% of first time donors are not interested in donating a second time, which is an important issue for Canadian Blood Services. This makes it clear that there are some issues with the first time donation experience that prevents the participants from donating again (McMaster Transfusion Research Program, 2005). Moreover, Canada's greater aging population is challenging the blood supply as the aging population is the major consumer of blood and by 2036, the number of seniors will double (Ali et al., 2009; Statistics Canada, 2010). However, it is not only the age of donors that affects the donation rate but other factors that may influence blood donation. (Boulware et al., 2002; Drackley, 2010; Hollingsworth and Wildman, 2004; James and Matthews, 1996; Murphy et al., 2009; Saberton et al., 2009; Saberton, 2010; Veldhuizen et al., 2009; Weidmann et al., 2011). Previous research has helped to identify a number of factors that influence the number of donors at the census tract level in major Census Metropolitan Areas (CMAs) in Canada. The research of Saberton et al. (2009) makes it clear that contextual effects are present in various Census Metropolitan Areas across Canada. This argues for more detailed analysis at the CMA level (Saberton et al., 2009).

The objective of this chapter is to develop a Generalized Linear Model to investigate the covariates of donor turnout in the Hamilton CMA. A spatial modeling approach is adopted to ensure that the model is statistically sound. It is a well-known fact that modeling of spatial data can be affected by the presence of residual spatial autocorrelation. Spatial autocorrelation is "the correlation among values of a single variable strictly attributable to the proximity of those values in geographic space, introducing a deviation from the independent observations assumption of classical statistics" (Griffith, 2003; p. 3). Furthermore, in the case of Generalized Linear Models for proportions or counts, over-dispersion, an inflation of the variance over its nominal value, is often an issue. Autocorrelation and over-dispersion combined can have a serious impact on inference, whereby the intervals of confidence of the coefficients are inflated, thus giving the impression of higher nominal significance. In order to address these issues, a spatial filtering approach is used to solve the problem associated with dependency in spatial data (Moniruzzaman and Paez, 2012). This is called eigenvector filtering approach which treats spatial autocorrelation as a missing variables effect and eliminates it from generalized linear regression model (Griffith, 2004). In addition, calculation of an over-dispersion parameter is used to obtain more accurate inference and reliable results.

The model is developed at the Dissemination Area (DA) level, which is the smallest publicly available Census geography in Canada. Each DA is a geographic unit with a population of 400 to 700 persons (Statistics Canada, 2010). Factors investigated include socio-economic and demographic attributes, and in addition accessibility to donation sites and distance to Central Business District. The remaining of this chapter is organized as follows. Section 2 is a review of the literature on blood donation and donor behavior. Section 3 outlines the methods and Section 4 includes the description of the data used in this study. Section 5 shows the results of the analysis, and finally, Section 6 summarizes the study and scope for further research.

2.2 Background

Behaviour regarding blood donation has been established as a noteworthy topic in health studies. Several empirical studies have shown that gender, age, education, financial condition, immigration status and urbanization level has a significant impact on blood donation, including Boulware et al. (2002), Cimaroli et al. (2012), Drackley (2010), Hollingsworth and Wildman (2004), James and Matthews (1996), Murphy et al. (2009), Pol et al. (2000) and Veldhuizen et al. (2009). Boulware et al. (2002) were specifically concerned with effect of race and gender in blood donation along with religion and trust on hospitals. Using a cross-sectional telephone survey of households in Maryland, results of their research represents the fact that whites and males are more willing to donate blood and this statement has made race and gender two important factors of donation. Drackley (2010) and Hollingsworth and Wildman (2004) both worked with motivating factors of donation and both of them have found correlation between socio-economic factors and number of donors. Using multiple linear regression analysis, Drackley (2010) found that blood donation rate in Census Metropolitan Area of Toronto was strongly influenced by socio-economic factors and immigration status. Hollingsworth and Wildman (2004) worked with the donors of Victoria, Australia using ordinary least squares regression (OLS) method. They found that young men, women from the age group 30 to 49 and immigrants are less interested in donating blood.

In current days, the United States is also having shortfall in blood supply which is focused in the research of James and Matthews (1996) and Murphy et al. (2009). James and Matthews (1996) have discussed returning behaviour of blood donors using survival regression method where their result suggested that, along with demographic factors, time is also a key factor of donation. Subsequent donation of a donor depends on the time interval between two donations which makes previous donation experience an influential factor. Murphy et al. (2009) mainly focused on blood donation by immigrants in United States because of their lower frequency of donation and emphasized the need of promoting new strategies to enhance immigrants' participation for donation.

To assess the effect of demographic factor of donors has always remained useful for managing them which is also motivated in the study of Veldhuizen et al. (2009) and Cimaroli et al. (2012). Veldhuizen et al. (2009) analysed Dutch donor characteristics and found that donors aged more than 24, with higher income level and with better living conditions are more interested in donating blood. Donor frequency determinants was analysed by Cimaroli et al. (2012) where Toronto donors were taken into concern. Discrete choice model is used to get the result and accessibility to donation site with other socio-economic factor has found as major determinant of repeating donation. Econometric models are used by Pol et al. (2000) to explore how socio-economic behaviours impact the number of donors in North of Scotland. They found population as the most influential factor that which has higher correlation with number of donors.

Several studies have been concerned with factors that affect the decision to donate (Gillespie and Hillyer, 2002; Holdershaw et al., 2003; Sojka and Sojka, 2003). Gillespie and Hillyer (2002) analysed some previous research, identified the reason for donating according to the donors, and assessed the factors that ensure long term retention of donors. Holdershaw et al. (2003) used statistical model and found that younger donors are more interested in donating blood. Moreover, their results suggested that people who know more about donating blood and donated more recently are more likely to donate (again in the case of previous donors). The aim of the research of Sojka and Sojka (2003) was to evaluate how blood donors are influenced by donation. Questionnaire survey was made in this regard which showed both positive and negative effect on blood donors. However major response came from the report of positive effect which depicts self-satisfaction and feelings of being responsible.

Saberton et al. (2009) and Weidmann et al. (2011) studied in addition the potential spatial variations of donor behaviour. Saberton et al. (2009) developed a model for 40 Census metropolitan Areas (CMA) in Canada, and Weidmann et al (2011) worked with 1533 municipalities in south-west Germany. Saberton et al. (2009) showed that, blood donation depends upon several factors like the proportion of younger residents, English language speaking ability, proportion of immigrants, educational background and accessibility to donation clinic. A multiple linear regression model was used by Weidmann et al. (2011) to find out blood donors' community characteristics and autocorrelation was controlled by using a spatial lag regression model. In this study the authors found that younger donors have a higher turn-out rate and abundant mobile donation sites are responsible for higher donation rates.

2.3 Methods

In this study the dependent variable is a vector of counts containing the number of blood donors in each Dissemination Area in Hamilton. An appropriate model for this type of data is a Poisson model with a logistic link function (Berk and MacDonald, 2007). The model is defined in the following way:

$$\log(D) = X\beta + \varepsilon \qquad (2.1)$$

Here, D = Vector of number of donors

β = Vector of Co-efficient

X = matrix of independent variable

ε = vector of error terms

There are two technical issues that are relevant from an inferential perspective, namely the presence of over-dispersion and residual spatial autocorrelation.

One characteristic of the Poisson model is that the variance of the process is nominally identical to its mean value. In practice, this assumption is seldom satisfied, and the variance can be smaller or (more commonly) greater than the theoretically expected value. The latter situation is termed over-dispersion (McCullagh and Nelder, 1989). Berk and Macdonald (2007) state that- “over-dispersion implies that there is more variability around the model's fitted values than is consistent with a Poisson formulation”. Over-dispersion can affect the ability of the analyst to conduct inference, by deflating the intervals of confidence of coefficients. Failure to account for over-dispersion can give the impression that more coefficients are significant than there should be (Moniruzzaman and Paez, 2012).

Over-dispersion causes the variance to be under-estimated (Griffith, 2003). This can be caused by “random variation in response probabilities and interaction (correlation) between binary responses” (Højsgaard and Halekoh, 2005, pp 15). One way to address this issue is by calculating an over-dispersion factor that can be used to adjust the confidence interval. The following formula is used to compute the over-dispersion factor:

$$\varphi = \frac{1}{n-p}\sum\frac{\left(y-n\pi\right)^{2}}{n\pi\left(1-\pi\right)} \qquad \text{(2.2)}$$

Here, φ = Over-dispersion parameter

p = Number of parameters in the model

$n\pi\left(1-\pi\right)$ = Nominal variance

n = Number of observations

Use of an over-dispersion factor helps to deflate the intervals of confidence. However, by itself, it does not address the underlying causes of over-dispersion. As noted above, over-dispersion can be at least partially caused by the presence of residual spatial autocorrelation.

The second consideration, spatial autocorrelation, has already been observed in the study of donor turnout by Saberton et al. (2009). Spatial autocorrelation can occur on different types of models and it can be dealt with using different techniques, including spatial error autocorrelation and spatial lag models (Anselin, 1988). Weidmann et al. (2011), for instance, implement a spatial lag model. In the case of Generalized Linear Models, where spatially autoregressive versions of the models are limited or non-existent, an alternative is to use a filtering approach (Griffith, 2004). This is the approach used by Saberton et al. (2009). The principle of spatial filtering is explained by Getis and Griffith (2002) where they calculated the Moran's *I* statistics based on eigenvectors obtained from the geographical connectivity matrix common in spatial analysis. The spatial autocorrelation effect of a Generalized Linear Model can be successfully handled in the mean response term by creating a synthetic variable, called a spatial filter, which linearly combines a subset of all available eigenvectors. According to Griffith (2004), this filtering approach improves the fit of the model and also can be used to visualize the latent pattern associated with the residual autocorrelation.

In order to generate the spatial filter, the following matrix is subjected to eigenvector analysis:

$$(I-11'/n)\ W\ (I-11'/n) \qquad (2.3)$$

Here, I= Identity matrix

W= Spatial Weight Matrix (nxn)

1= Vector of 1 (nx1)

1'= Transpose of vector 1

A Spatial Weight Matrix is a contiguity matrix that contains values 0 and 1 which shows the effect of a neighbouring spatial unit. The value 1 is depicted for contiguous spatial units (Anselin et al., 2004).

The result of the analysis is a matrix of n eigenvectors (each of size nx1). The eigenvectors are orthogonal (i.e. uncorrelated) latent map patterns, with a degree of spatial association that can be measured in terms of Moran's I coefficient. The corresponding eigenvalue, in fact, is the value of Moran's I associated with each eigenvector. The set of eigenvectors is a pool of latent map patterns that can be used to generate a synthetic variable with an arbitrary degree of autocorrelation, bounded between the maximum and minimum values of Moran's I possible for the configuration of the spatial system.

