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An evaluation of ambulance service performance using a Geographic Information System

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By

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Abstract

The accessibility, distribution and utilization of emergency health care services have a great impact on the effectiveness, efficiency and equity of health service delivery. The impact of these factors is heightened by the fact that ambulance resources, which are an important component of emergency health care, are often insufficient, resulting in performances below those required to respond reliably to emergency calls from demand areas. Measures of realized geographic accessibility of ambulances to call locations are of considerable importance in planning the deployment of this service as they allow planners to account for response time variations, often caused when ambulances are not available at the station closest to a call. However, the current body of related research does not adequately address important spatio-temporal analytical issues that are the result of this variation in response performance, for assessing realized geographic accessibility.

This thesis examines these analytical deficiencies in order to assist emergency health service planners and decision-makers improve accessibility and response performance to target populations. Towards this end, it examines issues related to assessing accessibility for emergency health-care service delivery. It also examines the current use of Geographic Information System (GIS) technology to improve service delivery. An analytic model and GIS design framework is developed in order to provide a conceptual framework for assessing realized geographic accessibility.

Further, it develops statistical and geographical modeling methods and outputs into a GIS-based application, to operationalize the analytical model and GIS design framework. In this context, a design methodology is proposed to develop a user-centred, task-based Graphical User Interface (GUI) to facilitate the navigation of a user through the components of the application in a decision support environment. The research methodology is applied to evaluate the usefulness of the application and its approach with a case study using empirical data from the Ontario Ministry of Health.

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I also wish to take this opportunity to express my gratitude to members of my oral defense examination committee, Professors J. Decker and B. Boots for their thoughtful questions and comments made during the thesis defense. Their expert guidance during the formulation of the thesis topic were instrumental to the development of the thesis.

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Chapter 1

Introduction

Availability of and access to health services are fundamental to the productivity, well-being and development of society. In this context, Smith notes that "health care is perhaps the most basic of all services, for on this may depend whether a newly-born child lives or dies, whether we survive illness or accident and, if we recover, whether we retain full use of essential faculties or suffer permanent handicap" [Smith, 1979, p. 246 in Joseph and Philips, 1984]. Emergency health care services, are especially important as they provide medical attention to those who have the most immediate and critical need. Hence, it is important to evaluate emergency medical service provision to determine whether these services are currently and will in the future meet the needs of society.

The accessibility, distribution and utilisation of emergency health care services have a great impact on the effectiveness, efficiency and equity of health service delivery. The impact of these factors is heightened by the fact that ambulance resources, which are an important component of emergency health care, are often insufficient, resulting in performances below those required to respond reliably to emergency calls from demand areas. When ambulances are not available at the station closest to a call, response time becomes a random phenomenon because ambulances are responding to calls from various locations often while returning to the station. Such response times cause anomalies and considerable variation in ambulance performance. Hence, one of the primary objectives of the provision of emergency ambulance services is to deploy a limited number of ambulances in a way that maximises the number of people or calls that have ambulance services available to respond within a maximum time with stated reliability [ReVelle, 1991]. Measures of realised geographic accessibility of ambulances to call locations are of paramount importance in accounting for response time variations and planning the deployment of this service according to response time standards. These measures are used and response and help plan service deployment based on these historical patterns.

Geographic Information Systems (GIS) technology is beginning to be used in emergency health care service deployment as a planning tool for visualising realised geographic accessibility and assessing ambulance response performance. GIS provides emergency health service planners with the ability to organise, manipulate and map large volumes of spatially referenced call data and to communicate spatial concepts to decision makers responsible for service deployment planning. Using GIS, decision-makers are able to understand geographic patterns and trends in ambulance response performance that would otherwise be unknown.

1.1 Problem Statement

Despite the advantages offered by the use of GIS in assessing the realised geographic accessibility of ambulances to call locations, the current body of research on this topic is limited both in terms of the number of GIS applications developed and in their coverage of three important spatio-temporal dimensions of response time patterns and trends. These dimensions are the result of 'real world' random phenomenon, such as ambulance travel time, that cause anomalies and considerable variation in response performance.

The first dimension of response time patterns and trends is the *independent analysis and visualisation of response time anomalies* and the *'normal' variation in performance levels*. Station deployment decisions that should be based on well-defined areas of normal or consistent performance levels can only be clearly visualised if anomaly response times are treated separately. The second dimension is the *appropriate application of a complementary set of response time performance indicators* to evaluate effectively trends in ambulance performance over space, time and by type of incident. In addition to average response time performance indicators, it is important to evaluate performance in relation to the response time standards of ambulance services and in terms of trends in response performance *help explain performance indicator patterns and trends.* In order to inform better deployment decisions it is important to understand why an ambulance service is not meeting performance standards in a particular area. In many cases, seemingly unusual spatial patterns and trends in performance can be explained by analysing the variation in response times and examining the variables that affect response time in any given area.

This thesis proposes that GIS technology can be applied to all three dimensions of ambulance service assessment to improve our understanding and forward planning of service provision.

1.2 Objectives

The purpose of the research presented in the thesis is to develop and validate a GIS-based application that utilises a robust and easy-to-use methodology, for improving the visualisation and analysis of ambulance service accessibility and the consistency of ambulance response performance over both space and time. The research seeks to address the deficiencies of current approaches reported in the literature and to provide a methodology that can be used by service deployment planners. The specific objectives of the thesis satisfy the above purpose by:

1. Developing a conceptual framework for evaluating and improving emergency health service vehicle response;
2. Developing a valid GIS-based spatio-temporal methodology for the assessment of emergency health service vehicle response;
3. Developing an easy-to-use interface, using commercial GIS software, to assist planners in mapping the spatio-temporal patterns of emergency health service vehicle response;
4. Demonstrating the usefulness of the approach and methods presented in the thesis using empirical data, from the Ontario Ministry of Health, in a case study.

1.3 Case Study Background

The GIS-based application, developed as part of this thesis, uses data from the Ontario Ministry of Health (MOH). This section provides a brief overview of the efforts by the MOH to analyse the spatial and temporal patterns of ambulance performance and how the case study in this thesis has contributed to their efforts.

The MOH Emergency Health Services (EHS) Branch use historical database records of call data to represent the history of demand for and response of ambulance services. Two geographic reports, called 'Geoplot Reports', are manually produced for these purposes (see Appendix A: Sample Geoplot Reports). These reports are manually produced choropleth maps of the total number of calls and average response time for each 1km^2 cell of a Universal Transverse Mercator (UTM) grid (the geographic map projection used in Ontario), to which every emergency call is geo-referenced according to user defined periods of time (dates, day(s) of the week and time of day) and types of calls (e.g. priority code 4 - life threatening).

In October 1995, the EHS GIS Technical Services Unit was requested by EHS management to recommend software and develop an application, to be used by the head office and six regional offices across Ontario, to automate the production of standard and *ad hoc* 'Geoplot Report' thematic maps. A user needs assessment was conducted by the GIS Technical Services Unit to identify system requirements, through two meetings at the MOH in Toronto, with Regional managers. MapInfo Desktop Mapping Software (a personal computer-based GIS with limited spatial analytical and no spatial topology capabilities) and its MapBasic programming language were selected as the main operating and application development environments for this application. The reasons for the selection of this software included ease of use, hardware requirements, cost, thematic mapping capability, quality of output, custom application development environment, and software. The author completed a prototype of this application in January 1996.

The prototype application, named Geoplot Standard Report (GSR), automated the existing manual production of standard Geoplot thematic maps and improved their cartographic content to show demand and the efficiency of ambulance response by location, type of incident and time frame. However, the application was limited to task automation and the same spatio-temporal analysis limitations that hindered the manual Geoplot reports, currently used by the EHS regional offices for decision support. The EHS Branch then solicited, through this thesis, assistance to improve the GSR application. An assessment was conducted to identify system requirements, through a series of consultative meetings with Dr. Bob Sharpe, Dr. Jody Decker, and Dr. Barry Boots of Wilfrid Laurier University; and Dr. Brent Hall of the University of Waterloo. Additional input was then sought from GIS Technical Services Unit staff and EHS Regional office managers.

1.4 Research Organisation

The thesis contains five chapters. Chapter Two places the research within the broader context of the current body of research related to the joint roles of space, time and GIS technology in emergency health service delivery. The topics discussed in this chapter collectively form a conceptual framework, presented in the chapter's final section, for evaluating and improving emergency health service vehicle response. Chapter Three describes the research methodology. This discussion includes the application's data requirements, analytic functionality and interface design. Chapter Four provides a critical evaluation of the methodology by using the application to analyse and visualise life threatening call data supplied by the MOH, to demonstrate the added value the analysis provides to addressing the understanding of spatio-temporal patterns of ambulance performance. Chapter Four then summarises and discusses the implications of the findings this research contributes to the current body of research related to the role of geography and GIS in emergency ambulance service delivery. Chapter Five then outlines directions for future work required to develop further this prototype application in the form of a more comprehensive ambulance service GIS-based Decision Support System (DSS).

Chapter 2

Conceptual Framework

This chapter places the research presented in this thesis within the broader context of the current body of research related to the joint roles of space, time and GIS technology in emergency health service delivery. First, the accessibility issues that influence health-care utilisation and delivery are examined. This discussion considers problems in assessing the accessibility of ambulances to call locations. The review then discusses how GIS software is currently being used to address this problem and how GIS technology can be improved to evaluate accessibility and use this information to improve ambulance service performance. The topics discussed in this chapter collectively form a conceptual framework for evaluating and improving emergency health service vehicle response. This framework is presented and discussed in the final section.

2.1 Accessibility Issues and Health Service Delivery

For several decades geographers have undertaken research examining geographical aspects of health-care. Birkin, Clarke, Clarke and Wilson note [1996] that valuable contributions to 'medical geography' have been made in four broad areas: "spatial epidemiology, the spatial transmission of disease, the link between deprivation and disease, and the relationship between access and utilisation" [Birkin, Clarke, Clarke and Wilson, 1996, p.112].

This thesis is concerned with the fourth area, the relationship between access to and use of health care services. As such it can be broadly categorised as falling within the bounds of medical geography. However, it also has implications for and draws upon related areas in spatial analysis and planning decision support. The thesis is particularly concerned with the problem of evaluating the accessibility and utilisation of ambulance services in order to improve emergency ... evaluate ambulance service provision to determine whether the services are currently and will in the future meet the needs of target populations. For ambulance services to meet these needs it is important to determine whether target populations can be reached in an acceptable time limit, given the current configuration and distribution of services relative to the distribution of demand and intermediate factors such as the transportation network and its attributes (congestion, traffic light, speed etc).

However, one of the fundamental problems with evaluating accessibility in general is that it "can embody multiple dimensions and be influenced by many factors" [Bowerman, 1997]. This reality has made the concept of accessibility difficult to define and open to much debate, especially with respect to emergency health care. In one dimension, Donabedian [1973] differentiates between geographic and social forms of accessibility to health care services. Geographic, or physical accessibility, emphasises the importance of space or distance as a barrier to facilitating access to the health care system. Whereas, social or socio-organisational accessibility emphasises the influence of social, economic, demographic, and health system organisation variables on accessibility [Bowerman, 1997]. In another dimension, Joseph and Philips [1984] differentiate between potential and realised forms of accessibility. Spatial and socio-economic aspects of a health care system measure potential accessibility, whereas realised accessibility or utilisation is the actual use of the system [Bowerman, 1997].

Khan and Bhardwaj [1994] offer a conceptual framework and typology of access to health care made up of the geographic/social dimensions and the potential/realised dimensions of accessibility. This typology distinguishes between four types of accessibility, as illustrated in Figure 2.1. Here, potential geographic, potential social, realised geographic and realised social accessibility are integrated into a simple, yet useful relationship. Potential geographic accessibility examines the spatial configuration of health care services relative to the spatial distribution of target population groups. Potential social accessibility examines the differential availability of health care resources, emphasising the importance of socio-demographic and geographic accessibility examines the spatial configuration of services relative to the spatial distribution of the actual use of the health care system. Realised social accessibility examines the actual use of health care services and the influence of non-spatial factors such as social, economic, demographic and organisational variables. Bowerman [1997] notes that in the Khan and Bhardwaj model "accessibility is moderated (negatively) by barriers and (positively) through facilitators that reflect characteristics of both potential users and the health care system itself" [Bowerman, 1997 p.10]. The availability of services and the characteristics of both the users and the health care system itself have a significant influence on utilisation patterns.

	Spatial	**Social**
Potential	l Potential Spatial Accessibility	ll Potential Social Accessibility
Realised	lll Realised Spatial Accessibility	IV Realised Social Accessibility

Figure 2.1: A typology of access Khan and Bhardwaj [1994]

Bowerman [1997] points out that there is a significant degree of commonality between these dimensions of health care accessibility. Specifically, accessibility is viewed as a property of the interaction between target populations and the services that are available to them. Various geographical factors, socio-economic characteristics of target populations, and organisational characteristics of the service delivery system intervene to either increase or decrease accessibility. Accessibility can represent either the potential for interaction or the actual/realised level of interaction. Hall and Bowerman [1996] offer a definition of geographical accessibility that represents this commonality. They note that:

> difficulty an individual has in obtaining services offered by a service provider. If a sub-area is inaccessible, it is difficult for an individual living there to obtain services; in an accessible region, attaining these services is relatively easy. Thus access is related to the ease of interaction, or the potential for interaction between service providers (supply) and relevant population subgroups or consumers (demand) [Hall and Bowerman, 1996, p.39].

In addition to examining the complexity that the multiple dimensions and many influential factors add to the evaluation of health care accessibility, this thesis is primarily concerned with the problem of evaluating 'realised' geographical accessibility. Realised geographical accessibility is particularly important for evaluating ambulance services relative to most other health care services because ambulance services are an emergency 'delivery system' and not a 'user-attracting system', as is the case with most health care services. In a user-attracting system, such as primary health care (i.e. general practitioners, public health clinics, nurses, and hospital emergency or outpatients) the service provider decides the location of services and in general the user travels to the service of his or her choice as a point of entry into the health care system.

Location can have varying degrees of influence in relation to other factors on a consumer's choice and use behaviour with respect to a particular service. In a user-attracting system, spatial interaction models have been used to estimate patient flows that result from the consumer decision process [Bowerman, 1997]. In contrast, for delivery systems, such as emergency ambulance services, the consumer receives the service, inverting the relationship between provision and use behaviour in user-attracting health services. In this case, the service provider is responsible for both determining the location of services and the provision of services from these locations to consumers. The consumer does not have a decision process regarding which service to use. The difference in the relationship between service providers and service consumers in a 'delivery system' versus a 'user-attracting system' is illustrated in Figure 2.2.

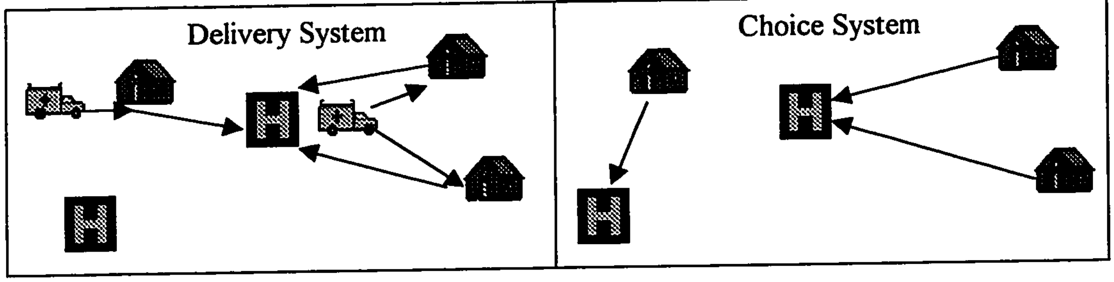


Figure 2.2: A 'delivery system' and a 'user-attracting system'

In the former case, the primary objective of the ambulance service provider is to be able to reach each consumer, in the shortest possible time using the closest available ambulance, while minimising the cost of service deployment. In this context, the evaluation of geographical accessibility is particularly important in evaluating whether or not the objective of minimising the response time of ambulance service providers is being met.

As previously noted, this thesis is concerned with the problem of evaluating realised geographical accessibility as it relates to ambulance response performance. There is a relatively large literature on measuring potential accessibility to health services [Bowerman, 1997]. However, the literature is much more limited and less effective in showing how various measures of realised geographic accessibility are used to examine the spatial configuration of ambulance services relative to their actual use and performance. In fact, several authors [for example Joseph and Philips, 1984 and Bowerman, 1997] have noted weaknesses, in the application of measures of realised accessibility, such as the inability to account for unmet demand, that potential measures account for. However, measures of realised geographic accessibility are needed in emergency health care service provision evaluation research to account for real world operational variables (e.g. non-station ambulance responses) that sometimes cause significant variation in absolute performance levels. These measures are of paramount importance in evaluating the responsiveness of service provision.

geographic accessibility of ambulance services, is to modify the characteristics of the delivery system using a service or facility-oriented approach. This approach uses two main methods to improve accessibility [Bowerman, 1997]. The first method reduces the distance deterrence between ambulance locations and population. The second method optimises the resource allocations at existing ambulance services to increase service capacity where it is most needed. Primary covering location-allocation models have been used to operationalise the first method. A location-allocation model is typically applied to emergency health service planning where resources are available for a fixed number of emergency services. The optimal location of those services and the allocation of population to those services should to be determined so that as many people as possible are served within some travel time standard. Birkin, Clarke, Clarke and Wilson [1996] describe location-allocation models as follows:

> Location-allocation models are concerned with the location of facilities to serve the distribution of population best. Thus, they both locate facilities and allocate individuals to those facilities. Their interest is based on what is commonly known as the equity-efficiency problem. This recognises that facilities need to be located to maximise their accessibility to individuals, yet at the same time that any network of facilities has to be efficient in relation to scarce resources. [Birkin, Clarke, Clarke and Wilson, 1996, p. 78]

The Maximal Covering Location Problem (MCLP) and the MCLP with a Mandatory Closeness Constraint are the two basic forms of location-allocation models designed to solve emergency service location problems. The objective of these models is to serve as many people as possible within a specified time or distance. The first model locates a fixed number of facilities in order to maximise the population covered within a distance or time threshold [ReVelle, 1991]. The constrained model is used to ensure that the target population that is not covered in the distance or time objective will be covered by a second threshold to ensure a reasonable degree of service. These basic models do not account for situations that occur, sometimes frequently, in which no ambulance is available at the closest station to respond to a call within the time or distance threshold.

models in order to help account for the availability of ambulances, resulting from the frequency of calls. In contrast to the primary covering models, these models allow for one or more ambulances to be located at each station. In the more advanced of these models each ambulance is weighted by population or call frequency to determine the number of ambulances required at each location [ReVelle, 1991]. However, RC models do not account for the availability of an ambulance to respond to a call at any given time. ReVelle [1991] notes that these models are "all attempting to come to grips in a deterministic way with what is essentially a random phenomenon: the actual availability of a server (ambulance) to an individual demand area within the time or distance standard" [ReVelle, 1991, p.477].

Probabilistic models were developed to begin to address this problem by measuring the portion of time that an ambulance is out on calls. These models represent only a primitive probabilistic approach because the time measure, or "busy fraction", is modelled deterministically when its elements are random variables and therefore it is itself a random variable [ReVelle, 1991]. Additionally, ReVelle notes that "travel time is a random variable, but not treated as such in these models" [ReVelle, 1991, p.477]. Although, the solution to these problems requires significant improvements to the existing models, both optimisation methods can contribute to the emergency vehicle response planning process by determining the location configuration of facilities to reduce distance deterrence, and by determining the allocation of resources to increase service capacity.

In fact, ReVelle's criticism of these models coincides with the general criticism that several other authors have made regarding these optimisation methods. These criticisms are based on whether the correct planning objectives are being optimised and whether the methods account for all significant aspects of reality. Regarding the first criticism, Bowerman [1997] notes that "the development of appropriate objective functions for the optimisation problems is crucial for the successful application of these models" [Bowerman, 1997, p.114]. In this context, efficiency and equity objectives are the two explains both of these objectives:

> Efficiency objectives measure the ratio of the total aggregate level of services or benefit relative to the level of inputs required to provide the services. When used in an optimisation framework, efficiency objectives preferentially allocate resources so that they have the maximum aggregate benefit. In the case of health care this would allocate the most resources to facilities in areas that have the largest target populations.
>
> Equity measures attempt to evaluate the fairness, impartiality, or equality of the resource distribution and service provision relative to the distribution of the target population. Thus, equity objectives allocate resources preferentially to areas or population groups with below average accessibility in order to reduce the variation in equality of access between areas and population sub-groups. [Bowerman, 1997, p.114-115]

In the case of ambulance services, the focus has traditionally been on maximising public welfare and achieving service provision efficiency through a cost minimisation objective. The objective of the MCLP in its original form was to deploy a limited number of ambulances so that the maximum (not the entire) population has an ambulance initially positioned within the time threshold. The MCLP sought to deploy ambulances as efficiently as possible, given that limited resources could not cover all demand. The probabilistic version of MCLP, named the Maximum Availability Location Problem (MALP), recognises that the ambulance resources are insufficient to have ambulances available with the required reliability for each demand area.

ReVelle notes that the objective of the MALP is "to deploy a limited number of ambulances in a way that maximises the number of people or calls that actually have a server available to respond within the time standard with the stated reliability" [ReVelle, 1991, p.479]. Efficiency, in this context, is reflected in the fact that ambulance services are generally located and resources allocated to service centres and nearby demand regions (also referred to as catchments or zones) that have the greatest potential need for this service. The nearest ambulance centre services each consumer. In fact, using regression analysis, Mayer [1981] showed the existence of a significant negative

Equity, in this context, relates to the minimum acceptable accessibility of individuals within a target population as represented by the time standard or threshold.