The spatial filter is generated using an iterative process, as follows. First, a base model is estimated, using explanatory variables as desired. The residuals of the model are tested for autocorrelation. If autocorrelation is found, the first eigenvector in the pool is introduced as an additional independent variable, and tested for significance and its ability to reduce the level of residual autocorrelation. If the candidate eigenvector is retained, it is synthesized as part of the filter, and the model is re-estimated with the new variable. Only significant eigenvectors at a predetermined level of significance (e.g. $p<0.10$) are retained as candidates for the spatial filter. Once the model is re-estimated, the residuals are tested for spatial autocorrelation. If autocorrelation has declined below a threshold level, so that it is not significant anymore, the search for the filter is terminated. Otherwise, a new eigenvector is selected from the pool, and the process is repeated.

2.4 Data

Data for the analysis comes from two main sources. Canadian Blood Services (CBS) supplied the CBS National dataset for 2008 containing information regarding blood donor profiles and blood clinics. The donor profile dataset is geo-referenced and contains donor postal codes along with some limited personal information, such as age and sex. The blood donation clinic dataset contains information for a total of 19,671 clinics with donors ID, location, type, hours of operation, and number of beds for Canada 2008 (Saberton et al., 2009). The donor profile dataset was geocoded using the 2006 Postal Code Conversion File, and aggregated to the level of Dissemination Areas (DA). Previous research by Saberton (2009) conducted for Toronto Census Metropolitan Areas used Census Tracts as a geographic unit of analysis. In this research, in contrast, DAs providing a higher geographical resolution are used. Clinics were geocoded using latitude and longitude. A total of 11,588 donors were found in 1,144 DAs of Hamilton Census Metropolitan Area (CMA). In the case of clinic data, there are a total of 39 unique clinic locations were considered within the Hamilton CMA boundary. Hamilton Census metropolitan Area (CMA) contains the land area of 1,371.89 square km, located at the west end of Lake

Ontario (Statistics Canada 2007, City of Hamilton 2007). This CMA is situated in southern Ontario and City of Hamilton has seven municipalities namely- Hamilton, Grimsby, Ancaster, Dundas, Flamborough, Glanbrook and Stoney Creek. City of Hamilton is the ninth largest city in Canada and 3rd Largest city in Ontario having the population of 692,911 (Dam, 2009). The distribution of donors and clinics in Hamilton is shown in Figure 2.1.

In order to develop the model of blood donor turnout, several socio-economic variables that have been found to be significant in the literature are considered. Socio-economic data are also taken from demographic profile of each DA obtained from the 2006 Canadian Census. These characteristics are included as they have been shown to explain donor turnout. A list of all variables considered is shown in Table 2.1. Characteristics of Hamilton's blood donors are representative of others in Canada (Lee et al., 1996). People of different age groups have different patterns donation behaviour and because of this, several empirical studies have considered age as an important variable (Gillespie and Hillyer, 2002; Holdershaw et al., 2003; Hollingsworth and Wildman, 2004; Murphy et al., 2009; Pol et al., 2000; Saberton et al., 2009; Sojka and Sojka, 2003; Veldhuizen et al., 2009; Weidmann et al., 2011). Following previous research, four different age groups are included as independent variables aged 15 to 24, 25 to 54, 55 to 64 and more than 65. Though the minimum age requirement of blood donation is 17, data is taken from age group 15. This is because Statistics Canada includes data from this and it would not be possible to isolate particular age groups.

Figure 2.1: Distribution of Blood Donors and Location of Blood Donation Clinics in Hamilton CMA

In this study average after tax household income is taken as another explanatory variable as it might have some impact on donation rates as shown in previous studies and it is expected that people will be more willing to donate blood with a higher income (Hollingsworth and Wildman, 2004; Saberton et al., 2009; Veldhuizen et al., 2009). The people working in health-related occupations is also expected to be more likely to donate, therefore the total number of people working in health occupations in each DA of Hamilton CMA are taken as an independent variable (Saberton, 2010). The total working population are taken as another variable following the study of Glynn et al. (2006). However, unemployment conditions may also influence blood donation rate, as unemployed people are more interested in altruistic works (Saberton et al., 2009). Level of education may also have some influence in voluntary activity like blood donation and donation rates increase with education level (Boulware et al., 2002; Gillespie and Hillyer, 2002; Hollingsworth and Wildman, 2004; Hupfer et al., 2005; Ownby et al., 1999). Education information is also included by the population that has any degree or diploma or any university certificate, diploma or degrees. Ethnicity seems to be an important characteristic of donors which influences blood donation behaviour as shown by previous studies which also indicates that immigration status of donors plays an imperative role for donation (Boulware et al., 2002; Gillespie and Hillyer, 2002; Glynn et al., 2006; Hollingsworth and Wildman, 2004; Murphy et al., 2009; Saberton et al., 2009; Veldhuizen et al., 2009; Weidmann et al., 2011; Wu et al., 2002). In addition, English speaking ability has become a potential factor to influence blood donation because of the effect of ethnicity and it is included as another explanatory variable to this study.

Distance to the Central Business District (CBD) and accessibility to clinics are two other independent variables that are included in the model. A distance variable is added to capture the effect of urban structure. CBD is the central commercial area of downtown which is the major concentration for business activities and this area attracts large number of visitors. For this reason, the CBD was taken as the geographic mean which represents the central part of the city. It is calculated as the mean of all latitude and longitude of all 1144 DA centroids of Hamilton CMA (Saberton, 2010). A distance matrix is calculated by this geographical mean for all the DAs and used as an independent variable.

Another explanatory variable is calculated to represent how accessible the blood donation clinics are. Accessibility in the present study is measured by means of the "Two-step Floating Catchment Area" method. This method was introduced by Radke and Mu (2000) and applied by Saberton et al. (2009) to calculate accessibility to each blood donation clinic by measuring clinic level of service. In this study the same procedure is followed to calculate the accessibility which is shown by the following equation:

$$\mathrm{LOS_i} = R_i \Big/ \sum_{d_{ij} \le d_0} P_j \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(2.4)}$$

i = 1, 2, 3,….n_i (number of Clinic)

j = 1, 2, 3,……, n_j (number of DAs)

R_i= Number of resources (Number of beds * hours of operation)

P_j= Population of all DAs

At first level of service (LOS) is calculated by dividing the clinic resources (Number of bed-hours at clinic) by the sum of the population of all DAs with centroid that lie within distance d_0 the clinic. After calculating LOS, the values are summed to obtain the accessibility of these services within distance d_0 of each DA, as follows:

$$A_j = \sum_{d=3} LOS_i \quad \text{……………………………………..………………(2.5)}$$

Where, A_j= Accessibility vector for Das.

Selection of distance d_0 can be based on the statistical fit of the model.

Table 2.1: Definition of Variables

Variables	**Definition**
Dependent Variable	
DONORS	Number of Blood Donor in each DA
Independent Variable	
TOT15TO24	Total population of 15-24 years of age in dissemination area (DA)
TOT25TO54	Total population of 25-54 years of age in dissemination area (DA)
TOT55TO64	Total population of 55-64 years of age in dissemination area (DA)
OVER65	Total population of 65+ years of age in dissemination area (DA)
ENGLISH	Total population that speaks English only in dissemination area (DA)
IMMIG	Total population that is an immigrant in dissemination area (DA)
UNEMP	Total unemployed population in dissemination area (DA)
HEALTHOCC	Total population working in a health occupation in dissemination area (DA)
UNIVERSITY	Total population with bachelor’s degree or higher in dissemination area (DA)
AVEHHDINC	Average after-tax household income in DA (in $ 100,000)
WORKFORCE	Total working population in dissemination area (DA)
DISTCBD	Distance form dissemination area (DA) centroid to CBD (in km)
ACCPOPXK	Population based accessibility within X km band (beds-hour/1000 people)

2.5 Model Result and Discussion

The first step in the analysis is to estimate a base model, including an over-dispersion factor, that serves both as a benchmark and the starting point for the generation of a spatial filter and final model with over-dispersion factor. This initial model is shown in Table 2.2. As seen in the table, most of the explanatory variables tested are significant at the 95% confidence level except population variables for age groups 15 to 24 and over 65, even after incorporating a relatively large over-dispersion factor of 2.789. Most variables have a positive sign, and thus are associated with increases in the number of donors. The only exception is the variable related to the presence of immigrants in the DA, which displays a negative sign. This is consistent with previous findings by Saberton et al. (2009). A pseudo-R-Squared value, simply the squared correlation coefficient, is calculated to describe how well the predicted number of donors matches the actual number of donors. A value of 0.256 indicates a modest fit. More worryingly, the model shows clear evidence of significant positive spatial autocorrelation with a Moran coefficient of 4.424.

In the research of Saberton et al (2009) it was shown that introducing a spatial filter to the regression model is an effective way to address the issue of residual autocorrelation, and can also help to improve the fit of the model. Accordingly, a spatial filter was generated using the procedure described in the preceding section. The spatial filter was incorporated as one additional independent variable in the Poisson model of donors in Hamilton. The result is the second model shown in Table 2.3. It can be seen in the table that the significance of the variables is improved and age groups 15 to 24 and over 65 have become significant variables. This is likely a consequence of the need to use a smaller over-dispersion factor, as the underlying causes of over-dispersion are more directly addressed.

In this model all three age groups are positively correlated to the number of donors. Normally, it is evident that donation rate decreases when person has become older and young people are more interested to donate blood (Holdershaw et al., 2003; Hollingsworth and Wildman, 2004; Sojka and Sojka, 2003; Veldhuizen et al., 2009; Weidmann et al., 2011). This is supported by the facts that, age group 15 to 24 are highly correlated with the donor rate compared with the elder age group. Reasons behind this behaviour may include the "High School Classroom Learning Session" arranged by CBS under their "Young Blood for Life" program which informed high school students about lifesaving voluntary work like blood donation (Canadian Blood Services, 2011, Canadian Blood Services, 2011). Even the 55 to 64 age group who are seniors have a high positive correlation with number of donors which indicates that they may be attracted by donation centers that operate during their work time (Hollingsworth and Wildman, 2004). The 65+ age group has a positive but smaller coefficient.