The second criticism suggests that the optimisation methods cannot account for every aspect of reality. Models by their nature do not represent all aspects of reality and are therefore meant more to provide information to assist in decision making rather than comprehensively account for all possibilities. In the case of ambulance services there are aspects of reality that can have a significant effect on ambulance performance that cannot be accounted for in optimisation methods, such as location-allocation models. For example, ambulances often respond to calls while returning to the station, after completing another call. In addition, ambulances from neighbouring services respond to calls when call demand exceeds the availability of ambulances from the closest station. In both of these situations ambulances are not responding to calls from the closest station, which is assumed by optimisation models. Moreover, route taken, traffic flow, time of day, season/weather, road conditions and travel restrictions can also contribute to causing response time anomalies and sometimes considerable variation in absolute performance levels. As ReVelle [1991] noted, the actual availability of an ambulance to respond to an individual demand area within a given time threshold is essentially a random phenomenon. In the case of ambulance services, only a realised accessibility measure can assess the significant effect of 'real world' variables on response times, such as, the location of the ambulance for a non-station call response, and a call response from a station in a neighbouring service.

Although realised accessibility measures can assess aspects of 'reality' that potential measures cannot account for, there are two main limitations to the general application of these measures to health care [Joseph and Philips, 1984]. First, it is difficult to obtain a robust and meaningful measure of demand because it is difficult to define the 'need' for health care services and the relationship between demand and need is fuzzy at best. Bradshaw [1972] suggests that four definitions of need apply to the delivery of need'. Felt need is an individual's perceived need for a health care service. A felt need becomes an expressed need when an individual creates a demand for a health care service by using a service. Both types of need rely on an individual to recognise the symptoms of illness and therefore provide only weak measures of a legitimate need for a service. Unlike felt and expressed need, both normative and comparative needs are professionally determined. Normative need is determined for the individual by a health care professional. Comparative need is usually an aggregate expectation of expressed need (that is, demand), determined by administrators, based on the characteristics of a group [Joseph and Philips, 1984]. This assumes that populations with similar characteristics should have similar needs and receive similar services. Joseph and Philips [1984] suggest that to operationalise the concept of need, a realised accessibility measure should be based on a professional judgement of need for the individual (normative need) or group (comparative need).

The demand for ambulance services is recorded for both expressed and normative need by assigning a priority code to rank the urgency and nature of a call on dispatch and again after emergency response professionals have evaluated the patient. Mayer [1981] notes that ambulance call data provide a surrogate measure of need that can be used to assess ambulance performance. The call data are a surrogate measure because they ignore unmet demand when individuals who may need ambulance services do not use them. Mayer [1981] also points out the fact that individuals can use ambulance services unnecessarily and this can also contribute to the surrogate nature of the call data. Regarding this last point, call data can differentiate when an ambulance service has been used unnecessarily, or under a wrong assessment of the urgency of a call, when emergency professionals attempt to assess the nature and urgency of a call before dispatch and then reassess when emergency professionals have evaluated the patient. Therefore, normative need for ambulance services can be defined and used as a surrogate measure of demand.

geographical, socio-economic, and organisational factors that influence the translation of health care need into utilisation. The relative importance of these factors cannot usually be determined by examining utilisation patterns [Bowerman, 1997]. This limitation refers back to the problem of accounting for unmet demand with measures of realised accessibility. Potential measures of accessibility, unlike realised measures, are designed to model the relative importance of these factors and account for unmet demand. However, measures of realised accessibility can be used to determine the relative importance of these factors on the normative need for ambulance services.

Socio-spatial differentiation is an important factor in determining both the use and potential use of ambulance services. Past research has shown that individual emergency calls are not unique random events but that they share common characteristics. Demand for particular types of calls tend to occur in the same types of areas (spatial clustering) and at certain times of the day (temporal clustering). Cadigan and Bugarin [1989], Williams and Shavlik [1979] and Aldrich et al [1971] have used multiple linear regression models to show that the spatio-temporal characteristics of demand can be explained by socio-economic variables (e.g. population density, population age, income), land use variables (e.g. land values) and activity variables (e.g. traffic volume). For example, the clustering of elderly populations in 'retirement communities' can create a greater demand for ambulance services in those areas.

The socio-spatial differentiation of actual demand, not the potential need, for ambulances can be used to assess the corresponding spatial and temporal patterns of realised response times. In either case, the various socio-economic characteristics of the population (e.g. age, sex and income) that influence accessibility have complex inter-relationships that make it difficult to isolate the influence of any one factor. Only the differentiation of the nature and urgency of demand, using priority codes, is fundamental to the assessment of the corresponding spatio-temporal patterns of realised response times and the evaluation of ambulance performance.

The weaknesses of [illegible]

strengths of measures of realised accessibility and vice versa. Unlike measures of potential accessibility, measures of realised accessibility account for response time variation caused when ambulances respond to calls from locations other than the closest station. Unlike measures of realised accessibility, measures of potential accessibility account for unmet demand. The strengths of both measures can be used together to compare the optimal solution to ambulance service location and response performance respectively, determined through measures of potential geographic accessibility, to the existing system, evaluated using measures of realised geographic accessibility. In this way, the evaluation of accessibility is enhanced by modelling the potential for individual use behaviour in relation to a surrogate measure of need that accounts for the variation in actual response times.

The value of any measure of geographical accessibility is dependent upon its operational practicality in addition to its conceptual integrity. Emergency service planners and decision makers need better geographical methods of planning and analysis to manage the practical difficulties of inadequate resources, widely dispersed and unevenly distributed populations, and everyday operational variables (i.e. non-station ambulances response) that affect ambulance service performance. Birkin, Clarke, Clarke and Wilson (1996) note the importance of geographical methods in the planning and management of health-care services:

> These various dimensions of spatial variation in health-care status, utilisation, resource allocation, and organisation have profound implications for the planning and management of health-care services. It is essential that methods of planning and analysis used to determine the form, level and location of service and resource provision reflect the important geographical components underpinning the health-care system. In other words, the planning process should have an explicit geographical focus. [Birkin, Clarke, Clarke and Wilson, 1996, p.125]

The problems faced in undertaking the planning process, in general, are typically ones of information availability and access to tools that will identify and evaluate a range of scenarios. The operationalisation of measures of realised geographic accessibility, in particular, is dependent upon suitable historical call data being available. In whatever form, the address locations, of all the calls that they respond to. With these data, the integration of model-based methods and GIS technology can be used to evaluate a range of scenarios that are inherently geographical in nature. This is discussed in the next section.

2.2 GIS Technology and its use in Emergency Service Response

GIS technology is increasingly used and recognised as an important planning tool for the acquisition, organisation, manipulation, analysis and display of large volumes of spatially referenced data. The success of GIS implementation in the planning field has been particularly notable in areas of spatial data creation, task automation and enhanced map production [Hall and Feick, 1997]. In regards to analysis, Openshaw [1991] has identified spatial pattern description and spatial pattern relationships as the primary spatial analytic needs that GIS is suited to address. He proposes three different application contexts within these areas: "testing a priori hypothesis about patterns and relationships present in spatial data; efficient spatial pattern and relationship description; and, analysis for the purposes of decision support and spatial planning" [Hall, Bowerman and Feick,1997, p.1]. Historically, predictive and explanatory models have lacked the sophisticated means of GIS to organise data and communicate spatial concepts to decision-makers [Feick, 1991]. However, model development provides a stronger, and more flexible framework than GIS offers to transform data into useful information for the decision-making process.

The integration of model-based methods and GIS technology can have substantial benefits for managing and analysing data to produce information relevant to decision making and in simulating the effects of different planning decisions [Feick, 1991]. In this context, GIS technology is particularly significant in its potential to provide a unifying framework to facilitate the development of real-world applications of geographical models and to enhance problem understanding through the visualisation of spatial, map-based data patterns not immediately evident in raw data.

increasing significance because of the spatial nature of their operations and information management requirements. New methods of spatial analysis and associated computer-based integrating technologies, such as GIS, are currently being developed to analyse the quality and timing of emergency service delivery. Practical real world applications of geographical models, based on GIS technology, are having a significant impact on the well being of those benefiting from these services.

GIS are increasingly being used for the purpose of spatial decision support in emergency service provision. In particular, they have been used for fleet management in automated ambulance, fire, and police dispatching, logistics, tracking and routing applications [see for example, Ward, 1994, Barry, 1991, Gamble-Risley, 1997, Bridgehouse, 1993, GIS Newslink, 1993, and GIS Newslink, 1994]. These systems use a variety of associated technologies including Global Positioning Systems (GPS), Automatic Vehicle Location (AVL), Computer-Aided Dispatch (CAD), routing algorithms, electronic maps and in-vehicle navigation systems to provide real time tracking, dispatching and routing of emergency vehicles. Dispatch managers use AVL to track the location of the ambulance fleet through GPS transponders attached to the vehicles and GIS based computer maps at the dispatch facility. Further, GIS is used in CAD to locate the address of an incident on a geocoded street network or property database. GIS is also used in CAD as a decision support mechanism to determine the optimum unit and route to respond to each call. The optimum unit is determined based on each vehicle's status and location in relation to the incident. Then the optimum route and directions to the incident are generated by applying a GIS function that uses a routing algorithm and network topology to find the quickest path along the street network to the incident.

relatively little written on these practical applications in either the academic or popular literature. One of the few cases studies reported, the Emergency Medical Services in Pinellas County, Florida, uses a real time fleet management system located at the Sunstar Communication Centre for emergency response [Badillo, 1993]. This system geocodes and displays on a wall-sized, colour-coded, digital map the address given to the dispatcher by a 911 caller. The digital map also tracks and displays the location, heading, direction, and status of each vehicle in the fleet. The system uses current information on the location, type, and status of each vehicle to select the optimal unit to respond to each call. The communication centre dispatcher then transmits a signal to notify the selected vehicle. The signal triggers the emergency vehicle's on-board computer to display a map of the surrounding area showing the vehicle's current location, the location of the emergency, and the direction to that location. The computer display also shows pertinent information below the map, such as, patient's name, nature of the injury, and whether lights and siren are required. The driver then transmits a signal back to notify the communication centre that the ambulance has taken the call.

In addition to implementations such as the above example, GIS technology is also integrated with automated traffic surveillance and control technology, in intelligent vehicle highway systems, to help manage emergency service operations. An example of this is the Transtar facility. This is a new 'state of the art' facility, in the Houston metropolitan area, that is designed to control traffic congestion and manage emergency response operations. Wiersig [1996 pg. 18] notes that "using this technology, personnel can quickly dispatch emergency response vehicles, more readily anticipate traffic delays, analyse possible trouble areas, and more smoothly divert traffic to alternate routes". The Transtar system uses lane control signals, control over traffic lights, changeable message signs, detectors and video surveillance in conjunction with GIS technology to change traffic patterns based on real-time traffic conditions, and enable emergency vehicles to reach the scene of an accident as quickly as possible.

assess potential geographic accessibility using a system of facility-based spatial performance indicators. These models assess the efficiency and effectiveness of a facility in relation to its catchment population. Birkin, Clarke, Clarke and Wilson [1996, pg. 45] note that "this type of model-based data transformation and spatial representation of performance indicators is of enormous value to many managers and planners: it lets them see data and information in a way they are not accustomed to, and to gain new insights". Some of these GIS systems include location-allocation modelling functionality to determine the optimum configuration of a fixed number of ambulance station and/or standby locations, and the allocation of population to those service locations.

For example, the commercial GIS package ARC/INFO (Environmental Systems Research Institute) was used to locate fire stations in San Diego [Parrot and Stutz, 1991 in Birkin, Clarke, Clarke and Wilson, 1996]. The location-allocation function reads in a set of demand locations and a set of candidate station locations. When applied to solve in ARC/INFO the MCLP, the software determines the locations for a specified number of stations to serve demand most efficiently within one (MCLP unconstrained) or two (MCLP constrained) specified distance or time thresholds. Three output files are written that describe the global statistics for the location-allocation configuration, the statistics for each station, and the allocation of demand to each station. The location-allocation output files contain information such as total weighted distance, average weighted distance, and amount of demand served. The model should be run to test a variety of scenarios and generate a number of alternatives for comparison. Running the location-allocation model several times will then help to assess potential geographic accessibility by enumerating the costs and benefits for each alternative configuration.

GIS applications are sometimes also used to assess realised geographic accessibility as well as potential geographic accessibility. Emergency service organisations, such as the MOH Emergency Health Services (EHS) branch, use GIS response and help plan service deployment based on these historical patterns. The London Ambulance Service (LAS), in the United Kingdom, recently invested in MapInfo desktop mapping software for the same purposes. Their application calculates and maps the number of calls made in each ambulance station's territory. A statistical model is used to calculate how many calls are expected in an area (potential demand) compared with how many calls actually take place (realised demand). This application also analyses ambulance response by mapping the number of calls that exceed the nation-wide target of 14 minutes to reach the location of an emergency. A review of this application concludes that "since the installation of the new control room systems, 95% of the calls were reached within 14 minutes, compared with 70% last year, and the use of MapInfo (software) has helped both demonstrate and reach this dramatic rise in efficiency" [MapWorld, 1997, p.16].

2.3 Integrating GIS technology with Emergency Service Delivery

Despite the advantages offered by the use of GIS in evaluating and improving emergency response performance, neither the MOH's EHS branch nor the LAS applications fully examine the three spatio-temporal dimensions noted earlier of response time patterns and trends in assessing realised geographic accessibility and thereby ambulance performance. These dimensions are the result of 'real world' random phenomenon, such as travel time, that cause anomalies and considerable variation in ambulance performance.

An approach to incorporating these dimensions in a GIS to analyse ambulance performance is illustrated in the analytical model shown in Figure 2.3. This model uses a set of five attributes for call data to assess ambulance response performance. These attributes include the number of calls, the response time for each call, the purpose of each call, the date and time when each call is received, and the station location of the ambulance that responds to a call (this is discussed further in Chapter 3.1 Data Requirements). This basic set of attributes is based on the common call data currently availability can vary considerably between ambulance services in terms of what data are collected and available for analysis. Hence, the intent of the model is to demonstrate how existing ambulance call data can be used more effectively and to facilitate the practical application of this model.

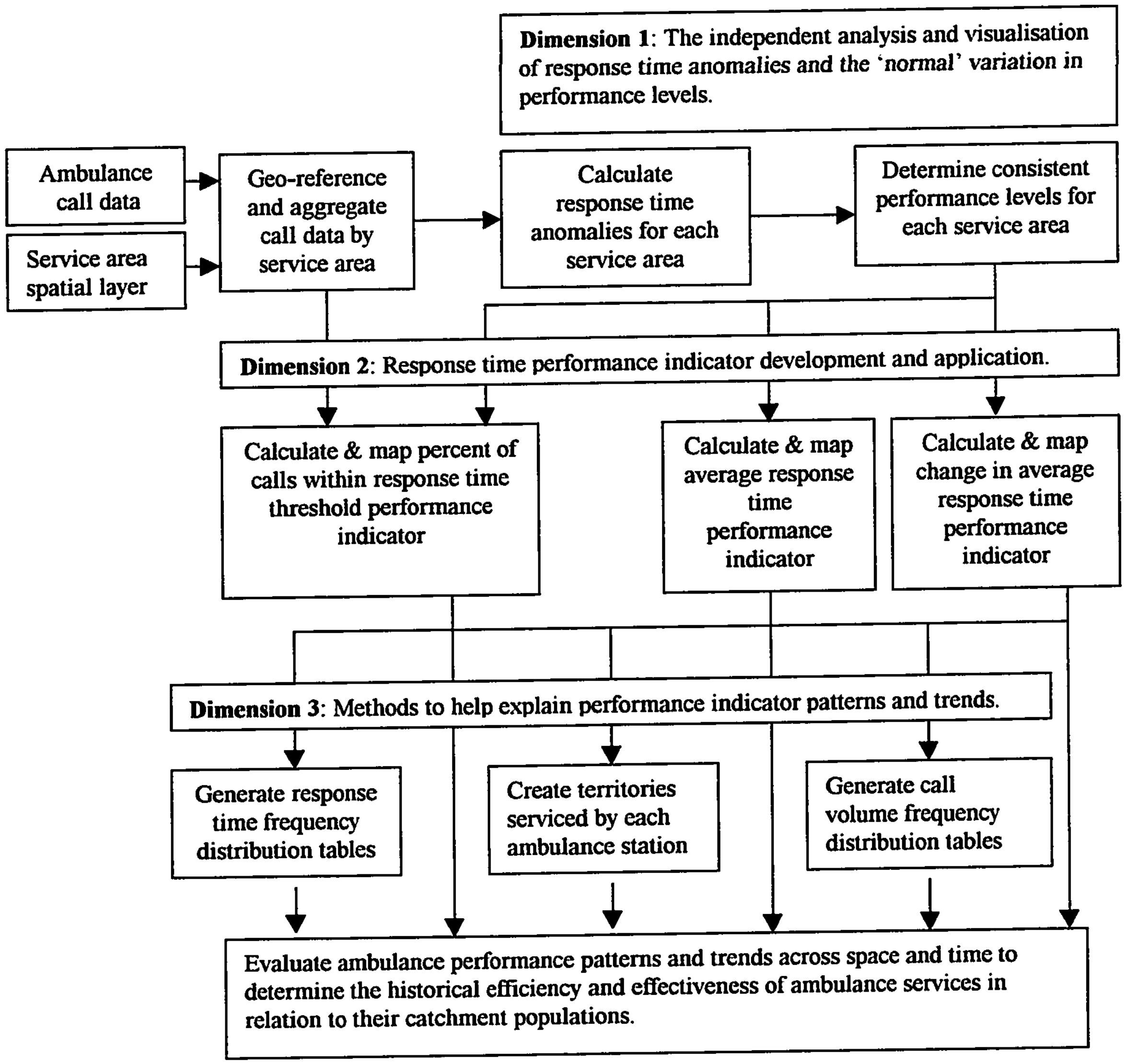


Figure 2.3: An analytical model to assess realised geographic accessibility and ambulance response time performance.

response time anomalies and the 'normal' variation in performance levels. This dimension is important, as the identification of areas where response times need to be improved should be based on well-defined areas of consistent performance levels that can only be clearly visualised if anomaly response times are removed. Moreover, it is important to visualise anomaly response times independently in order to help understand their cause, distribution, statistical significance and to identify their occurrence in the future.

Anomalous response times can be identified statistically and then treated separately from the other response times for calculating response time performance indicators. For example, response times in each service area can be converted into standardised z-scores to determine which cases are within 95 percent statistical probability, assuming a normal distribution, of the values with the greatest variance from the mean. The standardised or z-score shows how many standard deviation units a response time anomaly lies above or below the mean response time for the geographical service area to which it belongs. If x is a response time belonging to a set of response times in the same service area having mean u and the standard deviation σ, then its value in standard units, is expressed as:

$$Z = \frac{x - u}{\sigma} \tag{2.1}$$

This statistic allows cases more than two standard deviation units above the mean to be filtered from all other cases. Approximately five percent of the cases would be filtered based on frequency distributions having the general shape of a normal distribution. However, this methodology is limited by the fact that response times in each service area do not usually closely approximate a normal distribution. They are often positively skewed distributions because of the presence of some relatively high response time values often caused when ambulances respond to a call from a location other than the closest station. Thus, in these cases the number of statistical response time anomalies that will be identified will vary from 5 percent, because of these positively skewed distributions.

of a complementary set of response time performance indicators to evaluate trends in ambulance performance over space, time and by type of incident. Average response time performance indicators should be calculated based on the 'normal' variation in performance levels so that anomaly response times in each service area do not skew the averages and distort the spatial representation of ambulance performance. Moreover, a spatial performance indicator, using the percent of calls within a response time standard, can be used to provide a second effective measure to compare with the average response time indicator's representation of performance. This indicator provides an effective measure for visualising performance in relation to an ambulance service's response time standards. A relative performance indicator can also be used to measure all calls together since it is not affected by outlier (anomaly) response times.

In addition to using these two indicators to identify areas of adequate and inadequate performance for a given time period, it is also important to have a response time indicator that can evaluate trends in ambulance performance over time and by type of incident. Planners should know which of these contexts have improved, constant, or worse responses over time or by type of incident to help identify areas and time periods where ambulance performance needs to be improved.

A performance indicator that shows the statistical change or difference in average response times for two or more time periods or types of calls can provide an effective measure of trends in ambulance performance. Such an indicator can test the hypothesis whether or not response times have, for example, significantly improved after service modification; are better on weekends than week days; are worse during rush hour than the rest of the day; or are better for life-threatening types than less serious types of calls. GIS based spatial analysis can be used to subtract and compare two or more average response times for service areas. In addition, statistical analysis, using one-way analysis of variance (ANOVA) for unequal sample sizes, can be used to determine the probability of a statistical difference in two or more average response times. The probability of a statistical variability because if the standard deviation of the response time observations is known, it is possible to estimate how much the average response times should vary. The averages are compared to test the null hypothesis that the average response times are equal for two or more time periods or types of calls.

Using one-way ANOVA, the P-value or tail probability provides "the probability of getting a value greater than or equal to the observed value of F when the null hypothesis is true" [Freund, 1988, p.390]. It can be loosely interpreted as the degree of belief in the null hypothesis, namely that there is no statistical difference in the average response times 'between treatments'. As the P-value approaches a value of 1 from 0, the calculated F statistic will be smaller and the probability of a difference in average response times decreases (variation among average response times is close to the variation within average response times). The P-value shows what the treatment response times indicate concerning the credibility of a null hypothesis. It does not force a decision about the null hypothesis based on an arbitrarily defined standard level of significance, rather the P-value can be used to determine the probability of a statistical difference in the two (or more) average response times. In addition to being able to deal with one way analysis this statistical model can be expanded to deal with 2 way up to 'n' way analyses where two or more treatments or influences on response times are analysed.