Table 2.2: Regression Model Result without Spatial Filtering Approach

VARIABLE	ESTIMATE	p-value
CONSTANT	1.18774	0.0000
TOT15TO24	1.54443	0.1024
TOT55TO64	2.33966	0.0157
OVER65	0.30911	0.3975
IMMIG	-1.46932	0.0000
UNIVERSITY	0.99397	0.0424
AVEHHDINC	0.03557	0.0015
WORKFORCE	1.12251	0.0004
DISTCBD	0.24002	0.0000
ACCPOP3K	0.00245	0.0007
Over-dispersion parameter= 2.789 **Moran's I = 4.424** **Squared R, = 0.256** **n, = 1144**		

The immigration status of a population is another influential variable which has a negative association with donation rate. Many empirical studies have found that blood donation seems to be an unfamiliar behaviour for immigrants (Hollingsworth and Wildman, 2004; Saberton et al., 2009; Saberton, 2010; Weidmann et al., 2011). Few reasons have been identified by Hollingsworth and Wildman (2004) and Saberton et al (2009) regarding the lower blood donation rates. The authors suggested that immigrants may not feel comfortable engaging in voluntary activities of their host country and may be the blood donation agencies may not be catering to immigrants to encourage donation. Furthermore, people from certain regions may be deferred from donating because of the dangers of blood borne diseases in these areas (CBC, 2011). However, despite this situation in Canada, Gillespie and Hillyer (2002) and Murphy et al (2009) both found that, in the US, immigrants are more likely to donate blood for the first time than US born citizens, even with smaller differences between the rate of repeated donation compared to native donors.

Wu et al. (2001) also showed that the rate of donation among immigrants is increasing which causes a substantial decrease in the donation rate of the US population.

According to the final model, the educational background of donors has positive correlation to the number of donors, though this variable was insignificant in the first model. This result is again supported by previous studies which mention that educational background plays a role in motivating blood donation (Boulware et al., 2002; Hollingsworth and Wildman, 2004; Hupfer et al., 2005; Ownby et al., 1999). Gillespie and Hillyer (2002) found that, a large number of first time donors in the US, have at least college or university degree level education. There may be some correlation between University level education and ethnicity. Boulware et al. (2002) also revealed this correlation in their study by giving an example that visible minorities are less willing to donate blood as they are more likely to have a poor education background. Likewise, Saberton et al. (2009) mentioned that policy geared towards marketing and increasing donation motivation works well in the case of highly educated people which makes education an influential factor. Even though there is some baseless fear, altruism works as the main motivator for blood donation which leads the Canadian students to donate blood (Hupfer et al., 2005).

Average household income is another factor that associates positively with number of donors. A higher average income is correlated with a higher number of donors which is similar to the study of Veldhuizen et al. (2009). Higher income tends to relate to volunteerism which causes an increase in donation rates. Conversely, Hollingsworth and

Wildman (2004) and Saberton et al. (2009) found a negative association between income and donation rate, although this only in the case of major metropolitan areas in the latter study. The working population of Hamilton has a greater influence in blood donation which represents their willingness for donation. It is evident that some workplaces host donations for employees which also increase donation (Glynn et al., 2006). In Hamilton most of the blood donation clinics are located at the central part of the city, that means near Central Business District (CBD) and this give the scope to the donors to donate blood when they get free time from their work. Moreover, the positive influence of accessibility to donation clinics also indicates that people can easily move to the donation site which can be another reason for this positive correlation.

Table 2.3: Regression Model Result with Spatial Filtering Approach

VARIABLE	ESTIMATE	p-value
CONSTANT	1.1811	0.0000
TOT15TO24	2.4243	0.0000
TOT55TO64	1.7514	0.0000
OVER65	0.4365	0.0007
IMMIG	-1.4154	0.0000
UNIVERSITY	0.9743	0.0000
AVEHHDINC	0.0316	0.0000
WORKFORCE	0.9743	0.0000
DISTCBD	0.2547	0.0000
ACCPOP3K	0.0020	0.0000
Filter	1.0000	0.0000
Over-dispersion parameter= 2.515 **Moran's I =0.419** **Squared R =0.305** **n =1144**		

Similarly to the work of Saberton et al. (2009), the model makes it possible to assess the effect of accessibility. After testing several distance bands, it was found that the best fit was for accessibility calculations was 3 km. Therefore, this is the variable used in the final model. As seen in the table, accessibility to clinics is a significant and positive factor in relation to number of donors. This supports the thesis that improved access can increase donor turnout. The accessibility landscape by DA can be seen in Figure 2.2.

Recalling that accessibility is a function of bed-hours at clinic sites and population served, it is clear that higher accessibility levels will be found in places where there are well provided clinics and population tends to be low. From Figure 2.2, it can be seen that the highest levels of accessibility are found in the area where there are more donation sites. However, some exceptions can be seen in the middle of the CMA where accessibility exists between 31-60 units (bed-hours/1,000 people). This area contains 136 DAs having a total population 71,317 whereas the surrounding DAs which have accessibility within less than 5 to 10 units contain 218 DAs with 120,817 people. That means this region of the city has smaller population compared to the surrounding DAs, which leads to higher accessibility as accessibility increases with lower population. Moreover, people from this region have opportunity to donate in clinics that are placed in the surrounded region which also increases the accessibility.

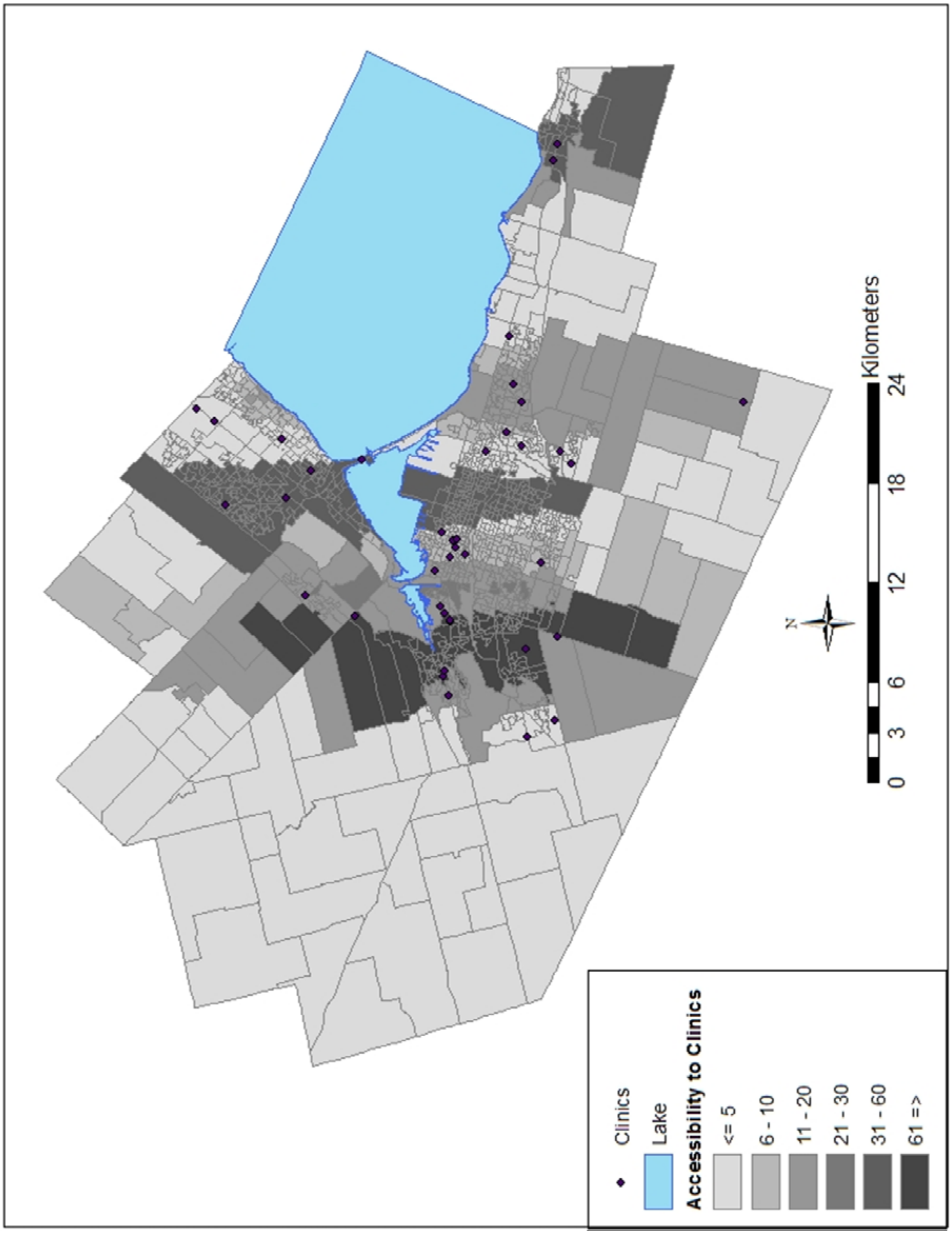

Figure 2.2: Distribution of Accessibility in Hamilton CMA (bed-hour/ 1000 people)