To use analysis of variance, each group of response times must come from randomly sampled populations with probability distributions that are approximately normal with equal variances. Like the identification of anomalous response times using z-scores, this methodology is limited by the fact that responses times often do not closely approximate a normal distribution. However, the identification and separate treatment of anomalous response times using z-scores, enables each group of response times, based on a time period or type of call, to more closely approximate normal distributions by reducing the skewness of positively skewed response time distributions. Norusis notes that "in quite hold" [Norusis, 1988, p. 263].

The third dimension that the existing applications do not address is the use of tools to help explain performance indicator patterns and trends. It is important to understand why an ambulance service is not meeting performance standards in a particular area to help plan corrective measures. In many cases, seemingly unusual spatial patterns and trends in performance can be explained by analysing the variation in response times and the variables that affect response time in any given area. For instance, frequency distribution tables can be generated to compare the frequency of unique response times and the variation in those response times represented by z-scores. The frequency of and variation in response times can help explain why a performance indicator value for one area is different from neighbouring areas.

Further, variables such as the location of an ambulance responding to a call, route taken, traffic flow, time of day, season/weather, and road conditions and restrictions can all cause anomalies and sometimes considerable variation in response times. These variables impact on response times by determining the distance and speed ambulances travel to respond to calls. The location of an ambulance at the time of response and its route taken are particularly important in helping to explain performance indicator patterns and trends because these variables are directly controlled and planned for by ambulance services. The other variables can be manipulated to varying degrees through resource deployment and route planning.

As noted above, information availability can vary considerably between ambulance services in terms of their capacity to identify the location of an ambulance at the time of a call and the route taken in response. At a minimum, the station that the ambulance is based at can be identified to help explain the impact of distance on response times. Using this information, territories 'normally' serviced by each ambulance station can be defined and mapped. Then frequency distribution tables can be generated to compare the volume of

calls answered by each station and the [illegible]
size area within each territory. Using these methods, it is possible to depict the Euclidean (straight-line) distances travelled by ambulances based at each station in relation to their performance levels and in relation to the distances and performance levels of other ambulances. With the integration of appropriate statistical and geographical modelling methods and outputs into GIS-based applications that examine these spatio-temporal dimensions, historical call data can be used to assess more accurately realised geographic accessibility and ambulance response performance.

A GIS-based framework for utilising facility-based spatial performance indicators is illustrated in Figure 2.4. This framework describes the operational GIS design for the analytic model discussed above (Figure 2.3). The framework is made up of the interaction between eleven components, including ambulance call data, spatial data, a graphical user interface, spatial models, GIS, statistical analysis, performance indicator calculations, cartographic presentation, mapping, evaluation, and decision making.

Within this framework, an intuitive and easily navigable graphical user interface (GUI) allows planners to interact with all features of the GIS application environment. The GUI is a conceptual link between a user's interaction with a computer-based application and what it offers them as a decision support tool. It includes all of the considerations that planners require to understand the application and to communicate effectively with it [Medyckyj-Scott and Hearnshaw, 1993]. The GUI is also task-oriented, in that it enables users to generate performance indictor thematic maps by specifying the parameters they need in order to customise individual maps without having to deal with a complex series of functions. Moreover, the GUI is the only part of the application that is visible and with which users interact. Thus, for the emergency health service planner, it is 'the system' and its usability is of crucial importance.

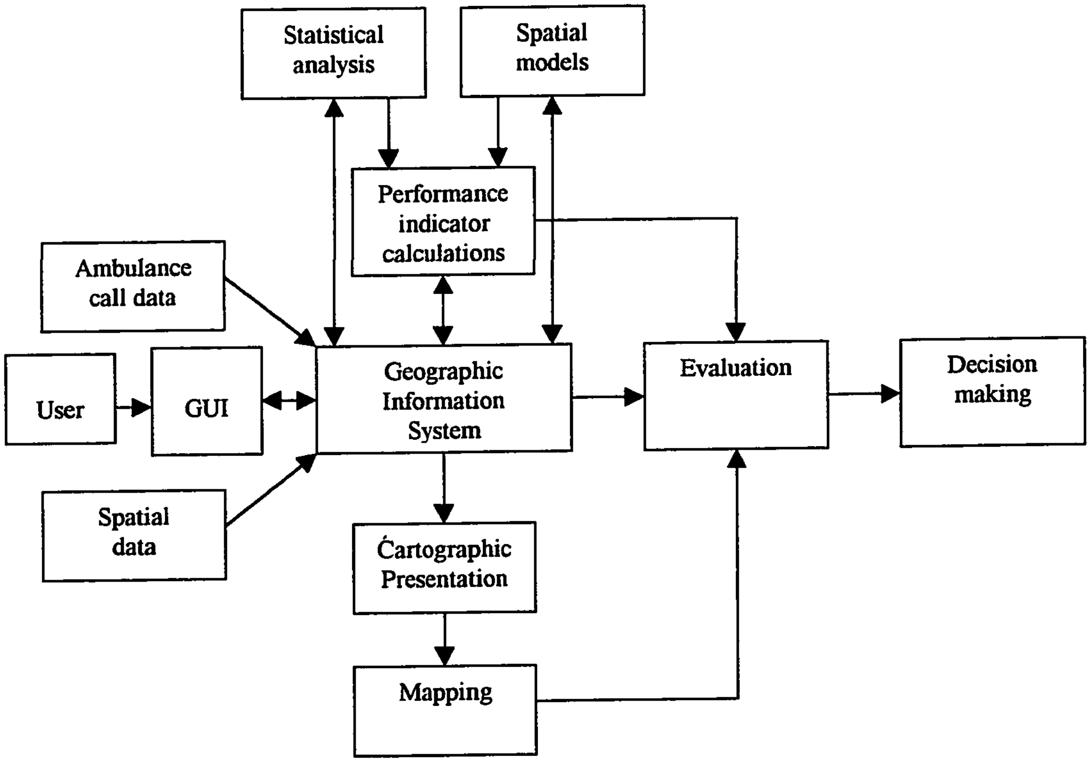


Figure 2.4: A GIS framework to assess realised geographic accessibility.

The application uses the parameters specified in the GUI to assess realised geographic accessibility through the use of appropriate statistical and spatial modelling methods and map outputs in the form of response-based spatial performance indicators. Models are designed for each type of performance indicator as well as the methods used to help explain performance indicator patterns and trends. Statistical analysis and GIS database manipulation, spatial analysis and mapping functionality are programmed to operationalise each model. For example, Structured Query Language (SQL) can be used to manipulate and help transform ambulance call data. SQL is a standard "user friendly" database query language, used in many GIS systems, that also includes features for defining the structure of the data, features for modifying data in a database, and features for specifying security constraints. SQL can be used for many tasks in the system, such as, be used to transform call data into performance indicators, demand indicators, response time variation indicators (e.g. z-scores) and frequency distribution tables. In order to accomplish these tasks, SQL uses aggregate functions to calculate averages and count records as well as data modification requests (e.g. update) to transform data such response times into z-scores using a customised algorithm.

In addition to GIS database manipulation, spatial and statistical analyses are used to transform call data into performance indicators and to generate service territories or catchments. Overlay analysis is a GIS function that spatially compares map features and attributes across two or more map layers. This tool can be used to generate a single change in average response time performance indicator map from two different maps, each showing average response times for two different time periods or for different types of calls. Further, ANOVA can be used to show where the difference in average response times is statistically significant. Feature generalisation is a GIS function that determines contiguous groupings of identically valued map features and attributes to make an underlying pattern more apparent. This tool can be used to generate service territories by combining service areas where a station has historically responded to the majority of calls. The interaction between the model, GUI, data, statistical analysis, and GIS components of the framework operationalises the calculation and mapping of each performance indicator.

Once performance indicators are generated, the cartographic presentation and mapping components of the GIS are used to generate a thematic map output based on both cartographic design specifications of the model and the system user. A thematic map can be generated for both hard copy output and interactive on-screen analysis of performance indicator patterns and trends. A thematic map is made for the sole purpose of communicating a theme or showing statistical information. Thematic mapping, like the spatial analysis methods discussed previously, is a standard function in most GIS software packages.

maps and choropleth (shaded) maps. The model specifies the appropriate type of thematic map, such as choropleth and graduated symbol for performance indicators. The model and GUI specify default options for map labelling, thematic ranges, thematic colours, territory boundary colours and legend specifications in order to provide an appropriate standard design for the visualisation of spatial pattern description and spatial pattern relationships. The GUI can also provide the user with the option to change these defaults in order to optimise the design for the visualisation of a particular scenario. The cartographic presentation and thematic mapping GIS functions enable the clear visualisation and evaluation of underlying patterns in performance indicator maps.

In the evaluation component of the GIS Framework, the spatial performance indicator outputs are used to evaluate a range of scenarios in terms of service provision efficiency and consumer equity in relation to catchment populations. Emergency health care service planners can assess the historical spatial distribution of supply relative to demand. Planners can also determine the underlying patterns of accessibility in relation to emergency service response standards and identify areas with deficient service provision. Moreover, they can determine the time and nature of the calls that have a significant impact on realised geographic accessibility.

Interactive tools from the GUI component are also used in the evaluation component to generate frequency distribution tables to help explain performance indicator patterns and response time anomalies. This allows planners to determine if unsatisfactory accessibility is caused as a result of calls that are responded to by stations other than the closest station. Once planners determine which station has responded to a call, they can determine how pervasive the problem is in terms of the frequency and variation in response times in relation to response time standards.

to improve service provision efficiency and consumer equity. The identification of areas where ambulance response is consistently outside of the response time standard can help decision-makers plan service deployment in order to improve ambulance response in those areas. Using this information, decision-makers can better target when, where, and for what type of calls ambulance response performance should be improved.

2.4 Chapter Summary

This chapter has reviewed a selection of existing research, organised within a conceptual framework, encompassing the joint roles of space, time and GIS technology in assessing ambulance response performance. The problems in assessing the accessibility and utilisation of ambulance services in order to improve service delivery were discussed. Further, the current use of GIS technology to improve service delivery and address these problems was reviewed. An analytic model and GIS design framework were proposed to address analytical deficiencies in existing methodologies for assessing realised geographic accessibility.

As noted previously, measures of realised geographic accessibility are needed in emergency health care service provision evaluation research to account for real world operational variables, such as travel time, that cause anomalies and considerable variation in ambulance performance. Geographic Information Systems (GIS) technology is beginning to be used in emergency health care service deployment as a planning tool for visualising both potential and realised geographic accessibility and assessing ambulance performance. However, the current body of related research is limited both in terms of the number of GIS applications used and in adequately addressing important spatio-temporal dimensions of response time patterns and trends. The next chapter describes the research methodology used to operationalise the analytical model and GIS design framework proposed to address these dimensions.

Methodology

This chapter describes the research methodology used to operationalise the analytical model and GIS design framework discussed in the final section of the last chapter. The research methodology uses data from the MOH to develop a GIS-based emergency ambulance response application. First, the data requirements for the research are examined. This discussion also considers data quality issues and their effects on the reliability of using realised accessibility measures to assess the effectiveness of emergency ambulance response times. The chapter then discusses the operationalisation of the analytical model and GIS design framework. The analytic functionality is described in terms of five processes that are operationalised together to address the three dimensions of the problem presented in the analytic model.

Together, the data requirements and analytic functionality discussions address the second research objective, namely to develop a valid GIS-based spatio-temporal methodology for the assessment of ambulance response performance. The last section examines software design and navigability issues that must be considered in developing an easy-to-use interface to assist health service planners in mapping the spatio-temporal patterns of emergency health service vehicle response. This discussion examines the importance of a well-designed graphical user interface (GUI) for the usability of the GIS design framework. The design methodology and objectives that contribute to usability are then examined to help address the third research objective.

To assess realised geographic accessibility it is necessary to establish a spatial reference framework and assemble historical ambulance call data. The spatial reference framework is required to geo-reference, aggregate, transform and visualise historical call data in the form of an accessibility surface or map. This framework sets the geographic terms of reference for all subsequent accessibility analyses. Once a specific model is applied to the framework, the results can be examined and compared for different population groups and different regions within a study area. Conceptually, individual ambulance call response times, can be combined into aggregate accessibility measures for different types of calls for each geographic region. These data are typically aggregated, as it is not feasible to represent effectively the spatio-temporal distribution of accessibility for individual calls because of the large volumes of call data. Moreover, continuous data, such as ambulance response times, must be aggregated in some way to represent a surface for areas where calls have occurred in order to describe the underlying patterns of accessibility. However, the effects of spatially aggregating individual calls impact on the reliability of using aggregated geographic measures of accessibility to identify areas with deficient emergency service response.

The nature of the spatial reference framework used controls the level of spatial aggregation of call data and the question of whether this allows a valid accessibility surface to be described must be assessed. In this context, Hall and Bowerman [1996] note that when highly aggregated irregularly sized and shaped zones are used as the basis for measurements of geographic accessibility the results and associated accessibility 'surface' may be more an artefact of the aggregation scheme used than a true reflection of the underlying patterns of access. Hence, the use of appropriately sized cells of given spatial resolution in a square or rectangular grid for the reference framework has distinct advantages for representing geographic accessibility over the use of census zones that are irregular in size and shape. Using a grid-cell approach minimises the effect of the Modifiable Areal Unit Problem (MAUP) of summarising accessibility for areas with zero spatial resolution and orientation of the grid cells. Openshaw (1984, p.4) notes that where "census data are collected for essentially non-modifiable entities (people, households) they are reported for arbitrary and modifiable areal units (enumeration districts, wards, local authorities)", which are defined based on "operational requirements of the census, local political considerations, and government administration". Thus, the areal units generally have no direct correspondence to the non-modifiable entities, which in the case of this thesis are ambulance call requests. However, areal units, such as enumeration areas, are related to ambulance call requests because the spatio-temporal characteristics of demand can be partially explained by socio-demographic characteristics of the population and these areas are defined to represent populations of relatively equal size. Thus enumeration areas have the advantage of representing the demand for ambulance services relative to areas that all show some indication of a similar potential need for these services. Although, both enumeration areas and a grid cell approach each provide advantages noted above, a grid cell approach also provides the important advantage of better representing the distances ambulances travel to help explain the underlying patterns of accessibility.

For example, the MOH uses a $1km^2$ UTM grid, as their spatial reference framework, for geo-referencing calls across the Province. The MOH's 1 km^2 grid cells are generally significantly smaller than the smallest census zones (enumeration areas) in Ontario, especially in rural areas where the zones are relatively larger and fewer calls occur. Their smaller and uniform size and shape provide a more accurate and consistent representation of the distances ambulances are travelling in relation to the response time performance indicators for each area. They are also more likely to represent the spatial distribution of calls better than larger and irregularly shaped census zones where no calls may occur and access is by definition zero (i.e. not measured).

Moreover, the imposed boundaries of modifiable areal units, such as census enumeration areas, have a tendency to distort the actual distributional properties of the call data. As a result, subsequent analyses and decisions that depend on the spatial reference contrast, the use of an appropriately sized grid can provide spatially convenient areas that represent the spatial distribution of a user-defined call analysis, providing a stronger basis for decision-making.

Further, unlike modifiable areal units, a grid-cell approach minimises the likelihood of committing the ecological fallacy of relating aggregate accessibility measures to individual calls within the spatial reference framework. Openshaw [1984, p.8] notes that "an ecological fallacy occurs when it is inferred that results based on aggregate zonal (or grouped) data are applied to the individuals who form the zones or groups being studied". Since grid-cells are of uniform size and shape, the effects of aggregating call data are similar, and the relationships of aggregate measures to individual calls are likely to be similar. Therefore, meaningful comparisons of accessibility can be made between grid cells and an accessibility surface can be displayed that reflects the underlying patterns of access. However, to make observations about individual calls within any or all grid cells still faces the risk of committing the ecological fallacy.

Aggregation error in general increases with the variance in the response times being aggregated. Aggregating calls that have similar characteristics and that have an important impact on accessibility, such as life-threatening calls can reduce this error. These calls must be responded to within a given time threshold, to minimise the response time in relation to the closest ambulance station. Spatial aggregation or distance error is caused by the fact that the distances between locations of individual calls and the closest station are not equal to the distance between the corresponding grid cell centroid where calls are measured from and the same station (Figure 3.1). Spatial aggregation error can be reduced by reducing the grid cell size of the spatial reference framework so that the variation in the distance of individual calls aggregated within each grid cell to the closest station is reduced. Aggregating calls after removing response time anomalies within each grid cell can also reduce spatial aggregation error by reducing variance in the response times.

distribution of calls, and the relative location of ambulances responding to the calls.

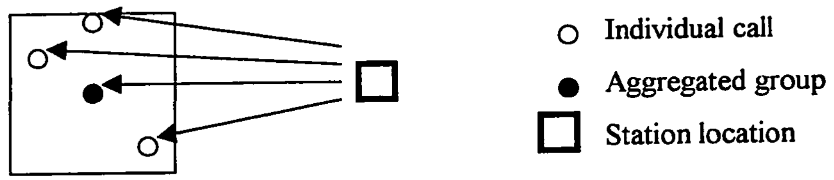


Figure 3.1: Source of spatial aggregation error.

For example, MOH's grid cell approach will likely have less variance in the response times being aggregated than enumeration areas because they are generally smaller. Thus, these grid cells will also have less aggregation error, as well as more consistent levels of aggregation error because they have uniform size and shape. Moreover, the response times in each grid cell will more closely approximate normal distributions because the variation in the response times is less. Moreover, the number of response time anomalies filtered from each grid cell, by removing cases more than two standard deviation units above the mean, are more likely to approximate 5 percent. The advantages of using MOH's grid cell approach instead of enumeration areas can contribute to the effective use of ANOVA because each group of response times should more closely approximate a normal distribution with equal variances.

Since the level of distance error in geographic accessibility measures caused by spatial aggregation is dependent on the particular situation there are no general rules for determining an aggregation scheme which causes the least error in the measurement of the minimum distance [Goodchild, 1979, Fotheringham, 1995, and Francis and Lowe, 1992]. However, Bowerman (1997) notes that it "is possible to derive worst-case error bounds for some common accessibility measures" [Bowerman, 1997, p. 85]. Specifically, Bowerman [1997] calculates worst-case error bounds for minimum distance measures, for

Manhattan distances. However, this approach is only useful in cases where the researcher has the ability to set a grid of user-defined spatial resolution and population is allocated from census zones to grid cells or, alternatively population is aggregated from point call locations to the spatial reference framework grid.

In the data set used in this thesis, a grid of given spatial resolution ($1km^2$) is predefined for all ambulance call data by the MOH and the call data are geo-referenced to the grid cell centroid (Figure 3.1), not to individual point locations. Hence, it is not feasible to determine the aggregation error bounds. Clearly, there is some degree of aggregation error associated with this spatial reference framework. However, this error is likely to be less than would be the case using the smallest modifiable areal units in, for example, the census (enumeration areas) or Canada Post Forward Sortation Areas. Moreover, it is also known that the effects of spatial aggregation error can be further controlled by removing response time anomalies within each grid cell, caused when ambulances are not available at the closest station, in order to minimise the variance in response times [Bowerman, 1997].

The MOH case study provides an example of how to geo-reference, aggregate, transform and visualise historical call data in the form of an accessibility surface or map. In their system, a UTM cell reference number is recorded along with the details of every call so that each call record in the historical database can be geo-referenced to the appropriate $1km^2$ square cell in the UTM grid. The individual call data are therefore automatically aggregated into grid cells and transformed into spatial performance indicators that measure, among other things, response times. These transformed call data can then be dynamically linked as required to a UTM grid map through a relational database 'join', based on the UTM number values stored in both databases. Thematic mapping can then be used to visualise the spatio-temporal surface (patterns and trends) of the response time performance indicator within the UTM grid reference framework.

address for each incoming call could be used to address match the call locations and subsequently geo-reference the call data to the grid. In this case, addresses recorded with every call in the database could also be geo-coded to a street network using common GIS geo-coding functionality. The geo-coded address points that fall within each UTM grid cell could then be selected using a GIS spatial query. Then each selected call record could be updated with the identifier value for the grid cell it is located in. Using either direct UTM cell coding or derived UTM cell coding through an initial street network address matching procedure a revealed emergency service demand surface is produced. This surface comprises grid cells as the spatial unit of analysis and, attached to each grid cell, associated data on the characteristics of each call aggregated to the grid cell level.

Five types of historical call data are used to implement the analytic model and to assess realised geographic accessibility in this research. These data include the number of ambulance calls; the response time for each call (the elapsed time between the receipt of a request for an ambulance and its arrival on the scene); the purpose of each call (the priority code), the date and time when each call is received, and the station location of the ambulance that responded to the call (the station code).

The number of calls that occur in each grid cell provides an indicator of the areas where various levels of demand have occurred (and are likely to occur in the future). This demand information is essential in helping to locate new ambulance services and to minimize response times in areas that have the greatest need for this service. The response time recorded for each call is a basic indicator of the service provision efficiency and consumer equity of ambulance service. Response time data can be transformed into spatial performance indicators to measure, for example, ambulance performance in relation to response time standards and the demand for services. The nature or purpose of a call indicates the type of demand and services required so that ambulance performance can be measured in relation to service standards and demand areas. For example, calls classified as life-threatening generally have a shorter response time requirement than other calls and classified as urgent but not life threatening. The date and time of a call is used to evaluate demand and performance in relation to a specified time frame and also to establish daily trends in receipt of calls. This information can be used to evaluate, for example, whether there are discernible lulls in activity and whether there are repetitive peak times when life threatening health events occur (such as early in the morning or late at night). The station location of an ambulance provides a means of estimating the (straight-line) distance travelled to respond to a call. This information, in addition to being useful in planning future deployment strategies, helps explain ambulance response time anomalies.

The quality of the spatial reference framework and historical call data affect the reliability of using realised geographic accessibility measures to identify areas with deficient emergency service response. Overall, three data quality issues are important to consider. First, as previously discussed in Chapter 2, historical call data inherently provide a surrogate measure of need that ignores unmet demand. Second, errors likely exist in the historical call data that have been generated by occasional mistakes made in the process of recording information and entering it correctly into the database. Third, as previously discussed in this section, the nature of the spatial reference framework used affects the level of spatial aggregation of call data and whether this allows a valid accessibility surface to be described. These data quality issues and the operationalisation of the analytical model and GIS design framework determine the reliability of using realised geographic accessibility measures.

3.2 Analytic Functionality

Several methods must be employed to operationalise the analytical model and GIS design framework with the data described above. These are described in terms of five processes that are operationalised together to address the three dimensions in the analytic model and their relationships. The relationships between the five processes discussed in this section are illustrated in Figure 3.2.

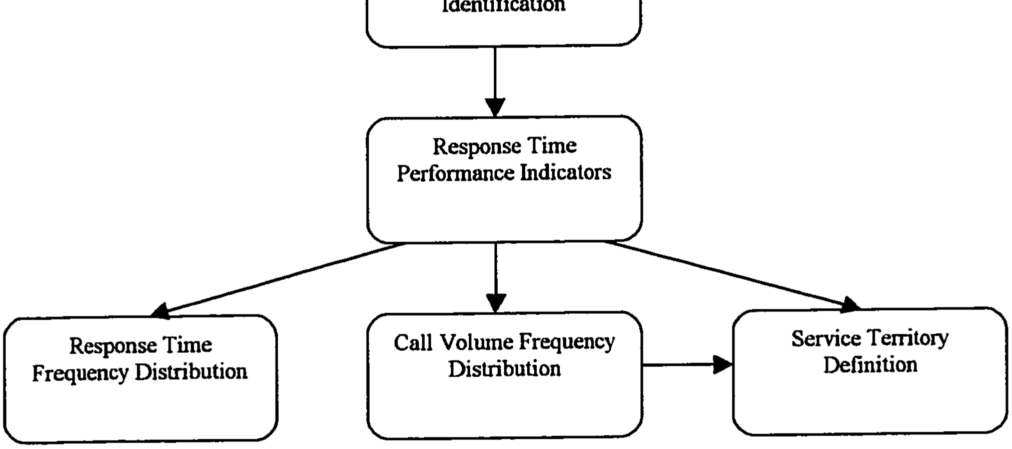


Figure 3.2: Relationship between the five processes used to operationalise the analytical model and GIS design framework

The first process, *Response Time Variation and Anomaly Identification*, addresses the first dimension in Figure 2.1 to enable the appropriate application of response time performance indicators. This process enables calls to be treated as normal or anomalous for the appropriate application of the second process, *Response Time Performance Indicators*. The *Change in Average Response Time Performance Indicator* is the only performance indicator process among the three described in the analytic model (e.g. *Response Time Threshold, Average Response Time* and *Change in Average Response Time*) to be described in detail here as the process used for this indicator is similar to the others.

The *Change in Average Response Time Performance Indicator* process specifically addresses the second dimension, namely to visualise spatio-temporal patterns and trends in ambulance performance by type of incident. The third (*Call Volume Frequency Distribution*), fourth (*Response Time Frequency Distribution*) and fifth (*Service Territory Generation*) processes all address the third dimension in Figure 2.1 and provide complementary methods to help explain performance indicator patterns and trends described through the second process. The *Service Territory Generation* process requires call volume information generated in the *Call Volume Frequency Distribution* process to responded to at least a user-specified proportion of calls. The models used and the steps required to operationalise each of these processes are discussed in the remainder of this chapter.

In order to explain the models and steps used to operationalise Figures 2.3 and 2.4, a series of data flow diagrams are presented. Data flow diagrams (DFD) are graphical representations of a total process in which symbols represent data flow, operations, data stores and outputs. Figure 3.3 outlines the established conventions used for the DFDs included in this thesis.

Description	**Data Flow Item**
Indicates an activity process that transforms the data flowing into the process into the data flowing out.	**Process**
An external entity is the origin or destination of all the information in the system. It represents the users or other client programs of the system.	**External Entity**
A data flow is represented by an arrow. The data flow links activities to other processes, data stores, external entities or outputs. It is labeled with the data flowing along it.	**Data-Item** ▶
A Data Store indicates key spatial or attribute data generated in the process that transforms the data flowing into the process into the data flowing out.	**Data Store**
Hard copy output	**Output**

Figure 3.3: Data flow components (Bowerman, 1993)

3.2.1 Response Time Variation & Anomaly Identification Process

The *Response Time Variation & Anomaly Identification* (RTVAI) process operationalises the first dimension of the analytic model to enable the independent analysis and visualisation of ambulance response time anomalies and the 'normal' variation in ambulance response times. This process helps to assess realised geographic accessibility when response times become random phenomenon in instances when, for example, framework's GUI, model, statistical analysis and GIS components are used to operationalise and automate this process.

The model used in this process defines two types of statistical anomalies, including single calls in a grid cell and response times that have a z-score of $\geq +2.0$. This model provides the user with the options to exclude calls with or without one or both types of anomaly from further analysis. A single call is considered an anomaly in this case because it is a poor indicator of a consistent performance level. A response time is considered an anomaly if it is within five percent of the values with the greatest variance from the mean (two standard deviations).

The DFD for the RTVAI process is illustrated in Figure 3.4. There are four steps in this, namely:

1. Select ambulance call data and set options for handling anomaly response times;
2. Calculate the total number of selected calls in each grid cell;
3. Convert each response time value into standardised z-scores;
4. Select call data, based on the options set in step one, to create a RTVAI table.

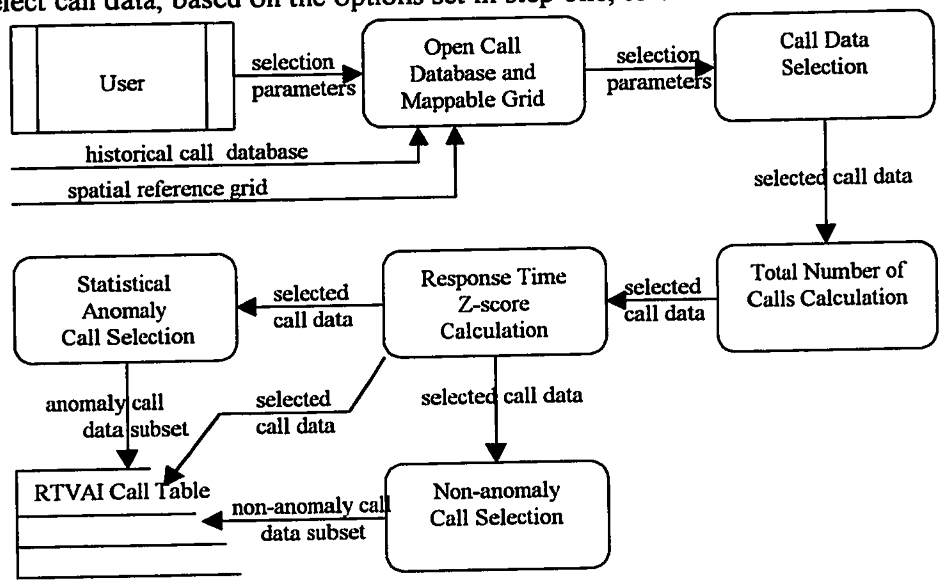


Figure 3.4: RTVAI process data flow

specify, in a dialog, the parameters for the historical call data to be used (e.g. the time frame of calls under consideration, the type of calls, and the station(s) that answered the calls) and the spatial database to use (e.g. the spatial reference grid area for calls). The socio-spatial differentiation of particular types of calls, in particular the nature and urgency of calls, reduces aggregation error and enables ambulance performance to be measured in relation to service standards and demand areas. The GUI component also presents users with several options to specify anomaly response times. These options include the selection of all calls that match the specified parameters (the default option), the selection of calls without one or both types of response time anomalies, or the selection of calls with one or both types of response time anomalies exclusively.

The call data are then selected, using a Structured Query Language (SQL) request, based on the specified required parameters only. For example, it may be of interest to assess life threatening (e.g. priority code 4) calls in the City of Niagara Falls that were responded to during morning rush hour in 1997 using a average response time performance indicator. If 'niagara' is the name of the call database table; including fields named 'return_priority' (the priority code representing the type of call), 'call_received_date' (the date when each call is received), and 'call_received_time' (the time of day when each call is received); and 'temp' is the name of the temporary resulting table, then an SQL request can be expressed as:

```
SELECT *
FROM niagara
WHERE return_priority = 4  And
Weekday(call_received_date) = Any (Mon, Tue, Wen, Thu, Fri) And
call_received_time between  07:00 And  09:00 And                    (3.1)
call_received_date between 01/01/97 And 12/31/97
INTO temp
```

total number of selected calls in each grid cell. The SQL update request is then used to assign each call record in the selected table (e.g. 'temp') with the total number of selected calls in its grid cell. For example, the following SQL statement defines a query that calculates these aggregate values from the results table created in Step 1. If 'utm' is the name of a field containing the grid cell reference for each response time, then the SQL request can be expressed as:

```
SELECT count(utm)                                            (3.2)
FROM temp
GROUP BY utm
```

Step three uses the statistical analysis component of the GIS framework to convert each response time value in each grid cell into standardised z-scores. The SQL update request used in Step 2 is again used to populate each selected call record with the z-score value.

Step four uses the GIS component to select ambulance call data, using an SQL query, based on the options specified in the GUI component for handling anomaly call responses. For example, the following SQL statement defines a query that selects calls without response times that have a z-score of ≥ + 2.0. If 'Z_score' is the name of a field containing the z-scores for each response time (step 3) and 'RTVAI' is the name of the data store and resulting table, then the SQL request can be expressed as:

```
SELECT *
FROM Temp
WHERE Z_score < 2                                            (3.3)
INTO RTVAI
```

RTVAI table represents either all selected calls, selected calls without response time anomalies, or selected calls with response times that represent anomalies. If the user chooses the default option, then the existing selected call data set becomes a RTVAI call table. If the user chooses the option to remove statistical response time anomalies from the selected call data set, then all call records that do not fit the anomaly criteria are selected, based on the z-score and total call values, to create a RTVAI table without the anomalies. Or, if the user chooses the option to map anomalies independent of all other response times, then all call records that meet the anomaly criteria are selected to create a RTVAI table representing calls with anomaly response times. The RTVAI table enables anomaly and non-anomaly calls to be treated independently for the appropriate application of response time performance indicators and assessment of realised geographic accessibility.

3.2.2 Change in Average Response Time Performance Indicator Process

The *Change in Average Response Time Performance Indicator* (CARTPI) process operationalises the second dimension of the analytic model to provide an effective measure of trends in ambulance performance over space, time and by type of incident. This indicator is calculated and thematically mapped to show the change in average response time for two different periods of time or types of calls. In this way, planners can determine where and when socio-spatial differentiation is a significant factor in relation to ambulance performance. All components of the GIS framework are used to operationalise and automate this process.

The actual model used defines the performance indicator as the difference between two average response times and calculates the probability of a statistical difference in the averages using a one-way ANOVA. The difference in average response times is defined as the second average, specified by the second time period or type of call selected in the GUI component, subtracted from the first average, specified by the first time period or type of call selected. Therefore, the first time period or priority code specified is the one the planner wants to test for a better average response time. For example, 1997 and 1990-

response times have improved in 1997 relative to the 1990-1997 time period, as a result of changes in the allocation of ambulance resources among stations in January of 1997. Negative change (e.g. –2 minutes) in average response time minutes shows an improvement in ambulance response in 1997 from 1990-1997. Likewise, positive change (e.g. 2 minutes) in average response time minutes shows a decline in ambulance response time.

Further, the one-way ANOVA test, conducted at the α= 0.05 significance level, for unequal sample sizes, determines the probability that the difference in average response times is statistically different from zero. As the associated probability approaches a value of 1 from 0, the likelihood of a significant difference in average response times decreases (variation between average response times is close to or less than the variation within average response times). The change in average response time values that show a statistically significant difference in average response times are identified and highlighted in this model.

The DFD for the CARTPI process is illustrated in Figure 3.5. There are six steps outlined in the process:

1. Define two or more call tables, based on two different time periods or types of calls;
2. Generate two spatial reference grids with the average response time attribute values calculated for each grid cell;
3. Generate one spatial reference grid with change in average response time attribute values;
4. Conduct ANOVA tests comparing response times for each grid cell of each table and update the table generated in step three with the probability values;
5. Create a choropleth map of the difference in average response time values;
6. Create and overlay a graduated symbol map of probabilities that show a significant difference in average response times, at the 0.05 significance level.

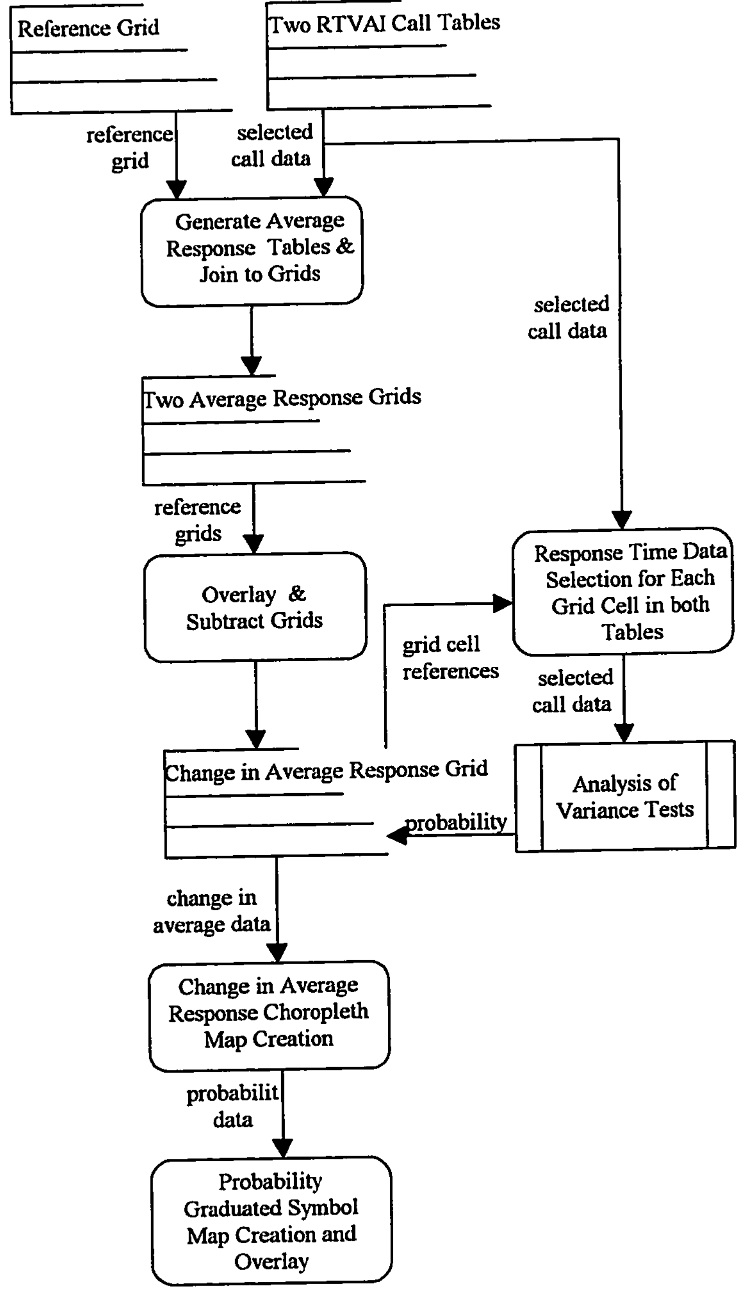


Figure 3.5: CARTPI process data flow

specify one set of parameters to select calls, except for specifying a second time period (e.g. date, days of the week, or time of the day) or type of call (e.g. MOH priority codes) to differentiate and compare them. The RTVAI process, discussed previously, is then used to create two or more ambulance response tables based on the specified parameters, without response time anomalies. As noted earlier, removing anomalies that skew the averages can make a more reliable comparison of average response times. Although these cases are flagged and excluded from the statistical analysis, they remain available so they can be examined to establish any trends they may offer insight into.

Step two uses the GIS component of the GIS framework to generate two spatial reference grids with the average response time attribute values assigned to each grid cell. Two new tables are generated from the two or more RTVAI call tables using a SQL average aggregate function to calculate average response time for each grid cell. The SQL average aggregate function aggregates RTVAI table records based on unique grid cell reference values and calculates the average response time for all the response times having the same unique grid cell reference. Each of these tables is joined to a copy of the spatial reference grid using a join operation, based on a common or key grid cell reference field in each table. If 'RVTAI' is the name of a RVTAI call table; including fields named 'response' (the response times), and 'utm' (the grid cell reference for each response time), and 'temp' is the name of the temporary resulting table, then an SQL request can be built and expressed as:

```
SELECT avg(Response)
FROM RTVAI                                  (3.4)
GROUP BY utm
INTO temp
```

Step three also uses the GIS component to generate one spatial reference grid containing the change in average response time values. An arithmetic overlay operation is reference grid created in step two. This procedure is facilitated by the fact that all grid cells are of the same area and occupy exactly the same locations in geographic space. Were the spatial reference units irregular in shape this aspect of the analysis would be significantly more complicated.

Step four uses the statistical analysis and GIS components of the GIS framework to conduct ANOVA tests for each grid cell and update the spatial reference grid generated in step three with resulting probability statistics. All response time values for each grid cell are selected in turn from the two or more RTVAI call tables using a SQL query. An ANOVA test is then conducted, at the $\alpha = 0.05$ level of significance, to compare the two or more sets of response times. The SQL update request is used to populate the spatial reference grid generated in step three with the F statistic probability results. The process in this step is repeated until all the cells in the spatial reference grid, are assigned the probability that the null hypothesis of no difference in average response times can be rejected at or beyond the 95 percent confidence level ($\alpha = 0.05$).

Step five uses the cartographic presentation and mapping components of the GIS to create a choropleth map of the difference in average response time values from the spatial reference grid that was populated in step four. Thematic mapping functionality is used to colour shade each grid cell in the spatial reference grid according to pre-defined ranges for the change in average response time values. In terms of cartographic presentation, for example, the MOH GSR application uses a short progression of two clearly distinguishable values of a green hue and two clearly distinguishable values of a red hue to convey respectively two classes for improved ambulance response and two classes for slower ambulance response. In this way, there is a clear distinction between improvements and decline in response and the changes in colour value clearly demonstrate the degree of change in response times. This is important, as the resultant surface must clearly convey where response times are higher or lower than the earlier time period and thereby allow potential problem areas to be identified quickly by an analyst.

create a graduated symbol thematic map, showing the probability of a statistically significant difference in performance, which is subsequently overlaid on the choropleth map created in step five. Thematic mapping functionality is used to add one type of graduated symbol of a uniform size to grid cells where the probability of a statistically significant difference in average response times is high, at the 0.05 level. Cartographic conventions are used to set the symbol type, size, and colour to complement the choropleth map and clearly distinguish grid cells where there is a high probability of a statistical difference from all the others. The output from this process and final step produces a change in average response time performance indicator thematic map. This map enables EMS planners to visualise the spatio-temporal patterns of the change in ambulance response and evaluate trends in realised geographic accessibility of people to ambulance services.

3.2.3 Call Volume Frequency Distribution Process

The *Call Volume Frequency Distribution* (CVFD) process operationalises the third dimension of the analytic model to help explain performance indicator patterns and trends in terms of the distances ambulances based at each station travel in relation to their performance levels. This process generates a frequency distribution table showing the volume of calls responded to from each station and the average response time for any given area by station on a performance indicator thematic map. This process helps to explain the various geographical factors of the service delivery system that intervene to either increase or decrease realised accessibility. The GIS framework's GUI, spatial model, and thematic mapping components are used to operationalise and automate this process.

The model used in this process defines an on-screen-interactive performance indicator thematic map, where the user can select a 'Call Volume Frequency Distribution' button from the GUI and using the mouse query the graphic display of response times by selecting one or more grid cells. The frequency distribution of responses for all stations provides planners with a tool to inquire easily about performance indicator patterns in terms of the ambulance stations that respond to emergency calls.

The data flow diagram for this process is illustrated in Figure 3.6. There are three steps outlined in this process.

1. Generate a call volume frequency distribution spatial reference grid;
2. Select the button tool and one or more grid cells interactively;
3. Generate and display a call volume frequency distribution table for the selected grid cell(s).