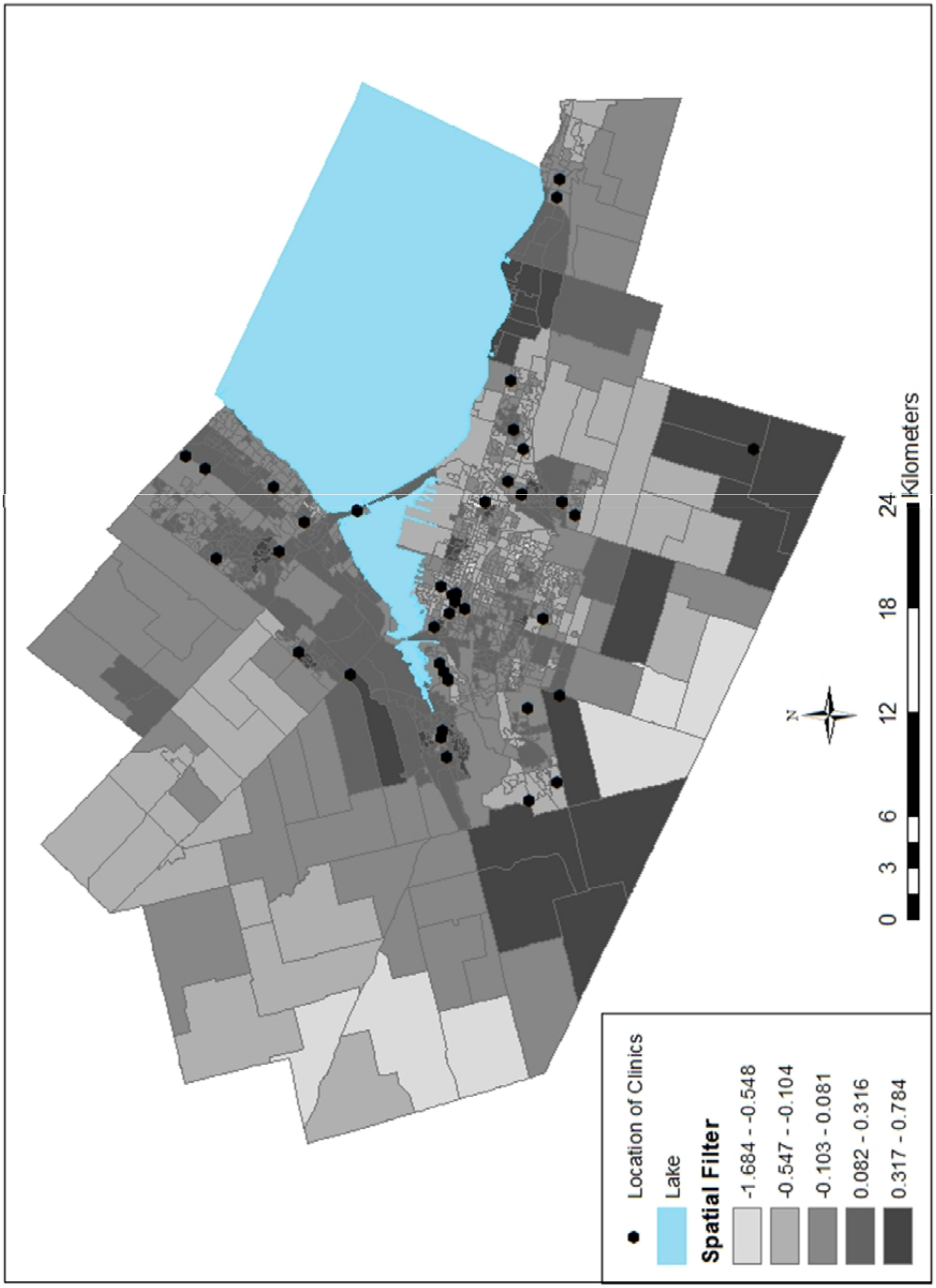

Figure 2.3: Distribution of Model-2 Spatial Filter Hamilton CMA

The last variable in the final model is the spatial filter. This is a surrogate variable that captures omitted but relevant variables that follow a spatial pattern. The objective of the filter is to clean the residuals and is not meaningful per se. In addition to addressing the issue of spatial autocorrelation, the filter helps to improve the fit of the model. As seen in Table 2.3, the model now has a pseudo-R2 of 0.305, a modest increase from the initial model. By introducing the spatial filter variable it has also become possible to reduce the residual autocorrelation from the model which decreases the z-value to 0.419 and increases the significance of some insignificant variables in previous model. The distribution of model 2 can be seen by Figure 2.3. In the second model, the dispersion parameter is also estimated along with a spatial filter and the result shows that over-dispersion is reduced to 2.515. This result supports the fact that autocorrelation has some sort of relation with over-dispersion which makes the value less than the first model value 2.789.

2.6 Conclusion

Blood and blood products are in constant demand due to advances in medical science. In order to ensure the sufficiency of the supply of blood it is important to understand the factors that affect the turnout of donors. Incidentally, it is important to find out the issues which encourage a person to donate blood (Schuber, 1994). In this chapter, an analysis of the socio-economic, demographic, and geographic factors that associate with the number of donors in the Hamilton CMA by DA was reported. Previous research by Saberton et al. (2009) had already pointed at some of these factors, however noting the presence of significant contextual effects and variations between metropolitan areas. Accordingly, the analysis presented here is specific to Hamilton CMA.

This study has been able to confirm some of the findings of Saberton et al. (2009), and refine them for the specific context under study. The analysis is able to identify socio-economic characteristics of donors that correlate with higher donor turnout. Population by age group, education background, work involvement and income are the factors that have noteworthy positive effect on donation whereas immigration has a negative impact. Moreover, apart from these socio-economic factors, two variables are introduced as distance to CBD and accessibility to clinics which explore the distinctive travelling pattern of the residents of Hamilton. These two variables also discover the efficient transit system of Hamilton by their positive significant effect to donation rate. Besides, it showed the use of a spatial filtering method and inclusion of an over-dispersion parameter to solve the problem of spatial autocorrelation and over-dispersion respectively which provides more inferential power to the model parameters.

Findings of this research would help CBS to concentrate on several factors that may support increased donation rates in Hamilton by evaluating donors' behaviour. Immigration is one of the factors that may get more attention from CBS as it has a negative impact on donation. As is the case of every other major Canadian city, Hamilton also has large number of immigrants; CBS may produce new campaigns to incorporate immigrant specific programs. In this case they may also follow the policies applied by US blood donation organization as they show substantial increase in immigrants' participation for blood donation. From this research it is also evident that several current programs organized by CBS are giving a fruitful result. For example- young age group has become significant which may indicate the success of the "High School Classroom Learning Session" program. In addition, the 25 to 54 age group is found an insignificant factor of donation in Hamilton. Therefore, CBS should target policy to make donation easier for this group. Inclusion of accessibility makes the study more evident that the locations of donation sites in Hamilton are accessible to the city people and CBS can acknowledge this result for their further analysis of accessibility to donation center. Nonetheless, more opportunity can be created to increase the supply of blood by establishing more clinics in distant locations from the CBD in Hamilton (Figure 2.2). Launching clinics in the Western part of Hamilton can also enhance the possibility to attract more donors.

The findings of this study may lead to wide range of future research which is explained as follows. As immigration showed a negative impact to donate blood, there is a chance to study donation behaviour more precisely. Gender differences in blood donation can also be an important factor of concern which is not discerned in this study. There is the possibility of a more detailed study about the effect of gender in donation. In case of the spatial filtering process, there is no existence of a filter variable in the real world which makes the removal of residual autocorrelation a controversial question. A solution of this problem is shown in the work of Saberton (2010) where a new model is created including some more detailed variables. His final model not only reduces the impact of the filter variable but also manages autocorrelation more effectively. Hence, there is an opportunity for further research concerning the effect of spatial filters in the model by introducing some new variables which may also describe the donor's behaviour more completely. Besides, data were not available about the trip pattern of donors which is another shortcoming of this research. Research about the travelling pattern of donors may reveal a new dimension about donor's willingness to donate. Nevertheless, this city model of Hamilton is another step for detailed analysis of blood donor behaviour after the city model by Saberton (2010) which discloses the possibility to understand the circumstantial behaviour of blood donors.

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Chapter 3 Designing optimal accessibility landscapes to increase number of donors: A case study of Hamilton CMA

3.1 Introduction

In modern health systems, blood donation is extremely important to ensure that the supply of blood is sufficient to satisfy demand. As it is a volunteer procedure, it is a delicate task to balance the supply and demand of blood. As mentioned in the previous chapter, in Canada, Canadian Blood Services (CBS) is the non-profit charitable organization who works with the blood supply in all provinces and territories except Québec. Along with the monitoring of safety threats, CBS has accountability for ensuring optimal use of blood products, optimizing donor recruitment and management and the effective and efficient delivery of blood products (Canadian Blood Service, 2009).

CBS maintains some basic eligibility requirements for blood donation. Among them the most important are that the donor must be at least 17 years old, must weigh at least 50 kg (110 lb), must not have donated less than 56 days prior and must have good health which also means meeting the haemoglobin (iron) requirements (Canadian Blood Services, 2011). According to CBS, there are multiple reasons for people not to donate blood. For example, individuals may have fear of needles, fear of infection and other diseases or worried that it will hurt, others are too busy with work and do not have time for donation and some people are unclear about donor eligibility. There are some donors who do not return to the system after donating blood for the first time because of lack of a convenient place to donate (Schreiber et al., 2006). Despite all these reasons, there are currently about 12.5 million potential blood donors in Canada. While this is a sufficient donor pool to satisfy current needs, demographic trends, such as a growing aging population, introduce new pressures to increase the pool of donors (Canadian Blood Services, 2011). Statistics show that, in 2009, about 1.3 million Canadians were at least 80 years old; this segment of the population is poised to grow to 3.3 million by 2036 (The Canadian Encyclopedia, 2011). The unprecedented increase in the number of senior citizens may have several effects in the blood supply and demand system (Drackley et al., 2012). Demand for health care will likely increase due to this large ageing population. In turn, this can be expected to result in increasing demand of blood and blood products. Furthermore, many of these older donors, who also happen to be more loyal and donate more frequently (Cimaroli et al., 2012), will begin to lose the ability to donate due to health deferrals (Canadian Blood Services 2011). For a blood service agency, it is important to develop devoted and experienced donors to maintain a safe level of blood supply by having frequent blood donation. As well, it is important to increase and sustain the number of new donors and encourage the existing donors for repeated blood donation (Godin et al., 2007). Optimal allocation of blood donation clinic resources, namely the number of beds and hours available for operation can be a good option to increase the blood donation rate by increasing the ease of access, and therefore, as indicated by the analysis in the preceding chapter, by encouraging potential donors to donate blood.

Allocation of scarce resources in society, like those in the health care system, is a primary ethical concern (Mooney, 1998). Nowadays, health care decision makers are anxious about the scarcity of resources and allocation of resources has become a challenge (Stinnett and Paltiel, 1996). The primary objective of this research is to design optimal accessibility landscapes, by allocating resources (i.e. bed-hours) to clinics in such a way that the number of donors is likely to increase. In this paper, the use of genetic algorithms is demonstrated as a tool for allocating blood donation resources. Genetic algorithm techniques are a suite of methods for globally solving constrained and unconstrained optimization problems that are capable of producing quality solutions in an efficient way (Houck et al., 1995; The MathWorks, Inc., 2011). Genetic algorithms solve optimization problems by using simulated evolution, in other words, by implementing “survival of the fittest strategy” (Houck et al., 1995). In this study clinic resources (number of bed-hours for operation) are allocated to existing clinic sites in the Hamilton CMA, in order to increase the estimated number of individuals that turnout for blood donation. There should be maximization of the total effectiveness of all bed hour units as well as improvement of accessibility to the clinics.

The chapter is organized as follows. Section 2 reviews the literature on optimization of health care resources. Section 3 describes the data used in this study and the study area and Section 4 outlines the methods used, with a focus on optimization and genetic algorithms. Section 5 presents the results of the analysis, and Section 6 draws the conclusion and scope for further research.

3.2 Background

Research regarding blood donation in Canada has become an interesting topic due to the increasing demand for blood by the rapid growth of aging population. Within 30 years, Ontario will potentially face a severe shortage of blood supply because of this aging group (Drackley, 2010). Several donation factors have been identified in the preceding chapter which can affect donor turnout. It was shown in Chapter Two that accessibility plays an important role in blood donation. Since accessibility is found to be a positive and significant factor that influences donor turnout, improving clinic accessibility provides a valuable policy handle in the efforts of CBS to increase the number of donors that participate in the system.

Optimization is the term used to describe the process of identifying the best solution (or one of the best) to a specific issue (Venkataraman, 2009, pp 3). The eminently practical need to allocate a fixed amount of usually scarce resources to health care systems has led to the development of programs and protocols for their optimum use (Stinnett and Paltiel, 1996). The purpose of these programs is to maximize the effectiveness of the health care system. Operations research techniques have been widely used for this purpose and researchers had developed variety of applications for resource allocation, including cost-effectiveness analysis (CEA), linear programming, integer programming, simulation, numerical procedures, optimal control methodologies, non-linear optimization, and heuristic approaches (Brandeau et al., 2004; Hillier and Lieberman, 1993). Among all these methods, Cost-effective Analysis (CEA) has often been used for health care resource allocation (Brandeau et al., 2003).