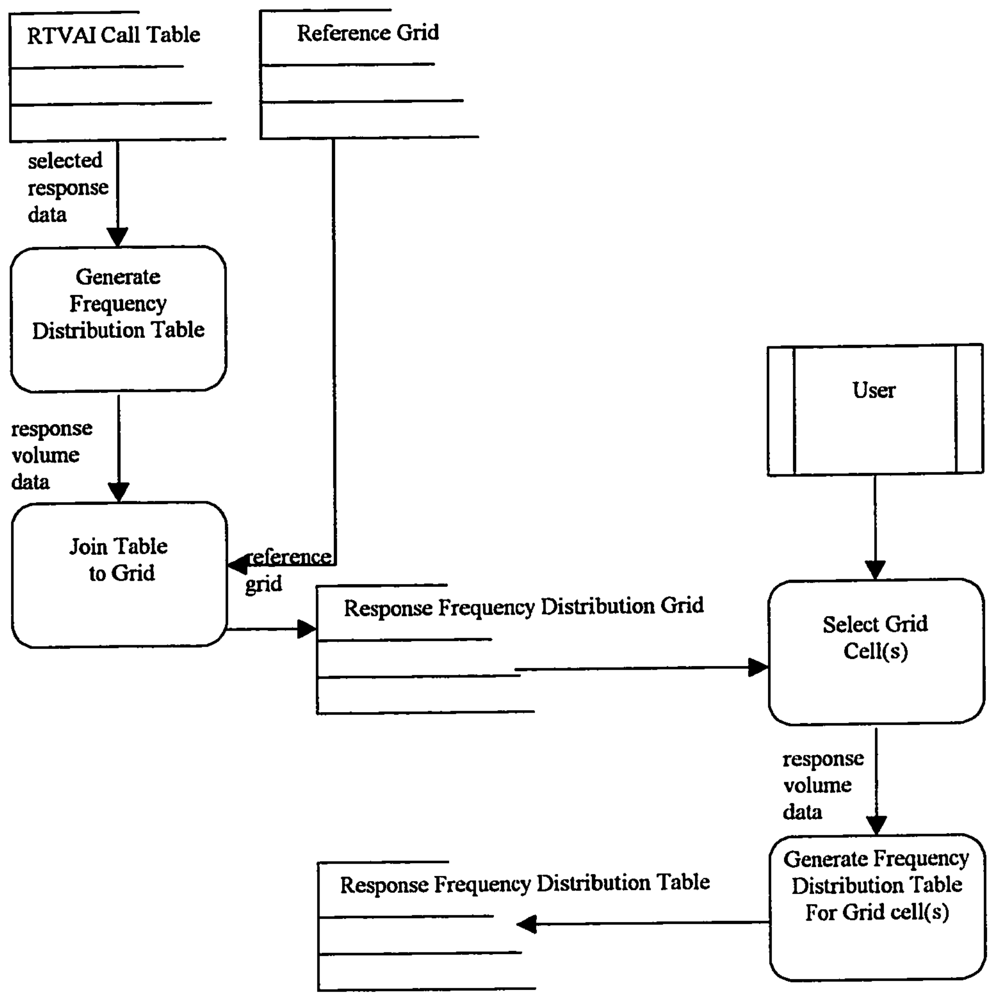


Figure 3.6: CVFD process data flow

distribution grid from a RTVAI response table. This is created each time a performance indicator thematic map is generated (e.g. CARTPI process). SQL query and update requests are used to generate a frequency distribution table with a record for each unique ambulance station that responded to a call in each grid cell, the number of calls each station answered, the percentage of calls that each station answered and each station's average response time to each grid cell in which a call was responded to by that station. The frequency distribution table is then joined to the spatial reference grid using a database join operation. The resulting frequency distribution spatial reference grid is added to the map display as an invisible layer so that it can be interactively queried based on the view of the performance indicator thematic map layer.

Step two uses the GUI and GIS components to allow a user to select interactively the 'Station Call Frequency Distribution' button from the GUI and one or more grid cells from the performance indicator thematic map display. Standard GIS selection functionality is customised for the button to enable the user to select a single grid cell or to hold the shift key down in order to select grid cells within a user-defined region.

Step three uses the GIS component to generate and display a frequency distribution table for the selected grid cell(s). SQL query and update requests are used to create and display a new response frequency distribution table with a record for each unique ambulance station that responded to a call within the selected grid cell(s). The frequency distribution tables help explain performance levels by defining each ambulance station's level of performance according to the Euclidean (straight line) distance travelled for any given area.

3.2.4 Response Time Frequency Distribution Process

The *Response Time Frequency Distribution* (RTFD) process operationalises the third dimension of the analytic model to explain performance indicator patterns and trends. Specifically, this process calculates the frequency of and variation in unique response times (e.g. the number of times each response time occurred and the percentage of calls that each response time represents) and displays the associated z-scores for each response time for any given area on a thematic map. A similar model and process is used to generate interactively the response time frequency distribution tables as described previously for the call volume frequency distribution process. The GIS framework's model, GUI, and GIS components are also used to operationalise and automate this process. The results of this process allow a user to help explain why a performance indicator value for one area is different from neighbouring areas in terms of the frequency and variation in response times.

3.2.5 Service Territory Generation Process

The *Service Territory Generation* (STG) process operationalises the third dimension of the analytic model. This process allows a user to establish the functional catchments of ambulance service depots by examining the (straight line) distances ambulances travel from their base station. Territories historically serviced by selected ambulance stations are defined and overlaid on thematic maps generated in the *Response Time Performance Indicator* process. The GIS framework's model, GUI, GIS, cartographic presentation and mapping components are used to operationalise and automate this process.

The model used in this process defines a station's functional catchment as the area covered by adjacent grid cells where a station has dispatched an ambulance to respond to a user-specified proportion of calls in each grid cell. For example, if 75 percent is specified as the majority of calls, then a station's catchment area is defined by all adjacent grid cells in which 75 percent or more of the calls were responded to by ambulances dispatched from that station. This approach allows a user to define catchments dynamically, according to a user-specified proportion of calls because there is no statistical or EHS industry standard for defining the percent of calls that comprise 'normal' catchment areas.

three steps outlined in this process:

1. Set percentage variable that will determine which ambulance station, if any, answered the majority of calls in each grid cell;
2. Generate a spatial reference grid made up of one record for each grid cell where a single station has responded to at least the user-specified proportion of calls;
3. Generate functional catchment polygons and display them on a thematic map.

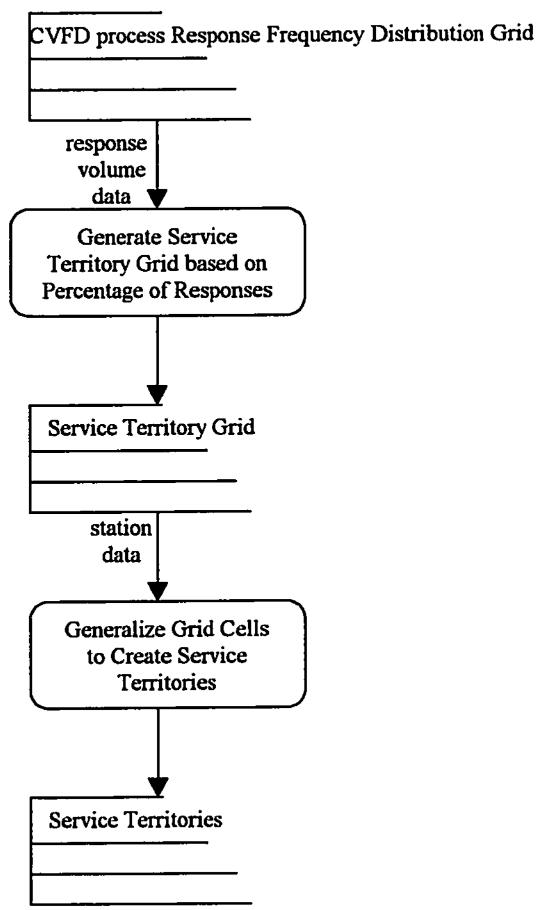


Figure 3.7: STG process data flow

enter the percentage of calls that will determine which ambulance station, if any, answered the majority of calls in each grid cell. Step two uses the GIS component to generate a spatial reference grid made up of grid cells where a single station has responded to at least the user-specified percentage of calls. These grid cells are selected using a SQL query from the call frequency distribution grid generated in the CVFD process. The CVFD process is used each time a thematic map is generated (e.g. CARTPI process). If 'CVFD' is the name of a CVFD grid; including a field named 'percent' (the proportion of calls each station answered), and 'user_percent' is the name of a variable containing the value for the percentage of calls specified by the user in the GUI component, then an SQL request can be built and expressed as:

```
SELECT *
FROM CVFD
WHERE percent >= user_percent                                    (3.5)
INTO temp
```

Step three uses the GIS mapping components of the application to generate territory polygons and overlay them on a performance indicator thematic map. Feature generalisation is used to enhance visualisation of catchments, on the grid generated in the previous step, by combining adjacent grid cells (remove common boundaries) where the same station responded to the percentage of calls of interest. Cartographic conventions are used to assign each territory polygon boundary a unique colour to provide a clear distinction between territories. The territory polygons generated in this last step help explain performance levels by defining functional catchments historically serviced by each ambulance station.

A GUI is used in all of the processes described above. Considerable thought was put into the design and functionality of the GUI as this facilitates the navigation of a user through the components of the application, described in this thesis. In particular, the GUI comprises all aspects of the environment through which the users interact with all features of the GIS application environment using graphical objects to operate the various processes.

The three main components that make up a GUI are "the windowing system, a set of tools for creating windows and their characteristics; the imaging model, controls the drawing of the screen representations such as fonts and icons; and the application program interface, acts as an interface to the program operations and controls feedback from screen representations" [Raper in Masser and Blakemore, 1991, p.105]. GUIs generally adopt the following characteristics: 1. Metaphors from the real world; 2. Direct manipulation by the user; 3. See and point (instead of remember and type); 4. Consistency; 5. what you see is what you get (WYSIWYG); 6. User control; 7. Feedback and dialogue; 8. Forgiveness; 9. Perceived stability; and 10. Aesthetic integrity [Raper in Masser and Blakemore, 1991].

The GUI is of crucial importance to the usability of the analytic model (Figure 2.3) and GIS design framework (Figure 2.4) developed in this thesis as it is the conceptual link between the user's interaction with the application and what the application can offer as a decision support tool. Thus, the GUI should include all the concepts that a user requires to understand the application and to communicate effectively with it [Medyckyj-Scott and Hearnshaw, 1993]. Moreover, the GUI is the only part of the application that is visible and with which the user interacts. Thus, the GUI '*is*' the system for the user.

Usability is a concept used in the human-computer interaction (HCI) field to indicate a positive quality in a computer system that makes the interaction between user and computer easy. Medyckyj-Scott and Hearnshaw [1993] note that there still is no seemingly robust. This view regards the usability of a product as "a function of the particular user or group of users being studied, the tasks they perform and the environment in which they work" [Bevan et al. 1991, p.651 in Medyckyj-Scott and Hearnshaw, 1993, p.87]. Thus the usability of the proposed computer-based application is determined by the context of its use.

The application presented in this thesis has attributes which determine its usability for the analysis of realised geographic accessibility and ambulance response performance in the emergency health services planning process. These attributes include the style and properties of its GUI (e.g. the dialogue structure) as well as other aspects of the hardware and software environment, such as the nature of the functionality, system performance (e.g. responsiveness and reliability) and output quality. In particular, the application must have utility so that health service planners perceive it as beneficial to their work and, as a consequence, are motivated to use it. The application GUI must also be easy-to-use and understandable in order to minimise the investments in time and effort required to use it. Thus, the application attributes must be designed correctly in order to create a useable system where its overall benefits are greater then the costs associated with using it.

Medyckyj-Scott and Hearnshaw note that "designing a usable system depends upon understanding and then solving the dynamic interacting needs of the four principal components of the context of use: the system, the users, the tasks that are to be performed with the system and the physical and social environment within which the work is done" [Medyckyj-Scott and Hearnshaw, 1993, p.90]. Moreover, the design should try to consider the context of use in the future as well as those of the present because emergency service organisations and their needs are continually changing. Thus, the application design should view the contexts of use as dynamic environments where needs are continually evolving.

and solve these four principal components of the context of use. Using this methodology, for the case study, the application development evolved interactively, where design changes were made based on empirical evaluation of usage and post-installation feedback from users in the MOH regional offices. Figure 3.8 illustrates the development process that was used. Application of this user-centred design involved early and sustained interaction with the MOH emergency health service planners as a formal mechanism in the application development process. Differences can exist between the needs of planners and how system designers interpret these needs. Hence, this user involvement is necessary to bridge the gap between users and designers and thus identify important system design concepts, parameters, and unforeseen problems early in the development process. Task-based design involves the identification and division of tasks into operational units and task flows so that users can see overall application objectives and not have to deal with a complex series of functions for performing the individual ambulance performance analyses. This methodology attempts to address GUI usability that is a crucial component of the application quality.

To facilitate input, the GUI for the application developed in this thesis was presented to a group of MOH regional office CACC managers from across the province. Three meetings were held during the development process with the managers to determine application requirements and then to evaluate and test the GUI. The evaluation and user testing resulted in changes to the terms used on the dialogues, the options for labelling the maps, the thematic mapping ranges used, and the map report layout produced. This improved the functionality by improving dialogues in terms of more logical task flows. The map output was also improved by providing options for customisation and more useful thematic mapping parameters and layout specifications.

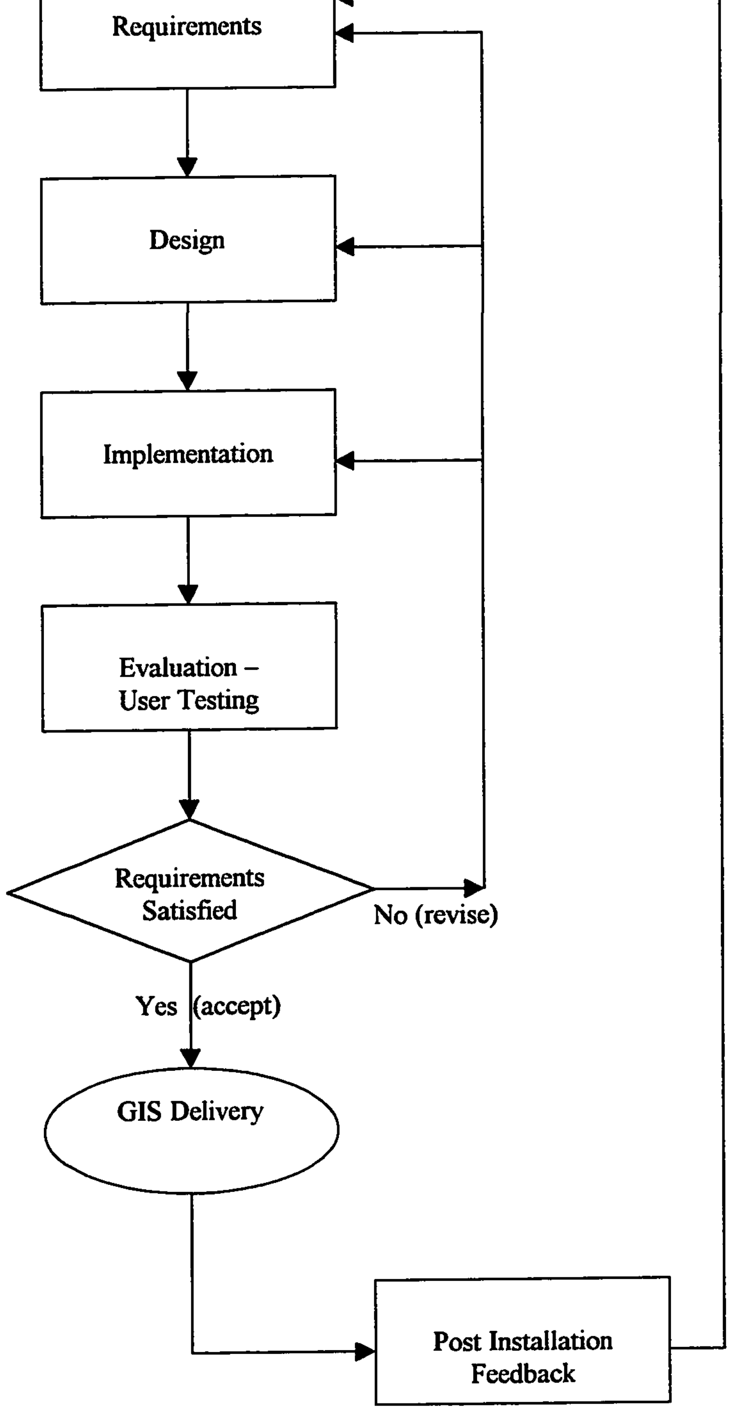


Figure 3.8: Stages in designing GIS for use [Medyckyj-Scott and Hearnshaw, 1993, p.91]

objectives such as task-orientation, user-control, standardisation and consistency were used. A task-oriented design should focus on testing *a priori* hypotheses about the patterns and relationships present in the ambulance call data. The design should also facilitate conducting the test to evaluate a range of scenarios to assess geographic accessibility by enumerating the costs and benefits for each alternative configuration. A task-oriented design can use 'wizards' or 'task assistants' to invoke a series of logically connected dialogues to step the user through the task of specifying parameters in order to create performance indicator thematic maps. These parameters include, in order of specification, the type of indicator map to produce, the historical call database and spatial reference grid area to use, the options for handling anomaly response times, the options for creating service territories, and the parameters for the historical call data to use (e.g. the time frame of calls, the type of calls, and the station(s) that answered the calls).

An appropriate default option for each parameter is specified in the 'task assistant' to help the user make the appropriate choices for each task. By default, no option to handle anomaly response times is set for average response time and response time standard indicators because any or none of the options could be equally appropriate depending on the user's objectives. The option to select calls without both types of anomalies is set as the default for the change in average response performance indicator because analysing the change in average response times for anomaly calls exclusively does not provide useful information and the anomalies skew the averages. Furthermore, by default, an option to create service territories should not be set because functional territories are not a part of any performance indicator and should only be generated to help explain performance indicator patterns and trends.

Figure 3.9 shows the content and sequencing of a performance indicator thematic map 'task assistant' from the application GUI. This assistant consists of two main dialogues and two secondary dialogues, but could include additional dialogues to break up the steps for specifying parameters into more manageable parts. The first dialog (Create

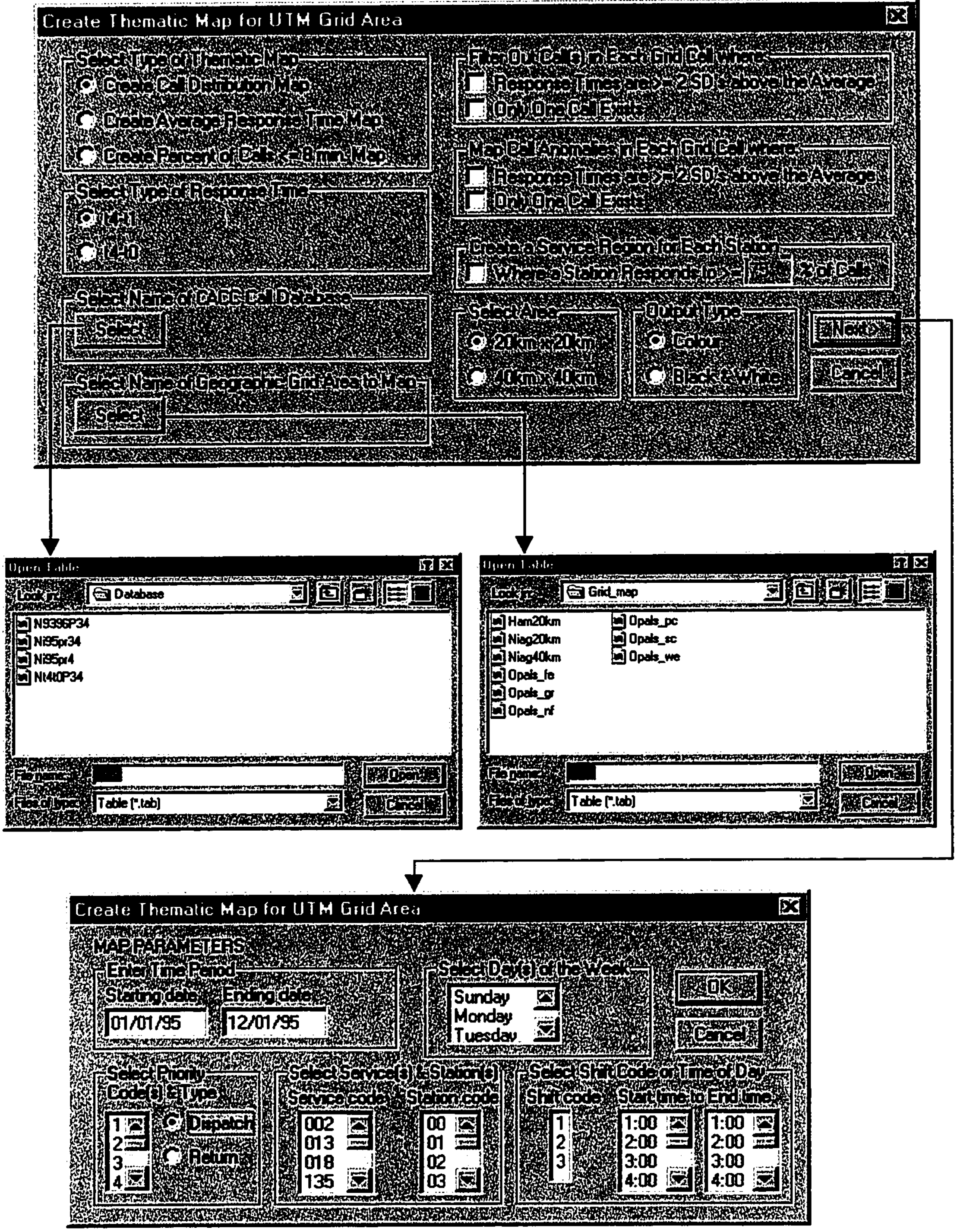


Figure 3.9: MOH GSR application performance indicator thematic map 'task assistant'

a performance indicator, except for the parameters for the historical call data that are specified in the second dialog. The first dialog also has two buttons to access two secondary dialogues for selecting the historical call database and spatial reference grid area to use. The task-oriented design enables users to generate performance indicator maps by specifying the parameters they need to customise maps without having to deal with a complex series of GIS functions.

Since useful software must be responsive to user needs, user-control is fundamental to the GUI design process. A user needs the flexibility and tools necessary to customise thematic map creation for their own individual needs while maintaining cartographic standards by setting default options to compare different geographic areas. In addition to the ability to customise performance maps such as those described above, users should have the option to modify default map design settings after the thematic map is generated to enhance the visualisation of a particular scenario. In this context, a 'task assistant' should have the ability to control which map layers (e.g. municipal boundaries, and ambulance services) and labels (e.g. average response times) are displayed, and to modify the thematic ranges, colour shading, symbols and legends.

For example, Figure 3.10 shows the map layout assistant (Select Layout Options) that is used to modify which map layers and labels are displayed on maps of ambulance responses to calls. Users also need the flexibility of interactive tool buttons to query any area on a performance indicator map to help explain performance patterns by generating call volume and response time frequency distribution tables. A main pull-down menu and button pad can be used to access these 'task assistants' and tool buttons respectively to provide users with the desired flexibility and control.

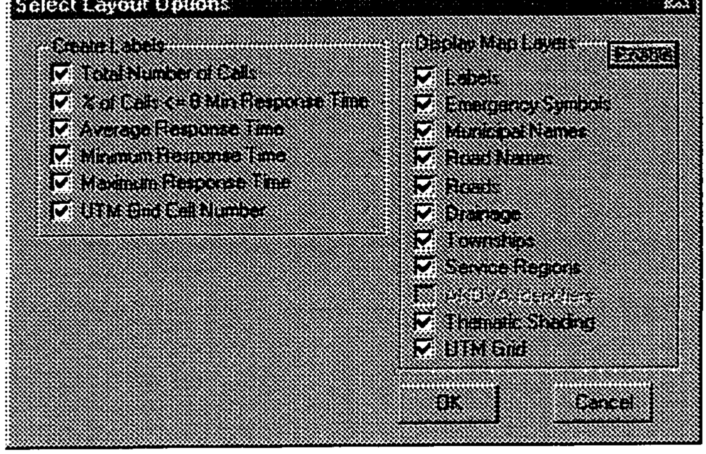


Figure 3.10: Application map layout 'task assistant'

A standard and consistent design with respect to Windows-based applications can shorten learning times, facilitate rapid task performance, reduce error rates, and improve retention in the use of the application. Standardisation refers to common user-interface features found in most software applications. Consistency refers to common action sequences, terms, units, layouts, colour, typography, and so on within an application program [Shneiderman, 1992]. For example, the dialogues shown in Figure 3.9 feature industry standard scrolling lists, option buttons, and open and save table dialogues that, for the most part, require only mouse click responses. The action sequences, terms, and layouts found on the dialogues for generating the different performance indicator maps are consistent throughout the application.

A standard and consistent design helps to shorten the application's learning curve and reduce error rates by providing the user with an environment that is familiar, intuitive and consistent with most Windows-based applications. A well-designed GUI provides an easy to use system that is key to the acceptance, uptake and usage of a computer-based application by emergency service professionals.

This chapter described the research methodology used to operationalise the analytical model and GIS design framework proposed in Chapter 2. The data requirements and the data quality issues that effect the reliability of using realised geographic accessibility measures were discussed. Analytic functionality to calculate and map accessibility indicators was described in terms of five processes that are operationalised together to address the three dimensions in the analytic model. Next, a design methodology and several objectives were proposed to develop an intuitive and easy-to-use GIS-based application to assist users in mapping the spatio-temporal patterns of emergency health service vehicle response.

The methodology uses a basic set of five attributes for response data to demonstrate how commonly recorded information can be used more effectively to assess ambulance response performance. The accuracy and surrogate nature of historical call data and the nature of the spatial reference framework effects the reliability of using realised geographic accessibility measures to identify areas with deficient emergency service response. Five processes operationalise the analytical model, GIS design framework and data requirements to visualise ambulance response performance. The models used to operationalise each process require statistical analysis and GIS data manipulation, spatial analysis and mapping functionality including SQL, z-scores, ANOVA, overlay analysis, feature generalisation, and thematic mapping. A user-centred, task-based GUI, was developed for the application as the method through which users operate the five automated processes to generate performance indicator thematic maps in a decision support environment. The next chapter demonstrates the usefulness of the application and its approach with a case study using empirical data collected by the MOH.

Chapter 4

Evaluation

This chapter applies the research methodology discussed in the previous chapter to demonstrate the usefulness of the approach and methods presented. The research methodology is operationalised through the development of the GSR GIS-based application in the context described in Chapter one. The fourth research objective and the objective of this chapter is to apply empirically the analytic model and GIS framework, proposed in Chapter two, using data supplied by the MOH. Therefore, the main emphasis is on applying the methodology to evaluate each of the three dimensions of ambulance service performance in order to improve our understanding and forward planning of service provision. The first section describes the context of the case study, including the study area and the associated ambulance call data. The subsequent three sections apply the methodology to the study area and data to address each of the three dimensions of response time patterns and trends. The final section summarises and discusses the implications of the findings from the case study.

4.1 Study Area and Data

The study areas consist of the cities of Niagara Falls, St. Catharines and Welland in the Regional Municipality of Niagara in southern Ontario. These three cities are current examples of urban study areas where the MOH assesses realised geographic accessibility using manual mapping methods (see Appendix A: Sample Geoplot Reports). These study areas comprise three adjacent ambulance service jurisdictions that provide a basis to assess and compare ambulance response performance in relation to the three dimensions of ambulance service assessment. The fact that the three ambulance services are in the same vicinity and respond to each other's calls, when an ambulance from the closest station is not available, helps to demonstrate the impact of ambulance availability and distance services, and available emergency service resources are different for each study area. These differences provide representative situations to assess and compare ambulance response performance in relation to the three dimensions of ambulance service assessment.

The MOH $1km^2$ UTM grid, discussed in the previous chapter, was used by the Ministry as the spatial reference framework to define the extents of the three study areas for their own analysis (see Appendix A: Sample Geoplot Reports). The same extents for the three study areas are used in this analysis to provide actual and consistent study areas where the methodology can be applied to effectively compare each of the three dimensions of ambulance service performance. Figure 4.1 shows the extents and geographic context for the study areas used in this analysis. In this figure, as in the MOH database, each ambulance station is uniquely identified by a combination of its service and station codes (e.g. service 143 station 00 is Niagara Falls station (143-00)). As discussed in Chapter 3, the spatial aggregation error associated with this spatial reference framework is likely to be less than would be the case using the smallest modifiable areal units available in other datasets, such as the Canadian Census of Population and Dwellings.

It is important to note that the Geoplot application developed in conjunction with this thesis enables the user to define the extents of each study area based on a view of the thematic distribution of each individual call analysis. In this way important properties of each distribution around and between the urban areas are taken into account. The thematic representation of ambulance response performance indicators around and between the study areas is shown only in figure 4.10 to represent the basis for the functional catchments in Figure 4.11 and to facilitate the explanation of why particular areas in each study area show unsatisfactory accessibility.

For this case study, call data are used from the MOH database that is set up to record and maintain the dispatch call data created during the processing of a call for ambulance service. The database contains a table that maintains the call data used in the

Figure 4.1: Study Areas
(St. Catharines, Niagara Falls and Welland)

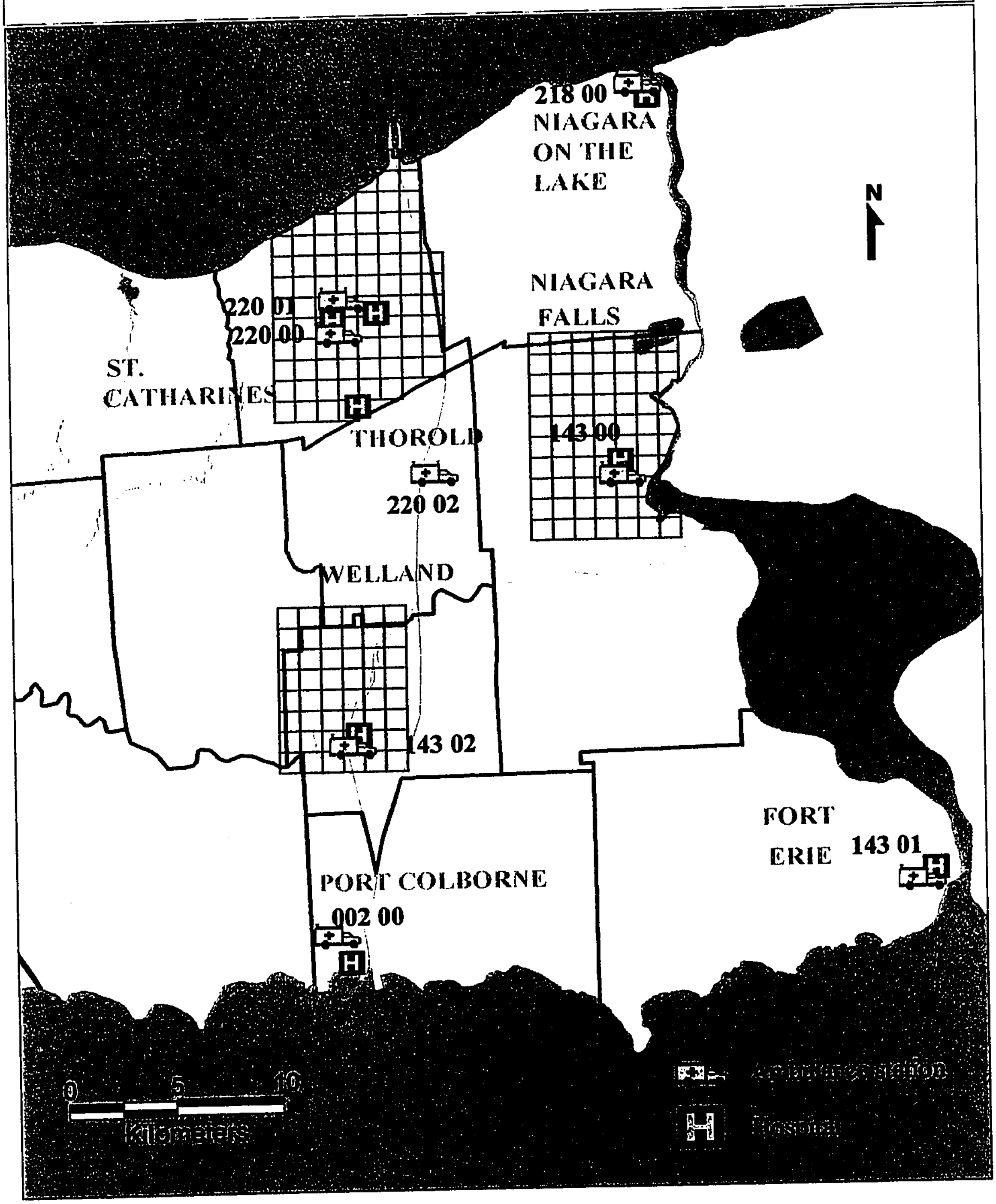


table is shown in Figure 4.2.

CALLNUM	UTM	CALL_DATE	HOUR	D_CODE	R_CODE	T4_T1	T4_T0	REGION	SERVICE	STATION
002662587	4794760	28/08/96	15	4	3	121	140	REGION1	220	00
B00015214	6154783	16/10/95	7	4	4	300	0	REGION1	013	00
B00015215	6444778	20/10/95	10	4	4	206	273	REGION1	220	00
B00024155	631172	10/02/95	8	4	4	669	692	REGION2	018	00
B00024157	631172	10/02/95	9	4	4	120	0	REGION2	018	00
B00027785	4874426	29/05/95	11	4	3	470	493	REGION2	135	00
B00027941	7994277	01/06/95	22	3	3	561	613	REGION2	135	00

Figure 4.2: A sample call data table from the MOH database

An analysis of MOH Priority 4, life threatening call data is conducted. Life-threatening emergency calls are the focus of this application since the response of ambulance services are crucial to a patient's survival after an emergency, such as a heart attack or accident. Moreover, response time standards are established for responding to life threatening emergency calls. For example, MOH response time standards require that life threatening calls have an average response time of eight minutes or less in urban areas. In addition, proposed MOH response time standards require that ninety percent of life threatening calls have a response time of eight minutes or less in urban areas. Response time standards are less stringent in rural areas because it is more difficult to consistently achieve these objectives in these areas with the available ambulance resources. These response time standards represent the equity objective in MOH emergency service planning. Thus, the differentiation of life-threatening emergency calls from less serious types of calls enables ambulance performance to be measured in relation to specific service standards and demand areas.

The analysis is conducted for a 2 year period, from January 1, 1995 to December 31, 1996. This time frame is sufficient to assess change in ambulance performance in terms of the time of day (e.g. ambulance work shifts) and types of calls (e.g. ambulance priority codes). In addition, it represents the first 2 years for which response times were recorded this research. Before 1995 response times were recorded to the nearest minute.

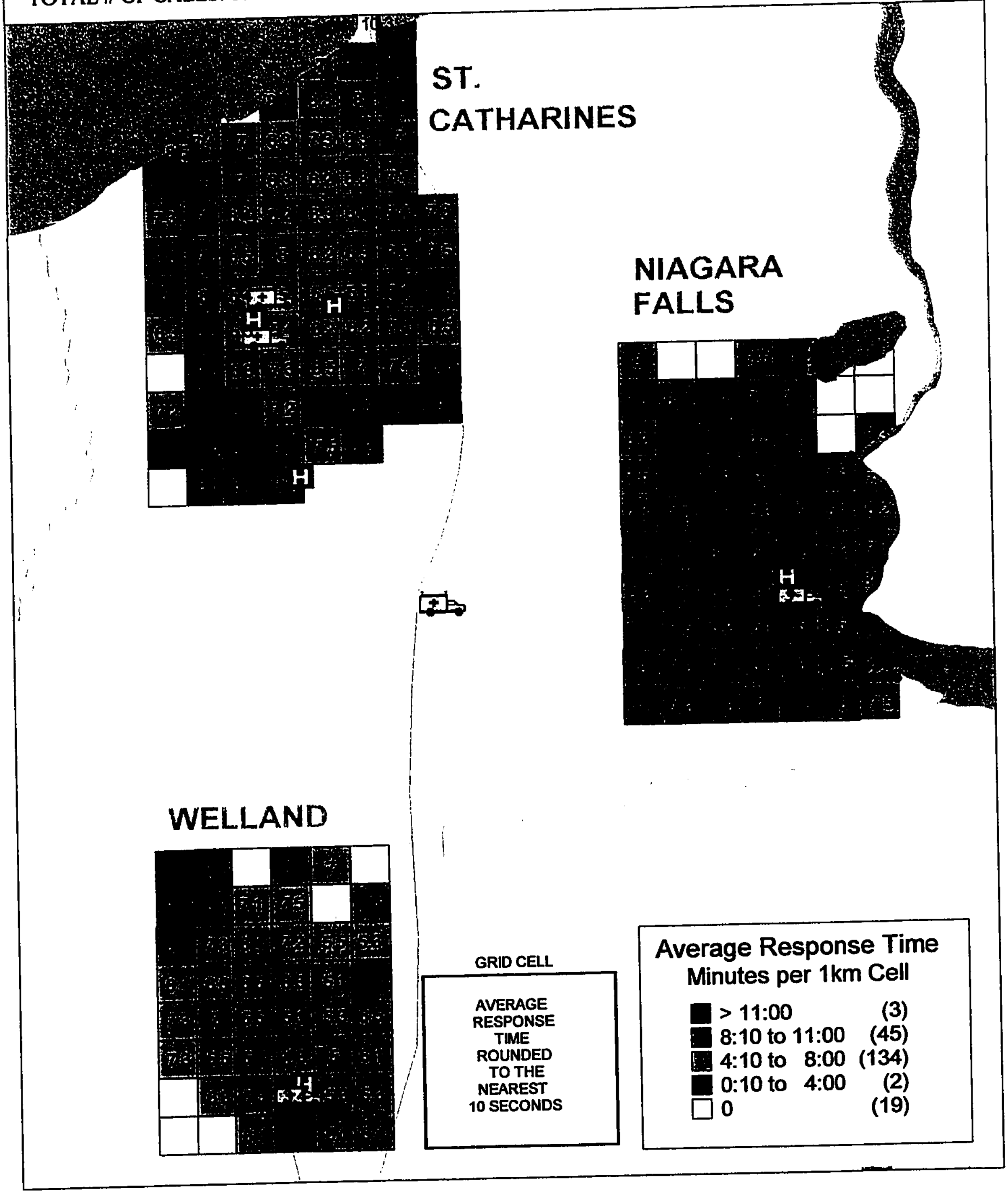
4.2 Response Time Variation & Anomaly Identification Evaluation

The results of the RTVAI process are evaluated for the Niagara Falls, St. Catharines and Welland study areas to assess the value of the independent analysis and visualisation of response time anomalies and the 'normal' variation in ambulance response times. The identification of areas where response times need to be improved should be based on well-defined areas of consistent performance levels that can only be clearly visualised if anomaly response times are removed. Figure 4.3 shows average response time accessibility surfaces for the three study areas before the RTVAI process is applied and anomaly response times are removed. The Figure shows that for all three study areas the lowest average response times, not surprisingly, occur in the grid cells closest to the ambulance stations and generally increase progressively for grid cells further away from the station. This general pattern becomes less consistent in all three-study areas as grid cells are further away from the stations because average response times are based on fewer calls and thus response time variation has a greater impact on skewing the averages. For example, each study area, as shown on Figure 4.3, has a considerable number of grid cells (shaded in light and dark red) located toward the periphery without acceptable averages interspersed with grid cells with acceptable averages (shaded in green). The underlying pattern of realised geographic accessibility is not clearly evident in these areas where the pattern is inconsistent making it difficult to accurately determine areas where ambulance response should be improved.

In this context, Figure 4.4 shows the distribution of the calls presented in Figure 4.3, where grid cells with the greatest number of calls generally have lower average response times and are closest to the stations. This distribution is supported by the efficiency objective in emergency service planning in which stations are generally located and resources allocated to areas that have had the greatest demand for this service.

Figure 4.3: Average Response Time Performance Indicator

TOTAL # OF CALLS: 6707   AVG RESPONSE TIME: 6:29   % OF CALLS <= 8 MIN: 82.8



a hospital on the periphery of the area showing the highest demand. This pattern is of an inverse relationship between demand and response time [Mayer, 1981] that appears to become less consistent in all three study areas for grid cells further away from the stations. This inconsistent pattern is partially a result of the same inconsistent patterns of response times often caused when ambulances respond to calls from a location other than the closest station.

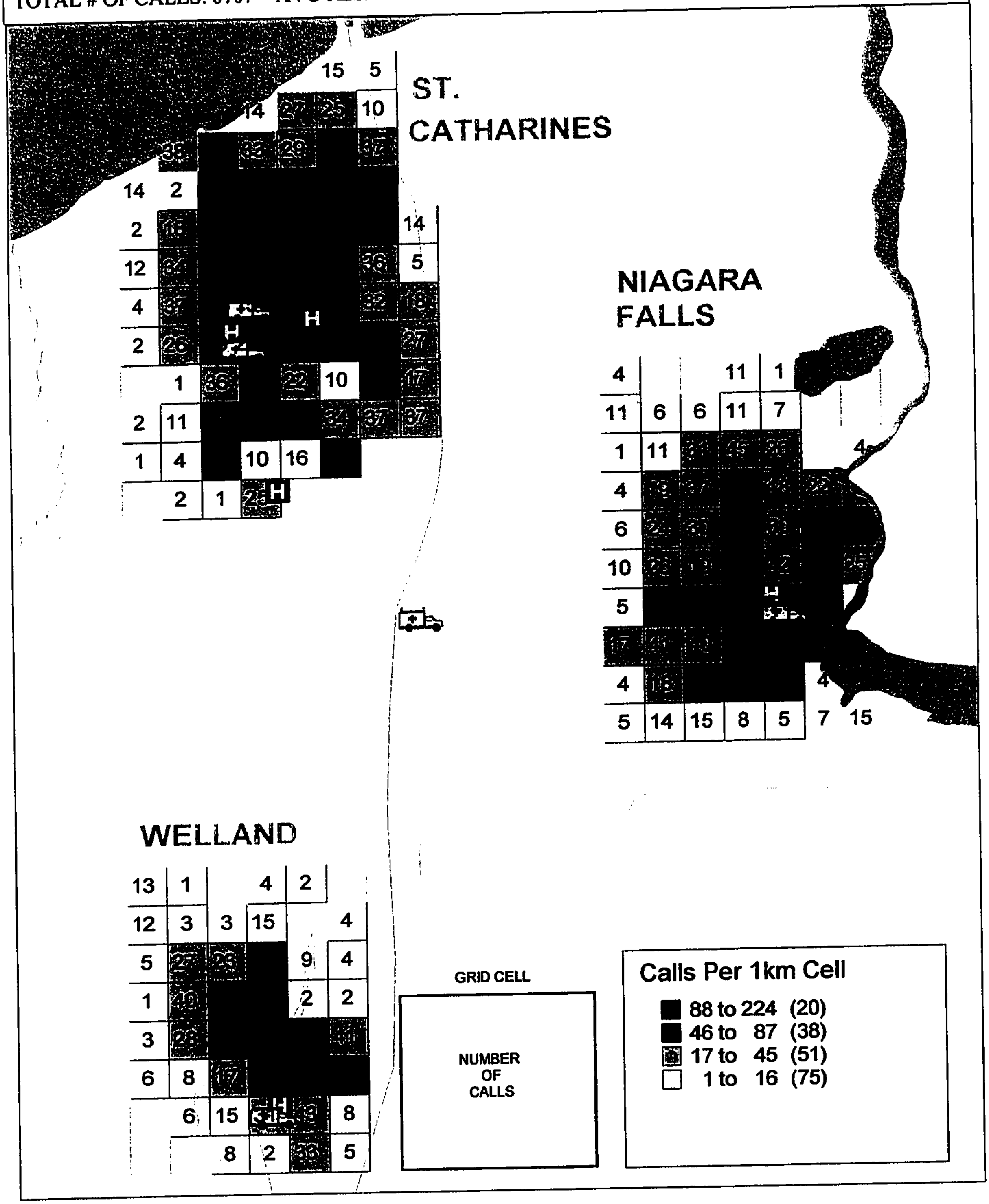
In addition to these similarities between the study areas, there are also important differences in terms of ambulance response. Table 4.1 shows that in the largest study area, St. Catharines (approximately 84 km^2), the greatest number of Priority 4 calls were dispatched (3523) with the highest average response time of 6 minutes and 52 seconds. St. Catharines also has the smallest proportion of any study area (approximately 60 percent or 50 out of 84 grid cells) shaded in green (Figure 4.3), showing acceptable average response times per grid cell of 8 minutes or less. In addition, St. Catharines is furthest from meeting MOH standards by responding to 78.5 percent of calls in eight minutes or less.