Stinnett and Paltiel (1996) showed that a mixed integer programming framework can be used for effective allocation of health care resources. They developed mixed integer programming as a combination of CEA (cost effective analysis) and pure integer programming by which they tried to maximize benefit (Stinnett and Paltiel, 1996). Several works on linear programming for allocation of health resources were developed by van Zon and Kommer (1999) and Kaplan and Pollack (1998). Both of these teams adopted a dynamic programming approach, but in their paper, Kaplan and Pollack (1998) were concerned about budget constraints and developed a model to allocate HIV prevention resources whereas the other authors promoted a model of patient-flow with resource allocation. The results of van Zon and Kommer (1999) showed that availability of resources can have a diverse effect on growth of population over time and over different health state and minimizing waiting time can ensure optimum use of health care resource.

Genetic algorithms (GA) are a suite of techniques used in global optimization problems that are inspired by evolutionary concepts. Global optimization techniques are designed to be robust to local minima, and are able to escape corners and other difficult spots that would pose problems to other approaches. According to Houck et al. (1995) genetic algorithms can give the best result by assessing a relatively small number of functions. Many researchers from various sectors were attracted to this method of solving optimization problems. For instance, Yang et al. (1999) worked with the reliability allocation of a nuclear power plant considering the minimum cost of plant. Another multiple-choice problem was discussed by Aickelin (1999) in his study. One of the problems he solved was allocation of shops in a shopping mall where the researcher used the genetic algorithm for maximization of income.

In the specific case of health care systems, there are also several examples of applications. Houck et al. (1995) showed the use of the genetic algorithm in MATLAB by discussing its method of solving problems, forming an objective function through the use of operators and finally computation of algorithms by MATLAB toolbox. Human resource allocation is another field of study in optimization with which Darvish and Vaezi (2005) have worked. After considering the cost of allocation and capacity of hospital they used the genetic algorithm to complete the optimization procedure and obtained a result indicating that optimum allocation of hospital staff can reduce cost and enhance efficiency (Darvish and Vaezi, 2005). Genetic algorithms can also be used to build mobility management models of healthcare for optimum use of network infrastructure, as shown by Khanbary and Vidyatri (2010) with their model for pervasive healthcare. The purpose of this model was to serve the maximum number of patients by controlling the movement of doctors at hospital nodes and thus minimizing service time. Vidyarthi et al. (2003, 1997) and Tripathi et al. (2006) have also worked with task allocation problems (Khanbary and Vidyatri, 2010). Though all these previous works showed diversified application of the genetic algorithm, our present work will give guideline for a more specific model of resource allocation.

3.3 Data

The data used in this paper are the same as described in Chapter Two (Section 2.4); the Canadian Blood Service National dataset for 2008 and Clinic dataset were used. These two datasets are utilized to obtain the location information of Hamilton DAs and blood donation sites in Hamilton CMA. The only difference is that, instead of latitudes and longitudes of Hamilton DAs and Clinic location, projected X and Y coordinates from NAD1983are used. Apart from these data, the model developed in Chapter Two is also included here which contains the value of coefficients from the log linear method. Those variables which were significant at $p<0.05$ including "Filter" variable are incorporated in this study. All variables were previously defined in Table 2.1.

The results of the analysis in Chapter Two indicate that donor turnout varies with different age group. As per the results of the model, four age-groups are considered here. The first age-cohort contained people between the ages of 15 to 24 who are termed as 'school-aged' donors. The second age group was from the age of 25 to 54 who are named as 'working-age donors' and have less time to donate. Individual having age of 55 to 64 are defined as 'pre-retirement group' and people having age of 65 and more are considered as the fourth age group. The latter group is comprised of seniors who are the major recipient of blood supply (Drackley et al., 2012). A total of 1,144 DAs of Hamilton CMA are incorporated in this dataset.

As mentioned previously, the clinic dataset contains the location of clinics, number of bed and total service hour available for all the 12 months of a year for each clinic. The data set comprises information from 39 unique clinic sites in the Hamilton CMA.

3.4 Methodology

3.4.1 Genetic algorithms

Genetic algorithms (GA) is an approach for evolutionary computing useful basis for optimization problems (Venkataraman, 2009). The principles of evolution and natural genetics are the basis of this technique (Khanbary and Vidyatri, 2010). Genetic algorithms were first used by John Holland and his students in 1970, but evolutionary computation was introduced before that (Aickelin, 1999). In the late 1980s GA began to be used as a tool for optimization. In the mid-1990s the process underwent serious development and currently this technique has become familiar in the field of optimization (Venkataraman, 2009).

Generating an initial population of solutions is the starting point of the genetic algorithm. This initial population is developed by introducing a range of random variations in the parameters of the solution. Subsequently, various operations, such as selection, crossover, and mutation, are performed in order to evolve the initial population information. At each step in the process, the fitness of each individual solution can be calculated by all these genetic operators and are included as the basis of probabilistic calculation of next generation population. GA works based on the principle of survival of fittest, whereby individuals having high fitness will tend to survive and individuals with low fitness will tend to be removed (Yang et al., 1999). Unlike natural selection, in this case evolution is directed towards the improvement of a pre-defined objective function. As mentioned above, GA introduces a degree of randomness in the algorithm; therefore it is capable of generating a range of solutions to the same problem. Today, GA is applied in different sectors in different ways; however, here it is used for the "optimization of a numerical function" as a problem of maximizing the number of blood donors (Burns Statistics, 2008).

3.4.2 Usefulness of GA

There are some specific situations where GA is useful. For example, if the problem has an uneven or "bumpy" objective function, GA is one of the best methods of optimization for this problem. In this study, the objective function is also not smooth and for this reason it is not recommended to use a deterministic, derivative-based algorithm. Therefore, GA is the right choice to solve this problem (Burns Statistics, 2008).

3.4.3 Global Optimization Tool

According to the MATLAB Global Optimization (GO) toolbox user guide- "Optimization is the process of finding the point that minimizes a function" (The MathWorks, Inc., 2011 pp 1-12). This minimum point may be local or global. As the definition of global minimum point they said- "A global minimum is a point where the function value is smaller than or equal to the value at all other feasible points" (The

MathWorks, Inc., 2011 pp 1-12). To find a local optimum, the optimization toolbox is used as it is designed to search one basin of attraction whereas the global optimization toolbox is the best to search more than one basins of attraction. The GO user guide gives the definition of a basin of attraction for steepest descent as "the set of initial values leading to the same local minimum" (The MathWorks, Inc., 2011 pp 1-13). However, GA contains a set of starting points and identifies the best point by iteration. The ability to examine several basins facilitates global optimization.

In this GO toolbox the user can specify the fitness function (objective function), number of independent variables and the constraints as a text file (Solomatine, 1998). After running the algorithm, the current iteration field shows the objective function value. The plot function option display plots which give indication about the performance of the genetic algorithm (The MathWorks, Inc., 2011).

3.4.4 Problem to be solved

In this paper the resource allocation model is designed as a genetic algorithm model illustrated by the following figure.

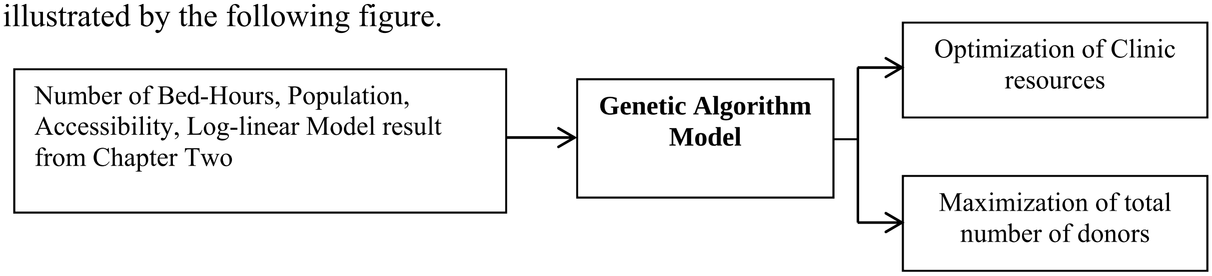

Figure 3.1: Modeling by genetic algorithm (Darvish and Vaezi, 2005)

In this model the resource to be allocated is bed-hours of operation, subject to a total capacity constraint. Bed-hours of operation are allocated using minimum indivisible units, to existing clinic sites. The objective function is total number of donors, which depends on accessibility and therefore the allocation of resources to clinics. Finally, with the help of all parameters (accessibility, selected socio-economic variable coefficient, total population by different age group and clinic bed hours) the objective function is developed and the model is run by the genetic algorithm technique, and as a result the optimal distribution of resources is obtained. Thus, the problem to be solved by this research is to optimize the fixed amount of resources to maximize the total number of donors served by these clinics.

3.4.5 Defining the Objective Function

To define the objective function, at first it is needed to describe all the attributes. Number of beds and hours of operation of donation clinics are two important resources which can improve the blood donation rate. In order to maximize the total number of donors, these resources should be considered in the objective function along with attributes like accessibility and socio-economic factors. A total of 18,370 bed hours are available for use in the Hamilton CMA.

Accessibility is the attribute by which it is possible to detect the level of service of a blood donation clinic. In this study, optimal accessibility is calculated with the equation 2.4 and 2.5 from Chapter Two following the two-step floating catchment area method. Other attributes that should be considered in objective function are the socio-economic variables of DAs. To get the effect of socio-economic variables on donation rate, the same data from Chapter Two is used. On that model the co-efficient of the generalized linear model is calculated by taking donor rate for each DA as a dependent variable.