	St. Catharines	Niagara Falls	Welland	**Total**
# of calls in total: Fig. 4.3	3523	2164	1020	**6707**
# of calls without anomalies: Fig. 4.5 & 4.7	3398	2074	978	**6450**
# of anomaly calls: Fig. 4.6	122	87	40	**249**
Avg. response for all calls: Fig. 4.3	6:52	6:10	6:06	**6:29**
Avg. response without anomalies: Fig. 4.5 & 4.7	6:34	5:44	5:51	**6:11**
Avg. response for anomalies: Fig. 4.6	15:12	12:49	12:15	**13:54**
% of calls <= 8 min. for all calls: Fig. 4.3	78.5	87.2	89.4	**82.8**
% of calls <= 8 min. without anomalies: Fig. 4.5 & 4.7	81.3	90.9	92.9	**86.1**
% of calls <= 8 min. for anomalies: Fig. 4.6	0	0	7.5	**1.2**
% of area <= 8 min. for all calls: Fig. 4.3	59.5	73.2	70.8	**67**
% of area <= 8 min. without anomalies: Fig. 4.5	67.9	76.1	68.8	**70.9**
>= 90% of area <= 8 min. without anomalies: Fig. 4.7	15.5	35.2	50	**31**

Table 4.1: Performance indicators for the three study areas

Figure 4.4: Call Distribution

TOTAL # OF CALLS: 6707 AVG RESPONSE TIME: 6:29 % OF CALLS <= 8 MIN: 82.8



second largest number of Priority 4 calls dispatched (2164), with the second highest average response time of 6 minutes and 10 seconds; 42 seconds less than St. Catharines. Niagara Falls has the largest proportion of any catchment area (approximately 73 percent or 52 out of 71 grid cells) shaded in green. Further, unlike St. Catharines, Niagara Falls is close to meeting MOH standards by responding to 87.2 percent of calls in eight minutes or less.

In the smallest study area, Welland (approximately 48 km^2), the smallest number of Priority 4 calls were dispatched (1020) with the best average response time of 6 minutes and 6 seconds, only 4 seconds better than Niagara Falls. Welland is also similar to Niagara Falls in terms of the proportion of its catchment shaded in green. At approximately 71 percent (34 out of 48 grid cells) it is only 2 percent less than Niagara Falls. Further, similar to Niagara Falls, Welland is just under MOH standards by responding to 89.4 percent of calls in eight minutes or less.

Figure 4.5 shows average response time accessibility surfaces for the three study areas after the RTVAI process is applied. Anomaly response times are removed from each service unit where a response time has a z-score of plus two or greater and where only one call exists. This figure shows that for many of the grid cells in all three study areas, the average response time is less than when response time anomalies were included in Figure 4.3. These findings are supported by Tables 4.2 to 4.4 that show, in each of the three study areas, the number of fewer calls included in Figure 4.5 (the frequency change) with response times (rounded to the nearest minute) above the average response time (z-score = 0). These tables also show that more response time anomalies were removed based on the response time distribution in each grid cell than would have been removed based on the response time distribution for each study area as whole, or likely for any other larger spatial units, such as, enumeration areas. For example, Table 4.3 shows that only 4 anomalies, or 0.2 percent of all calls, with a z-score of 2 or greater would have been removed based on the positively skewed distribution for Niagara Falls as a whole.

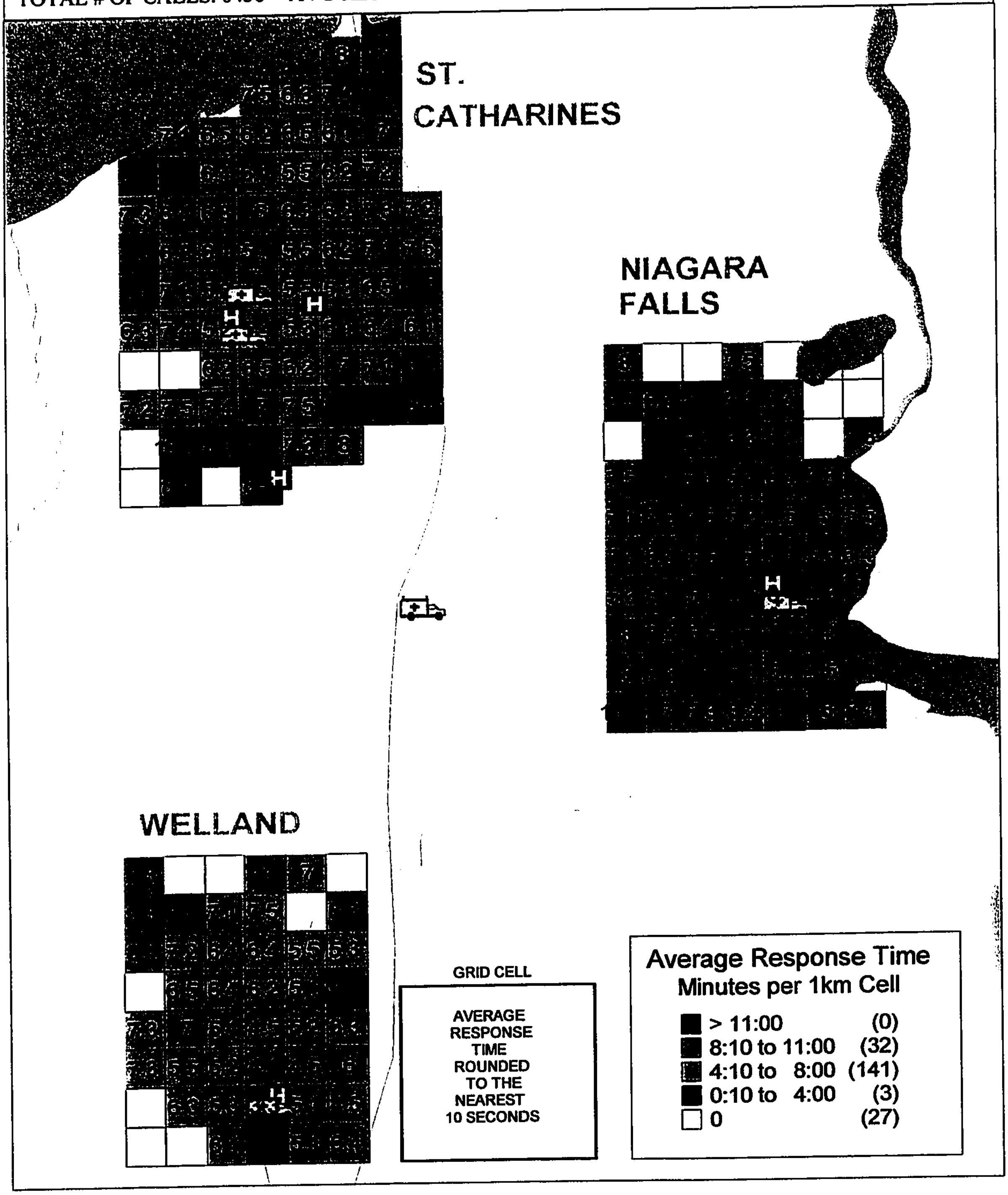
removed based on frequency distributions that more closely approximate normal distributions for each grid cell. This table also shows that even though the grid cells as a whole more closely represent normal distributions, their are still statistical anomalies not being removed (e.g. 27 and 31 minute response times) because response times in each grid cell vary in terms of how closely they approximate normal distributions. Table 4.3 also shows the frequency distribution or response times for two sample grid cells in the Niagara Falls study area before the RVTAI process was applied. Both tables and graphs (Table 4.3) provide an indication of how the percent of statistical response time anomalies in each grid cell will vary from the 5 percent expected with a normal distribution. Both frequency distributions are positively skewed and 3.3 and 6.3 percent of response times in each grid cell respectively are greater than 2 z-scores.

In St. Catharines and Niagara Falls in particular a clearer and more consistent pattern of realised geographic accessibility is shown where response times need to be improved as a result of the excluded anomaly response times. Significantly large total areas of 7 km^2 in St. Catharines and 3 km^2 in Niagara Falls that were shaded in light red with poor averages are now acceptable. In addition, areas of 3 km^2 in St. Catharines and 2 km^2 in Niagara Falls which were shaded in red with poor averages were eliminated as poor areas because the averages were based on a single call. The changes to the accessibility surfaces for both St. Catharines and Niagara Falls provide a clearer and more accurate representation of where accessibility is consistently deficient.

The accessibility surface in Welland did not change as much as in the other two study areas, with the exclusion of response time anomalies. However, performance indicators for both Welland and Niagara Falls show an important difference. Specifically, in Table 4.1, after the RTVAI process, Niagara responded to 90.9 percent of calls (a 3.7 percent increase) in eight minutes or less to meet MOH standards and Welland meets MOH standards by responding to 92.9 percent of calls in eight minutes or less; a 3.5 percent increase.

Without Response Times >= 2 z-scores and Single Calls in each grid cell

TOTAL # OF CALLS: 6450 AVG RESPONSE TIME: 6:11 % OF CALLS <= 8 MIN: 86.1

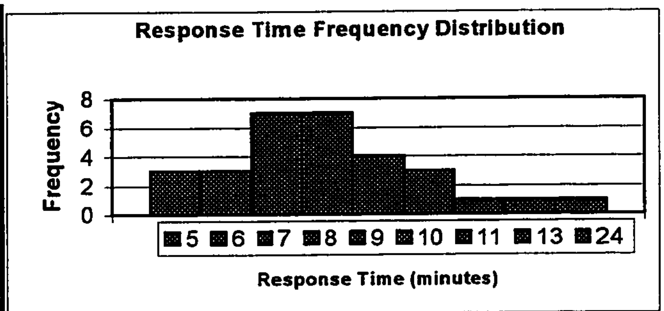


Resp. time (minutes)	Number of calls	Percent of calls	z-score	Number of calls	Percent of calls	z-score	Frequency change
1	10	0.3	-0.5	10	0.3	-0.5	0
2	57	1.6	-0.4	57	1.7	-0.4	0
3	195	5.5	-0.3	195	5.7	-0.3	0
4	401	11.4	-0.2	401	11.8	-0.3	0
5	552	15.7	-0.2	552	16.2	-0.2	0
6	587	16.7	-0.1	587	17.3	-0.1	0
7	532	15.1	0	532	15.7	0	0
8	421	12	0.1	420	12.4	0.1	-1
9	269	7.6	0.2	268	7.9	0.2	-1
10	162	4.6	0.2	160	4.7	0.3	-2
11	125	3.5	0.3	110	3.2	0.3	-15
12	60	1.7	0.4	40	1.2	0.4	-20
13	45	1.3	0.5	23	0.7	0.5	-22
14	35	1	0.5	17	0.5	0.6	-18
15	16	0.5	0.6	4	0.1	0.7	-12
16	14	0.4	0.7	6	0.2	0.8	-8
17	5	0.1	0.8	2	0.1	0.8	-3
18	8	0.2	0.9	2	0.1	0.9	-6
19	6	0.2	0.9	2	0.1	1	-4
20	1	0	1	0	0		-1
22	2	0.1	1.2	0	0		-2
23	2	0.1	1.2	1	0	1.3	-1
25	1	0	1.4	0	0		-1
26	2	0.1	1.5	1	0	1.6	-1
27	2	0.1	1.6	0	0		-2
31	1	0	1.9	0	0		-1
32	1	0	1.9	0	0		-1
35	1	0	2.2	0	0		-1
37	1	0	2.3	0	0		-1
38	1	0	2.4	0	0		-1
40	1	0	2.6	1	0	2.8	0
50	1	0	3.4	1	0	3.6	0

Table 4.2: Change in the frequency of calls after the RTVAI process for St. Catharines

Resp. time (minutes)	Number of calls	Percent of calls	z-score	Number of calls	Percent of calls	z-score	Frequency change
1	17	0.8	-0.6	17	0.8	-0.6	0
2	59	2.7	-0.5	59	2.8	-0.5	0
3	177	8.2	-0.4	177	8.5	-0.4	0
4	340	15.7	-0.2	340	16.4	-0.2	0
5	435	20.1	-0.1	435	21	-0.1	0
6	379	17.5	0	378	18.2	0	-1
7	303	14	0.1	303	14.6	0.1	0
8	176	8.1	0.2	176	8.5	0.2	0
9	100	4.6	0.4	89	4.3	0.4	-11
10	54	2.5	0.5	44	2.1	0.5	-10
11	50	2.3	0.6	33	1.6	0.6	-17
12	21	1	0.7	8	0.4	0.7	-13
13	19	0.9	0.8	8	0.4	0.8	-11
14	8	0.4	1	1	0	1	-7
15	7	0.3	1.1	1	0	1.1	-6
16	1	0	1.2	0	0		-1
17	6	0.3	1.3	0	0		-6
18	1	0	1.4	0	0		-1
19	2	0.1	1.5	1	0	1.6	-1
20	1	0	1.7	0	0		-1
21	1	0	1.8	0	0		-1
22	1	0	1.9	0	0		-1
23	1	0	2	0	0		-1
24	1	0	2.1	0	0		-1
27	1	0	2.5	1	0	2.5	0
31	1	0	3	1	0	3	0

Niagara Falls	random grid cell		Fig. 4.3
Resp. time (minutes)	Number of calls	Percent of calls	z-score
5	3	10	-0.9
6	3	10	-0.6
7	7	23.3	-0.3
8	7	23.3	0
9	4	13.3	0.3
10	3	10	0.6
11	1	3.3	0.9
13	1	3.3	1.4
24	1	3.3	4.6



Niagara Falls	random grid cell		Fig. 4.3
Resp. time (minutes)	Number of calls	Percent of calls	z-score
1	1	0.9	-2.1
2	5	4.6	-1.6
3	18	16.5	-1
4	29	26.6	-0.5
5	26	23.9	0
6	12	11	0.5
7	8	7.3	1
8	3	2.8	1.6
9	2	1.8	2.1
10	2	1.8	2.6
11	2	1.8	3.1
14	1	0.9	4.7

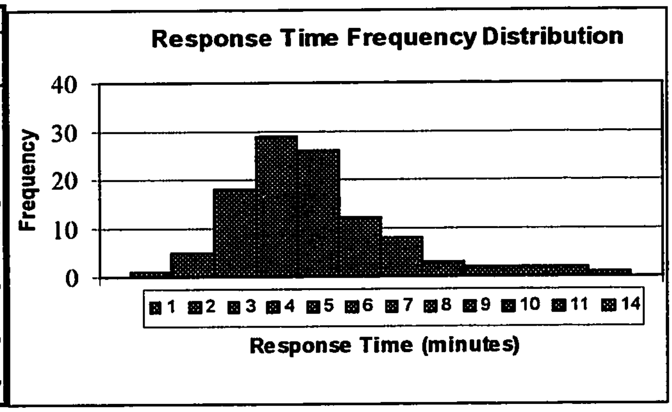


Table 4.3: Change in the frequency of calls after the RTVAI process for Niagara Falls

Resp. time (minutes)	Number of calls	Percent of calls	z-score	Number of calls	Percent of calls	z-score	Frequency change
1	6	0.6	-0.7	6	0.6	-1	0
2	24	2.4	-0.5	24	2.5	-0.8	0
3	74	7.3	-0.4	74	7.6	-0.6	0
4	135	13.2	-0.3	135	13.8	-0.4	0
5	185	18.1	-0.1	185	18.9	-0.2	0
6	209	20.5	0	209	21.4	0	0
7	160	15.7	0.1	158	16.2	0.2	-2
8	117	11.5	0.3	115	11.8	0.4	-2
9	43	4.2	0.4	35	3.6	0.6	-8
10	33	3.2	0.5	23	2.4	0.8	-10
11	13	1.3	0.7	7	0.7	1	-6
12	6	0.6	0.8	4	0.4	1.2	-2
13	2	0.2	0.9	0	0		-2
14	3	0.3	1	0	0		-3
15	2	0.2	1.2	1	0.1	1.8	-1
16	2	0.2	1.3	1	0.1	2	-1
18	1	0.1	1.6	0	0		-1
22	1	0.1	2.1	0	0		-1
23	1	0.1	2.2	0	0		-1
24	1	0.1	2.3	0	0		-1
25	1	0.1	2.5	0	0		-1

Table 4.4: Change in the frequency of calls after the RTVAI process for Welland

Additional notable differences within each study area as a whole before and after the RVTAI process was applied and between the three study areas are shown in Table 4.1. The table shows that in St. Catharines 3.5 percent less Priority 4 calls were mapped (3398) resulting in an 18 second reduction in average response time to 6 minutes and 34 seconds. In St. Catharines (approximately 68 percent or 57 out of 84 grid cells) grid cells shaded in green increased by eight percent, showing acceptable average response times per service unit of 8 minutes or less. After anomalies were removed, St. Catharines responded to 81.3 percent of calls in eight minutes or less, a 2.8 percent increase, but is still the furthest from meeting MOH standards.

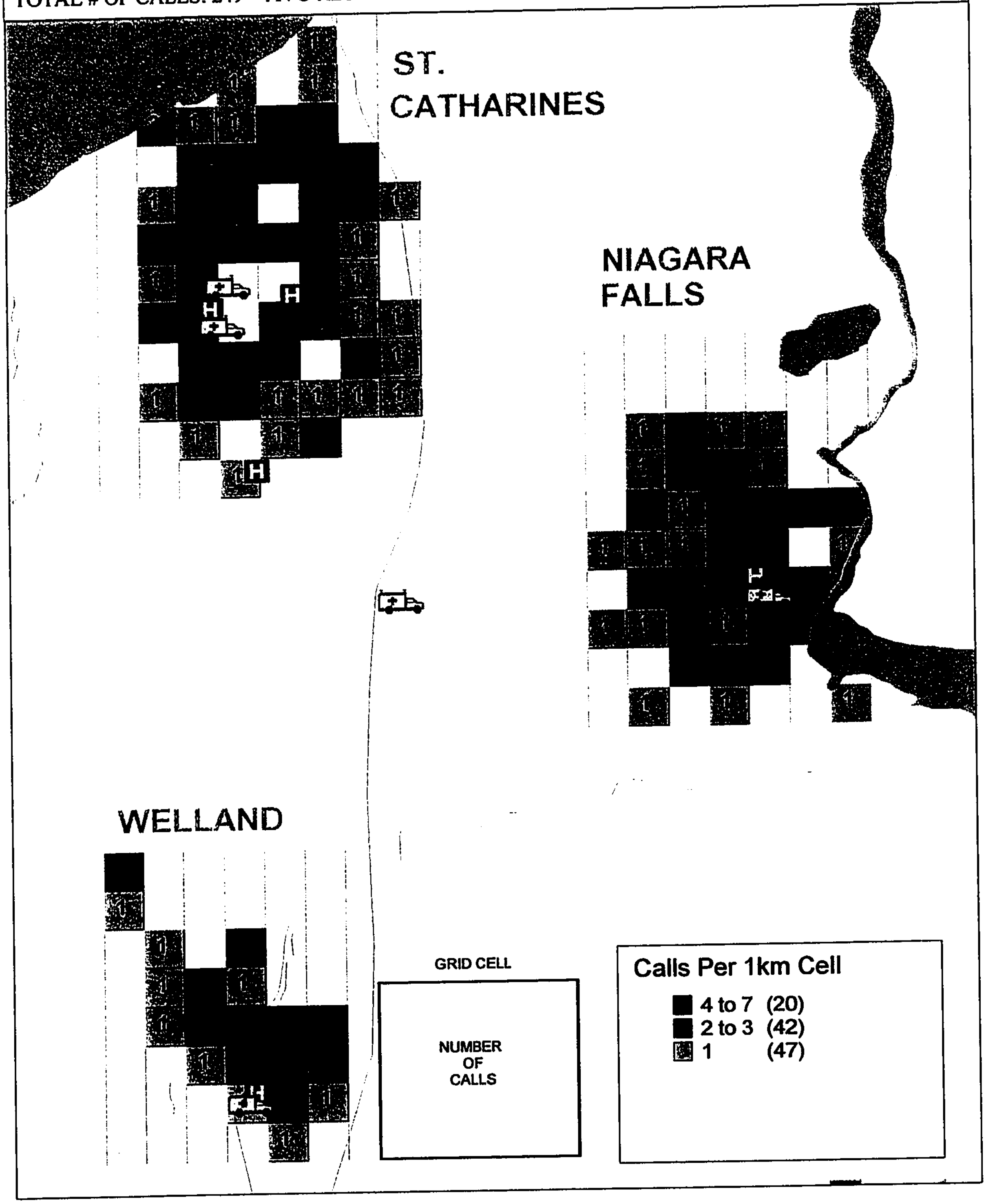
In Niagara Falls, 4.2 percent less Priority 4 calls were mapped (2074) resulting in a 26 second reduction and the lowest average response time of the three study areas to 5 minutes and 44 seconds. Niagara Falls still has the largest proportion of any study area increase.