Finally, the value of β is used in the Poisson regression model with other parameters and the objective function is formed. So, the final objective function for maximizing the total number of donors is defined as,

$$\min_{A(R)} D_0 = -f(X, \beta, A, P(R)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where, $\sum_i R_i \leq K$

$R_i \geq LB\ \forall_i;\ \ R_i \leq UB\ \forall_i$

D= Total number of donors

β = estimated coefficient from previous model (see Table 2.3)

R= Resource vector (Number of bed*Total time of operation in hour at each clinic)

X= matrix of explanatory variables (see Table 2.1)

A= Accessibility to clinics for each Dissemination Area (see Equation 2.5)

P= Population matrix of different age group

K= Capacity constraint: Maximum number of bed-hours (set to 18,370)

LB = Lower bound of resources (minimum 4 bed-hours for smallest clinic)

UB= Upper bound of resources (maximum 6697 bed-hours for largest clinic)

3.5 Model Development and Result

In this research, the genetic algorithm is implemented by the global optimization toolbox. To run the model, two important components are required as inputs: the fitness function and the number of independent variables. For this study the number of independent variables is 39, as there are 39 blood donation clinics. It is necessary to insert the appropriate limiting values which are called "linear inequalities" and "bounds values". Linear inequality constraints are given in the form of $\boldsymbol{A} \cdot \boldsymbol{x} \leq \boldsymbol{b}$. $\boldsymbol{A}$ is a m-by-n matrix, where m is the number of variables with n component. Again, $\boldsymbol{b}$ is an m-component vector (The MathWorks, Inc. 2011). For this study,

$\boldsymbol{A}$= [1 1 1……m]; m= 39

$\boldsymbol{b}$= 18,370; total number of bed-hour available

The value of $\boldsymbol{A}$ indicates the minimum number of resources to distribute to a clinic which is one resource unit (i.e. 1 bed-hour) and $\boldsymbol{b}$ is the total number of bed-hours to allocate.

Value of 'Bounds' means the lower (***LB***) and upper bound (***UB***) of variable. For lower bound the value is given as 4 times of the matrix $\boldsymbol{A}$ and upper bound is mentioned as 6,697 times of the $\boldsymbol{A}$ matrix. The conditions are: each clinic should have a minimum 4 units of bed hours (for the smallest clinic) and a maximum 6,697 units of bed hours (for the largest clinic) which is the highest number of resources that can be distributed. These conditions are given based on the current resource distribution of all blood donation clinics.

Allocating a minimum of 4 bed-hours to each site implies a decision not to close any existing locations where clinics are held. The upper bound is selected so that no clinic can be bigger than the biggest existing clinic. When all these inputs are given, the model is prepared to run.

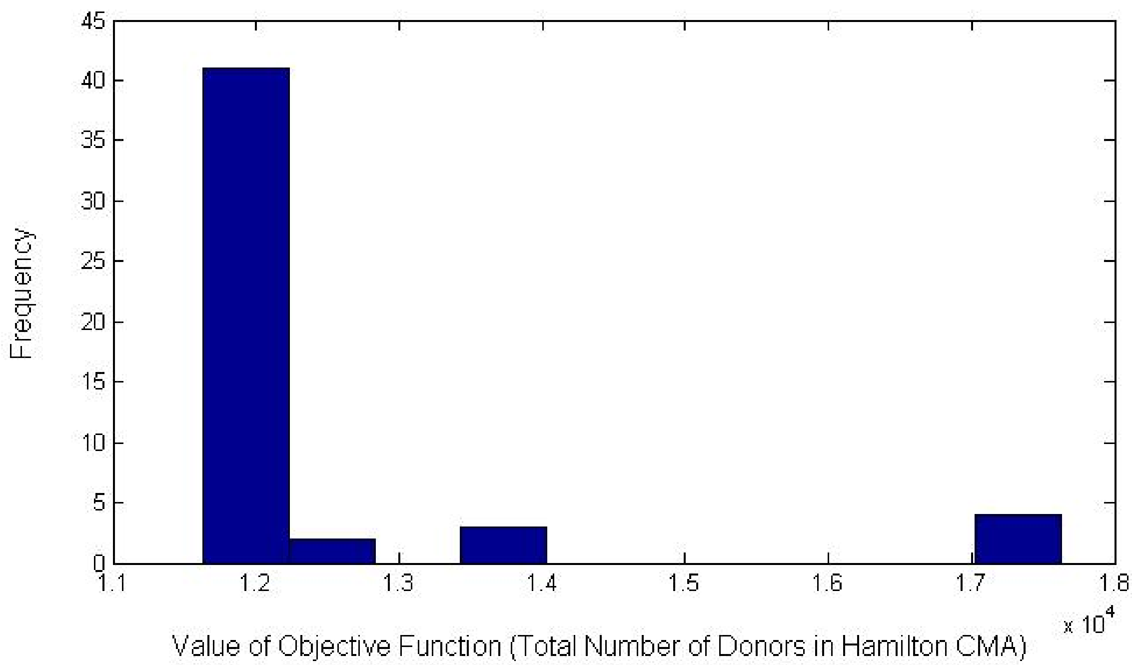

Figure 3.2: Histogram of Objective Function Values

Finally the total number of donor is calculated by MATLAB. Using as an input the data of resources into the objective function, it gives the value of ***f(x)*** and it is possible to obtain the distribution of number of blood donors for each DA. In order to assess the range of possible solutions obtained from the application of Genetic Algorithms, the model was run s=50 times and the solutions were recorded. The histogram in Figure 3.2 shows that the value of the objective function which indicates the total number of donors in all DAs varies from 11,630 to 17,625. Most solutions are in the proximity of 11,700. In comparison, the actual number of donors was 11,588, as calculated from the source data. The number of donors is at the lower end of the range of optimal solutions. Optimal accessibility landscapes can be generated that in every case increase the estimated number of total donors. That means that optimization by the genetic algorithm not only allocates the resources but also increases the number of blood donors by this optimum allocation.

Optimization using Genetic Algorithms has allocated the resources (bed-hours) while retaining the total number of resources as the total number of donors varied. As genetic algorithm gives random results, the highest value is taken as Scenario 2 and the most common value is taken as Scenario 1. The results can be visualized by mapping the allocation of resources and the number of donors. Figure 2.1 shows the actual distribution of total number of donors in all DAs of Hamilton based on the source data. Figures 3.3 and 3.4 show the distribution for Scenarios 1 and 2, respectively.

Here Scenario 1 shows the donors' distribution when total number of donors is 11806 and Scenario 2 depicts total number of 17626 donors which is the highest value resulting from the optimization model. Form Map 1 it can be seen that, number of donors is dispersedly distributed to all DAs and most of the DAs of West Hamilton have less than 7 donors.

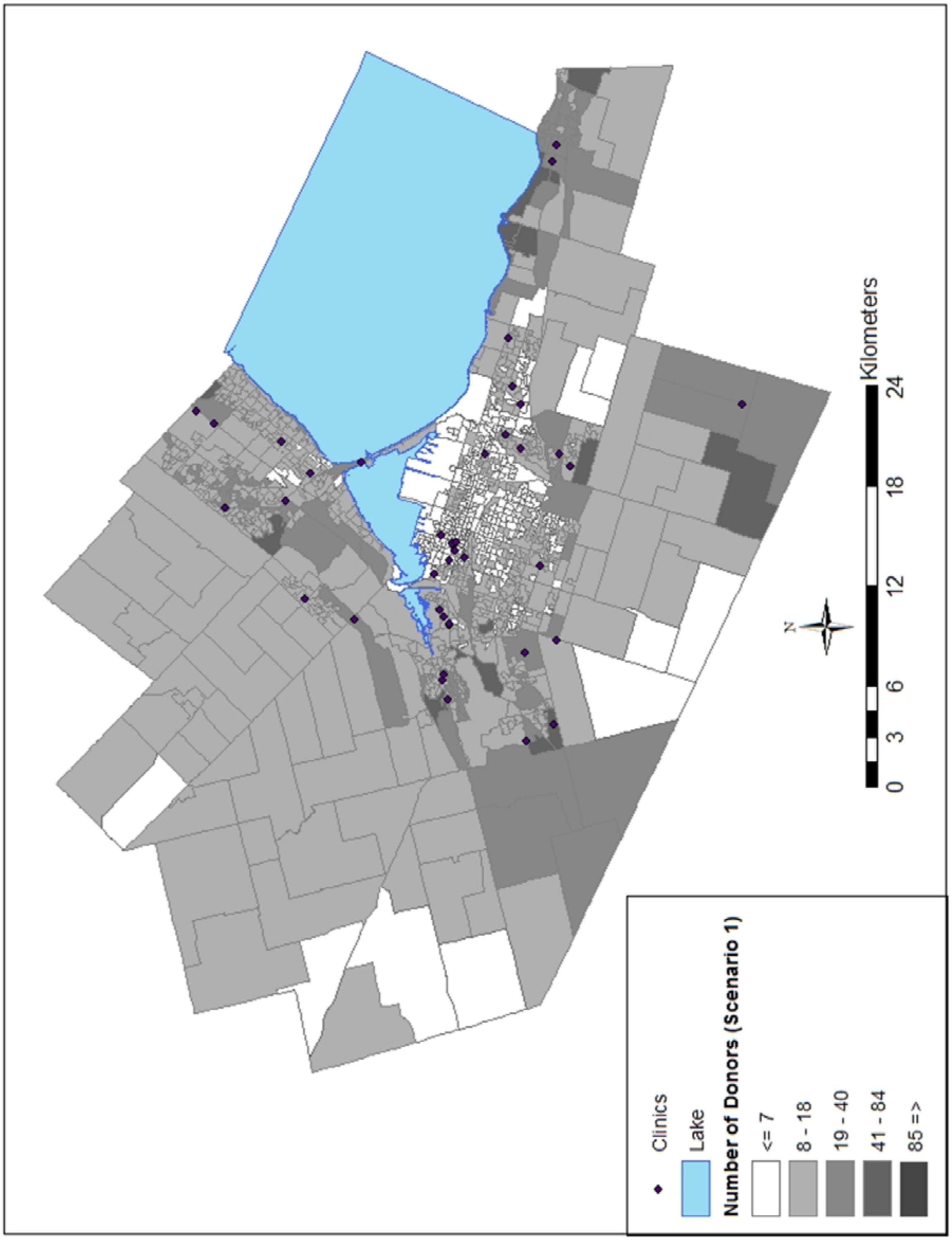

Figure 3.3: Distribution of Donors after Optimization (Scenario 1)

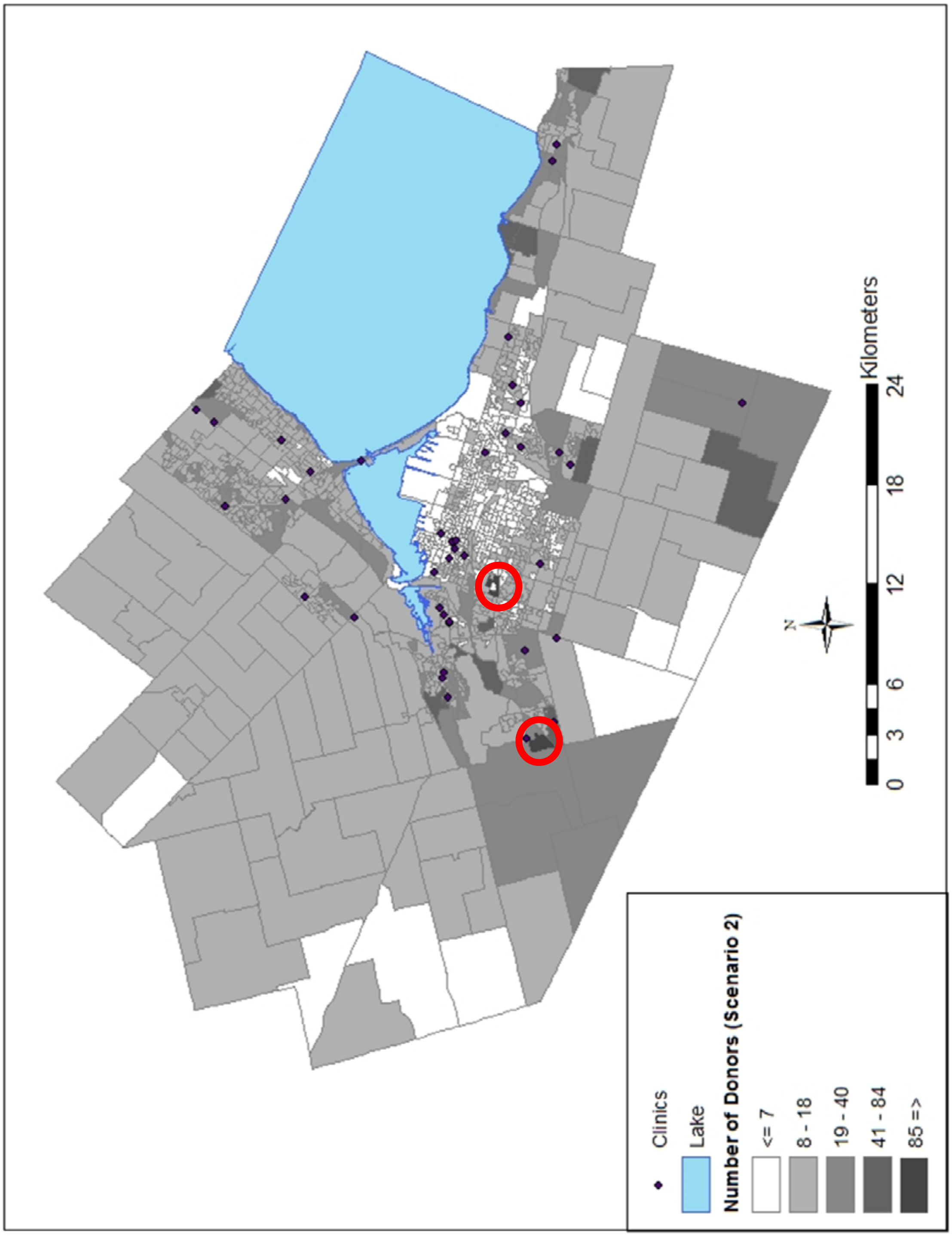

Figure 3.4: Distribution of Donors after Optimization (Scenario 2)

Large changes can be observed in Figures 3.3 and 3.4 with respect to the actual distribution of donors (Figure 2.1). Most DAs are now in the range of 8-18 donors. From Figure 3.3 it is evident that a slight change in resource allocation can makes an improvement in the number of donors. Figure 3.4 does not vary much from Figure 3.3 and shows a similar result except for the red circled region. This region shows great improvement in the number of donors which turns to more than or equal to 85. So it is evident that to get higher improvement in the result, more changes are needed.

Accessibility to donation site also varies with optimization which can be seen from Figure 3.5 and 3.6. Figure 2.2 which indicate that actual distribution of accessibility to clinics (bed-hours/1000 people) is showing that accessibility is higher in DAs which are close to downtown Hamilton. Changes can be seen from Figure 3.5 where accessibility of red circled DAs have improved. Figure 3.6 shows quite a different result by radical improvement of some DAs around downtown rather than improving accessibility of the whole CMA. By this Figure of Scenario 2 it is again clear that this result is more concerned with a broader change in donor distribution as well as accessibility to donation sites.

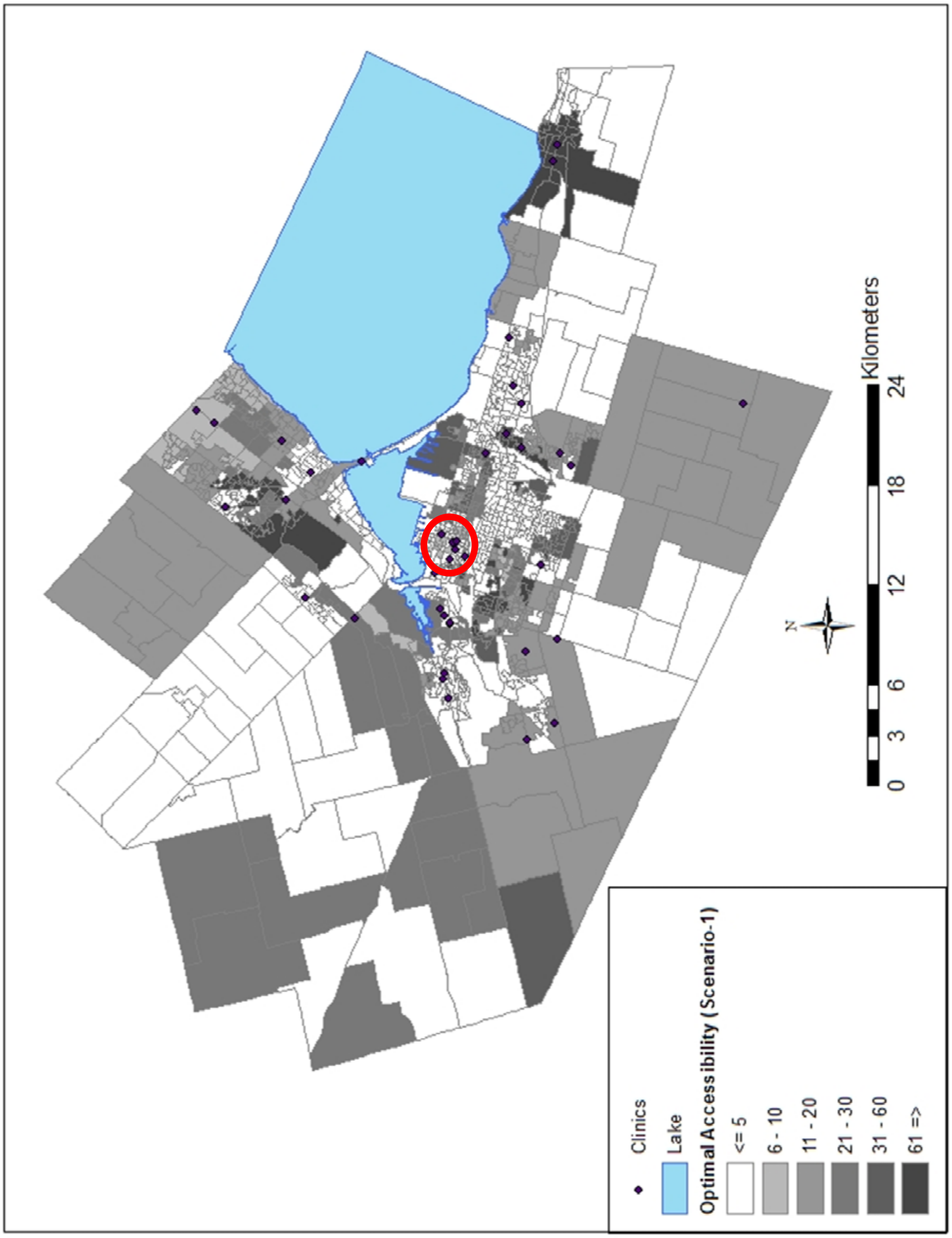

Figure 3.5: Distribution of Optimal Accessibility (Scenario- 1) (bed-hour/ 1000 people)

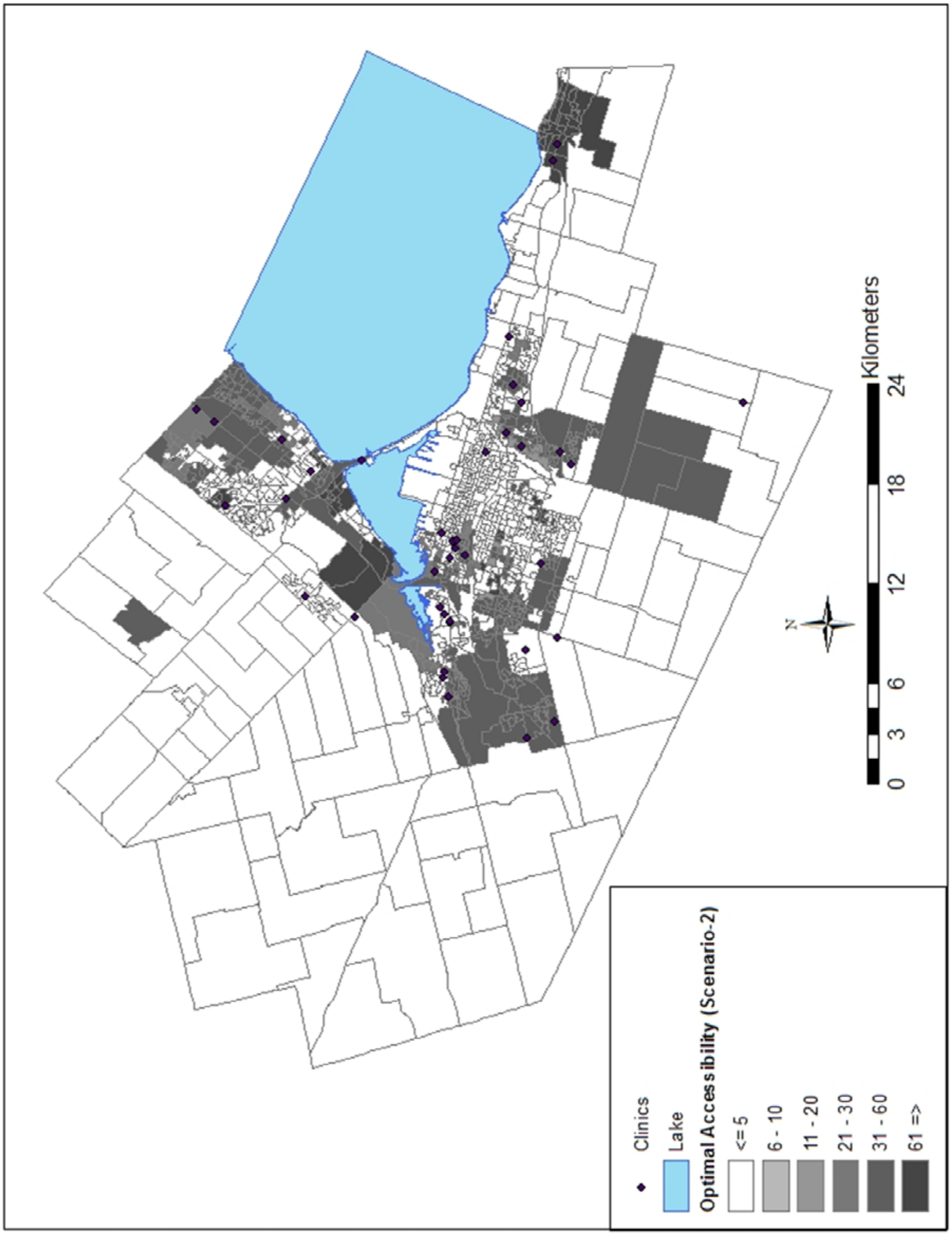

Figure 3.6: Distribution of Optimal Accessibility (Scenario- 2) (bed-hour/ 1000 people)

Although the total number of resources is the same, different allocation patterns of resources can be derived from different model results. Differences in resource allocation can be seen from Figure 3.7.

The above map is showing how resource allocation varies with a different model result. Scenario 1 indicates change in the downtown area while Scenario 2 makes changes in the south-eastern part of Hamilton. From this map it is apparent that Scenario1 gives a smaller change in the model results in a smaller outcome. This Scenario is basically concerned about reducing resources in centrally located clinics and increasing capacity in more distant clinics from CBD. However, Scenario 2 concerned more specifically with clinics in the southern region and increased the allocation in this area.

The result of Scenario1 shows that the total number of donors has increased to around 1.3% while Scenario 2 shows a 52% increase in result. Therefore, the result clearly indicates that by optimum allocation of resources, it is possible to increase the number of blood donors.

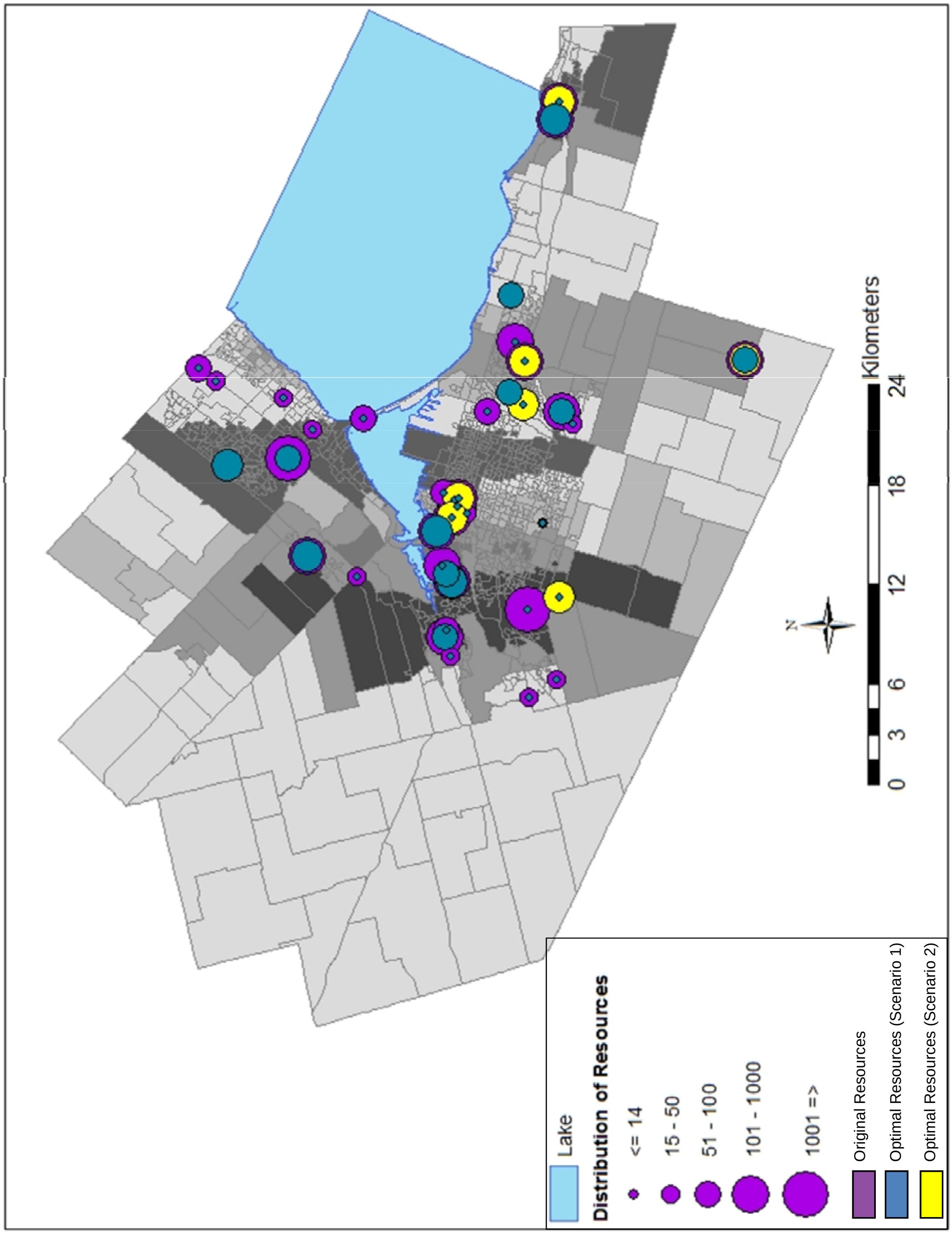

Figure 3.7: Allocation of Resources in Hamilton CMA

3.6 Conclusion

Blood is an indispensable component in contemporary health care, and one that lack any synthetic substitutes. Therefore, it must be obtained from human donors in order to provide life-giving care. In Canada, from the past 12 years Canadian Blood Service (CBS) plays a strong role for blood donation across the country. According to CBS, in 2009-2010 there was a decrease of 0.5% in donation. CBS has developed new strategy to enhance blood donation by raising awareness and involving more donors which allowed the collection of more than one-million units of blood (Canadian Blood Service 2010). Apart from their strategies, it is important to develop policies to increase the blood donation rate. There may be two ways to improve the blood donation condition- first is to increase the number of donors and second is to maintain the repeat donors. The present study is an attempt to help CBS maximize the number of donors by reallocating the resources and exploring the effect of accessibility and other social donor attributes on donor turnout.

In this research a procedure is developed to investigate optimal accessibility scenarios that could increase the number of blood donors. Accessibility is a function of resources allocated to clinics, and provides a policy handle for the blood agency. As seen in this research, accessibility can be changed by reallocating the resources given to blood donation clinics. As well, it is clear that some accessibility landscapes lead to higher numbers of estimated donors. A case study in the Hamilton CMA demonstrates the potential of the optimization procedure. In terms of implementation, an objective function was defined based on the results of the statistical analysis reported in Chapter Two. Optimization was conducted using the global optimization toolbox available in the MATLAB computing environment. Genetic algorithms were selected for the optimization problem, because the approach is better able to deal with a bumpy objective function, and because the range of solutions that results from initial random conditions helps to generate various scenarios for visualization and further exploration. The outcome of the optimization procedure is a vector of resources to be allocated to different clinics, and finally the total number of donors for each DA. The final result indicates that by reallocating a limited amount of resources, it is possible to increase the total number of donors from less than 1% to 52%. Adopting this model can assist decision makers to increase the number of blood donors by dealing with fixed amount of clinic resources.

In this paper we have not evaluated the cost-effectiveness of the clinics and the research was based on the data provided by CBS. Further research should consider the financial impact of resource allocation. Here, the study area is limited to Hamilton CMA, but similar research could be conducted for other metropolitan areas in Canada. This will also give an overview of possible supply of blood for CBS.

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Chapter 4 Conclusion

4.1 Summary of Major Findings

Blood and blood products have become essential for today's health service and the use of these products has increased due to the advancement of health science. A sufficient level of blood supply depends on the balance between blood donation and transfusion. The objective of this study was to understand the socio-economic, demographic, and geographic factors that influence donor turnout, with a particular focus on the role of clinic accessibility. The Hamilton CMA in Canada was taken as the study area and all analysis was conducted at the Dissemination area level with the data provided by Canadian Blood Services and Census Canada.

The regression model in Chapter Two calculated accessibility, included it as an explanatory variable along with socio-economic factors of each DA in Hamilton CMA such as age, income, employment, education, number of immigrants etc. and number of donors in each DA was included as the dependent variable. The result of this study suggests that immigrants are less likely to donate blood. Accessibility, the ease of reaching a clinic from the place of residence, was found to have a positive and significant effect on number of donors. Additionally, this analysis of spatial data made it possible to consider spatial effects with the use of the spatial filter approach along with improving the statistical fit of the model.

In Chapter Three, an optimization model was formulated by developing an objective function of maximization based on a linear model of donation which is a function of accessibility and other socioeconomic factors found significant in Chapter Two. Genetic algorithm was used to develop an optimization model for allocating fixed amount of resources in each clinic depending on the accessibility of each DA. The allocation was done in such a way that the total number of donors is increased from 1% to 52%.

4.2 Study Limitation

There are some limitations associated with both of the studies in this thesis. In Chapter Two, a national data set from Canadian Blood Services was used and for socio-economic data, census data was used. The research would have been more effective if it was possible to obtain detailed socio-economic data for each person who donated as the donor dataset contained limited information about the donors. Again the census data used in this study is from 2006 which may not have properly represented the demographic profile of donors in 2008 according to the donor data provided by CBS. Another limitation associated with Chapter Two is regarding the possibility of error during the conversion of postal code to a geographical spatial unit. Furthermore, it was not possible to get census information for three DAs as they are located within a restricted region and this information is not open to all.

In Chapter Three, the optimization procedure was developed by the Genetic Algorithm where resource allocation was done to all the DAs. This process did not consider locational allocation of blood donation clinics which shows a disparity of distributing donation sites in Hamilton. Dealing with the fixed located clinic is another limitation of this research.

4.3 Future Research

There are varied scopes of future research of this study. The present number of blood donors in Canada is not sufficient to meet the demand and the aging population is emerging as a threat in the future. An increasing size of the Canadian aging population and their use of health services has become a great consideration for policy makers. So, future research can be made by population projections to see how the number of donors changes in future. Forecasting demand and supply of blood can also be done to see how blood demand varies in future due to this change in age structure.

The presence of large immigrant populations is also a significant issue, since lower participation of immigrants in blood donation is also a matter of concern. A detailed study about the donation patterns of immigrants can also be valuable for further research. As there is no detailed socio-economic information associated with CBS data, a web-based survey can be initiated to examine the donation factors more elaborately. In this thesis, no acknowledgement has been made regarding non-donors who are the major concern of blood donation agencies. Studies may be completed to find out the factors that prevent people from donation as well as donor turnout factors. Nevertheless, optimization is done in this study only for Hamilton CMA which can be extended to the whole country to provide policy guidelines to CBS.