In Welland, 4.1 percent less Priority 4 calls were mapped (978), resulting in a 15 second reduction in average response time to 5 minutes and 51 seconds. The area of Welland (approximately 69 percent or 33 out of 48 grid cells) shaded in green, decreased by 2 percent because one of the grid cells at the west end of the study area, that had an acceptable average response time before RTVAI process, was excluded since the average was based on a single call. Overall, after the RVTAI process, response time performance indicators generally improved in relation to MOH standards for all three study areas, based on response times that are more representative of consistent performance levels. In St. Catharines and Niagara Falls in particular a clearer and more consistent pattern of realised geographic accessibility is shown where response times need to be improved.

Figure 4.6 shows the distribution of the calls presented in Figure 4.4 that represent response time anomalies where a response time has a z-score of plus two or greater. These calls represent between 95 and 98 percent of both types of response time anomalies excluded in the RVTAI process in each of the three study areas. It is important to visualise these anomalies independently in order to help understand their distribution and significance. In each of the three study areas these response time anomalies represent between only 3.5 (St. Catharines) and 4.0 percent (Niagara Falls and Welland) (Table 4.1) of all the call responses shown in Figure 4.4. Approximately five percent of the cases should be filtered based on normal distributions. The spatial distribution of these anomaly calls generally appears to be consistent with the distribution of all the calls (Figure 4.4) in each of the three study areas. Yet, their important effect on performance indicator levels and the pattern of realised geographic accessibility is better indicated by the fact that the overall average response times for these anomalies in each study area (St. Catharines: 15:12; Niagara Falls: 12:49; and Welland: 12:15) are over twice as long as the averages after the RVTAI

Calls with Response Times >= 2 z-scores

TOTAL # OF CALLS: 249 AVG RESPONSE TIME: 13:54 % OF CALLS <= 8 MIN: 1.2



and very poor response performances increase the variation in response times, skew their average, and increase the spatial aggregation error in each grid cell resulting in the change in performance levels and the pattern of realised geographic accessibility as discussed previously in relation to Figure 4.5.

4.3 Response Time Performance Indicator Evaluation

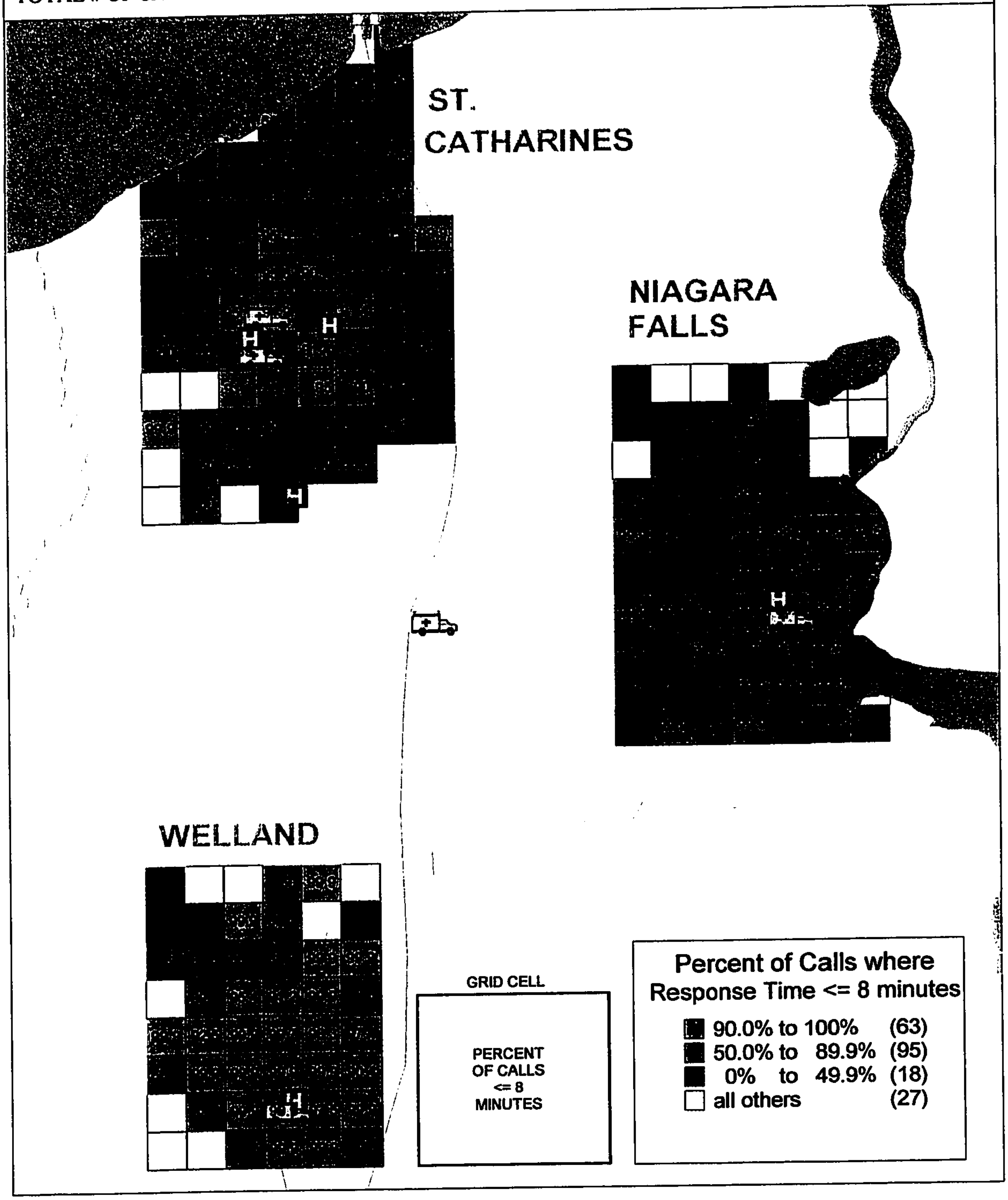
After the RTVAI process is applied, the results of the Response Time Threshold Performance Indicator (RTTPI) and CARTPI processes are evaluated for the three study areas to assess the value of the complimentary set of response time performance indicators proposed in the analytic model. As discussed in Chapter 2, this complimentary set of response time performance indicators can provide a more effective evaluation of realised geographic accessibility than average response time performance indictors alone.

The RTTPI process uses the percent of calls within a response time standard, to provide a second measure to compare with the average response time indicator's representation of performance. This performance indicator provides an effective measure for visualising performance in relation to MOH response time standards, which require that at least ninety percent of life-threatening calls have a response time of eight minutes or less. Figure 4.7 shows RTTPI accessibility surfaces for the three study areas describing the same calls represented by average response time indicators in Figure 4.5. In this Figure, the grid cells shaded in green show areas where at least 90 percent of response times are 8 minutes or less. In all three-study areas a substantially smaller portion of each study area meets the 90 percent MOH standard then the 8-minute average response time standard described in Figure 4.5. St. Catharines still has the smallest proportion of its catchment area (approximately 15.5 percent or 13 out of 84 grid cells) shaded in green; a substantial 52.5 percent decrease in area showing acceptable accessibility from Figure 4.5 (Table 4.1). Niagara Falls no longer has the largest proportion shaded in green. Approximately 35.2 percent (25 out of 71 grid cells) represents a substantial 41 percent

Figure 4.7: Percent of Calls

Without Response Times >= 2 z-scores and Single Calls in each grid cell

TOTAL # OF CALLS: 6450 AVG RESPONSE TIME: 6:11 % OF CALLS <= 8 MIN: 86.1



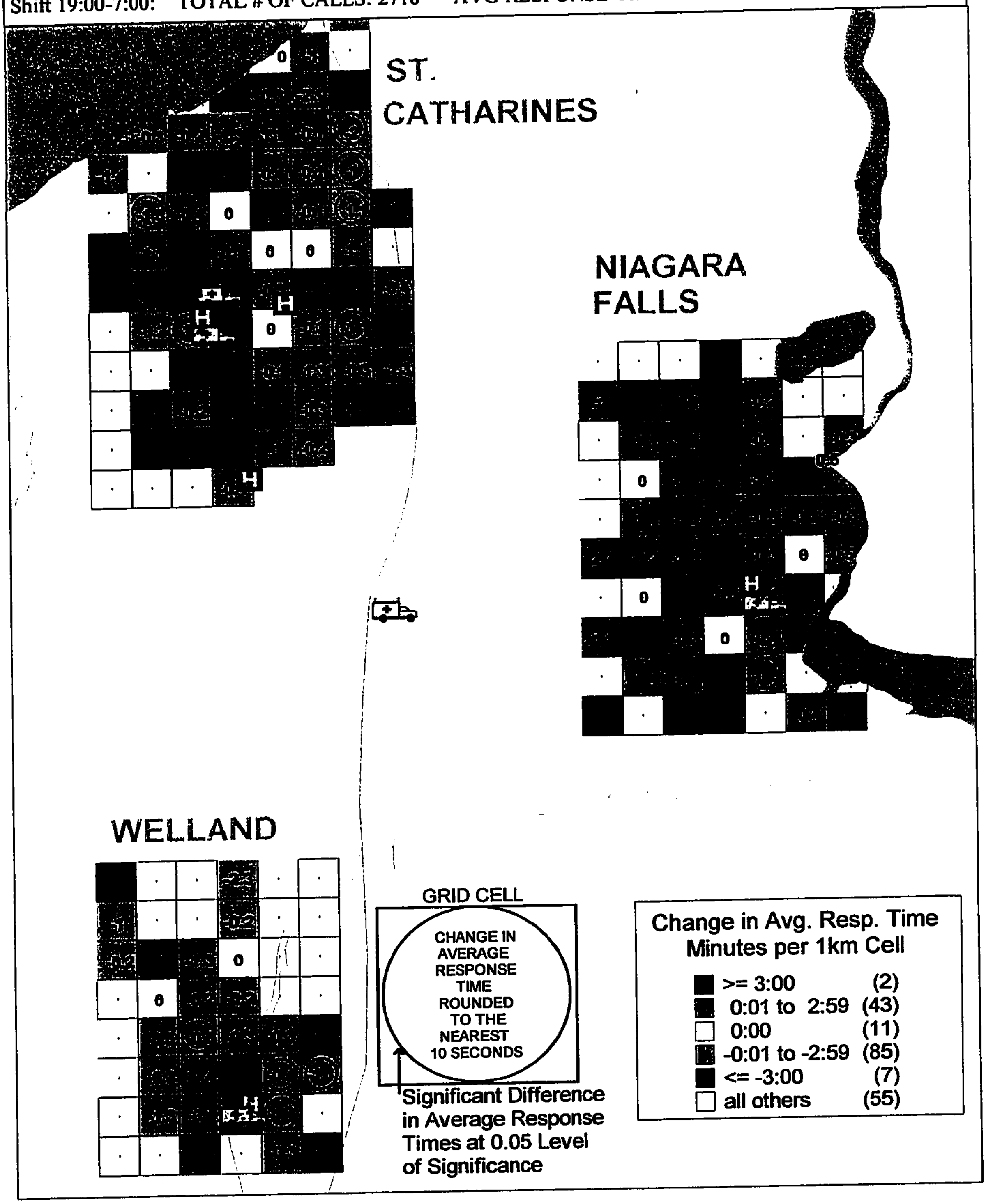
largest proportion (approximately 50 percent or 24 out of 48 grid cells) shaded in green, which represents the least substantial (19 percent) decrease in area showing acceptable accessibility from Figure 4.5. All three study areas, in particular St. Catharines, show a much poorer and less clear pattern of accessibility in Figure 4.7 compared to the results shown in Figure 4.5. However, all grid cells and areas that showed poor average response times in Figure 4.5 did not meet the 90 percent MOH standard in Figure 4.7. This helps substantiate the view that these are areas where ambulance response must be improved. Similarly, all grid cells and areas that met the 90 percent MOH standard in Figure 4.7 also showed acceptable average response times in Figure 4.5. This in turn helps substantiate the view that these are areas where ambulance response is satisfactory based on both response time performance indicator standards evaluated.

Complementing the RTTPI process, the CARTPI process uses the change or difference in average response times for two or more different time periods or types of calls and their statistical significance to provide an effective measure of change in ambulance performance over space, time and by type of incident. Unlike the other two response time indicators, this variable shows where and when socio-spatial differentiation is a significant factor in relation to ambulance performance. Figure 4.8 shows CARTPI accessibility surfaces for the three study areas describing the difference in average response times for calls answered on the day shift (7AM to 7PM) and night shift (7PM to 7AM) in each grid cell. Ambulance service agencies can compare ambulance performance by work shifts and by different times of the day, using the CARTPI process in this way. The relative level of demand during these two shifts is similar in each study area, with between 56 and 60 percent of the calls occurring during the day shift.

In all three areas, there are more grid cells shaded in green then red, showing where the average response times for the day shift are lower than the night shift averages. The service units that have graduated circles indicate that the difference in the averages is statistically significant at 95 percent confidence level. The majority of grid cells with

Without Response Times >= 2 z-scores and Single Calls in each grid cell

Shift 7:00-19:00: TOTAL # OF CALLS: 3688 AVG RESPONSE TIME: 6:04
Shift 19:00-7:00: TOTAL # OF CALLS: 2718 AVG RESPONSE TIME: 6:18



average response time for the day shift. ANOVA tests conducted on the combined calls for each study area confirmed this general pattern with a probability less than or equal to 0.05 in all three-study areas.

The general pattern showing this significant difference is represented in each study area by different levels of accessibility. In St. Catherines, the day shift average response time for the whole study area is 6 minutes and 27 seconds based on 1,897 calls. The night shift average response time is 10 seconds more at 6 minutes and 37 seconds, based on 1,480 calls. Both the day and night shift averages are the highest of the three study areas. An ANOVA test conducted on the combined calls for the whole study area resulted in a probability of 0.05, showing a significant difference where the average response time for the day shift is lower than the night shift average (Table 4.5). Approximately 59 percent of the area where differences in averages are represented (40 out of 68 grid cells) are shaded in green, showing where the average response times for the day shift are lower than the night shift averages. Nine of these grid cells, six of which are in the north part of the study area, have graduated circles that indicate a significant difference. These nine grid cells correspond to ones in Figure 4.7 that represent areas that do not meet the MOH response time standard. This fact suggests that the night shift response times in these areas are contributing more to the poor ambulance performance than the day shift performance.

In Niagara Falls, the day shift average response time for the whole study area is 5 minutes and 38 seconds, based on 1,208 calls. The night shift average response time is 12 seconds more at 5 minutes and 50 seconds, based on 845 calls. Both the day and night shift averages are the lowest of the three study areas. Similar to St. Catharines, an ANOVA test conducted on the combined calls for the whole study area resulted in a probability of 0.025, showing a significant difference where the average response time for the day shift is lower than the night shift average (Table 4.6). Moreover, Niagara Falls has the largest portion of its area where differences in averages are represented (approximately response times for the day shift are better.

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Day shift	1897	734392	387.1334	20783.79
Night shift	1480	587315	396.8345	19703.82

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	78241.86	1	78241.86	3.852281	0.04976	3.844207
Within Groups	68548022	3375	20310.52			
Total	68626264	3376				

Table 4.5: Day shift vs. night shift ANOVA test result for St.Catharines

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Day shift	1208	407806	337.5877	14375.05
Night shift	845	296067	350.3751	18774.84

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	81301.61	1	81301.61	5.023085	0.025118	3.845997
Within Groups	33196651	2051	16185.59			
Total	33277952	2052				

Table 4.6: Day shift vs. night shift ANOVA test result for Niagara Falls

In Welland, the day shift average response time for the whole study area is 5 minutes and 43 seconds based on 583 calls (Table 4.7). The night shift average response time is 24 seconds more at 6 minutes and 7 seconds, based on 393 calls. Like both other study areas, an ANOVA test conducted on the combined calls for the whole study area response time for the day shift is better than the night shift average. Also similar to Niagara Falls, a large portion (approximately 68 percent or 19 out of 49 grid cells where calls took place) of the study area is shaded in green, showing where the average response times for the day shift are better than the night shift averages. Overall, the CARTPI accessibility surfaces shown in Figure 4.8, indicate that the socio-spatial differentiation of response times based on these two-ambulance work-shifts likely had a statistically significant and similar impact on ambulance performance in all three-study areas.

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Day shift	583	199978	343.0154	15057.4
Night shift	393	144195	366.9084	14541.29

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	134014.3	1	134014.3	9.024723	0.002732	3.851028
Within Groups	14463596	974	14849.69			
Total	14597610	975				

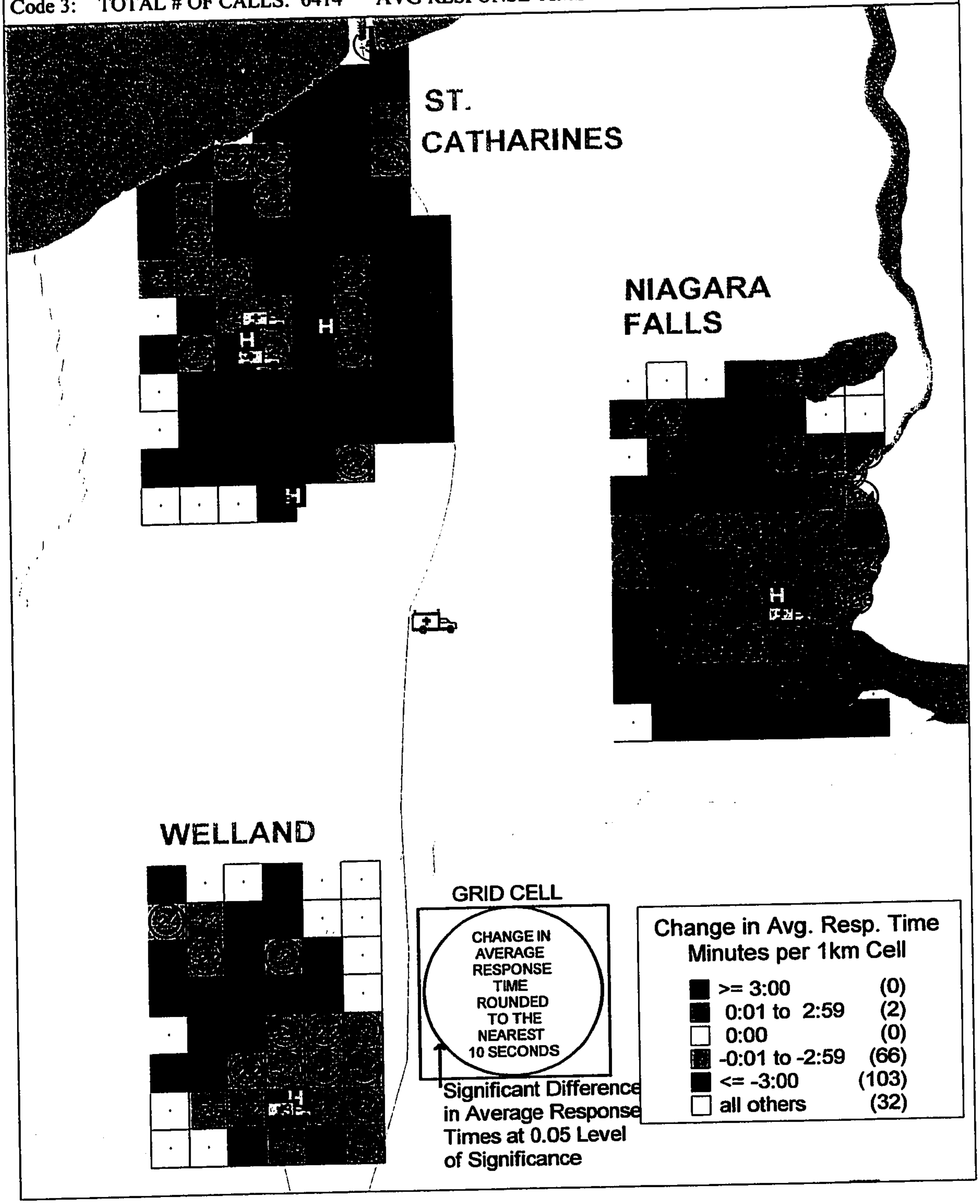
Table 4.7: Day shift vs. night shift ANOVA test result for Welland

Figure 4.9 shows CARTPI accessibility surfaces for the three study areas describing the difference in average response times for calls dispatched as priority code 4 life threatening calls and priority code 3 prompt calls. The MOH analysis of the demand for and response of ambulance services focuses on these two types of calls, where ambulance response and the deployment of ambulance services are most important. The relative level of demand for these types of calls is similar in each study area. In each study area between 66 and 67 percent of the two types of calls was code 4.

Without Response Times >= 2 z-scores and Single Calls in each grid cell

Code 4: TOTAL # OF CALLS: 12692 AVG RESPONSE TIME: 6:08

Code 3: TOTAL # OF CALLS: 6414 AVG RESPONSE TIME: 9:23



in green, that have graduated circles, showing a strong probability of a significant difference where the average response times for code 4 are lower than the code 3 averages. At least 97 percent of grid cells in each study, where differences in average response times are represented, are shaded in green and of these at least 85 percent have graduated circles. ANOVA tests conducted on the combined calls for each study area confirmed this pattern with a probability close to zero in all three-study areas. The difference in average response times in the two grid cells shaded in red, showing where the average response times for code 4 are higher than the code 3 averages, were not found to be statistically significant. This common pattern is expected as ambulance services plan to respond to life threatening calls more quickly than prompt calls.

The pattern showing this significant difference is represented in each study area by different levels of accessibility. In St. Catherines, the code 4 average response time for the whole study area is 6 minutes and 28 seconds, based on 6,703 calls (Table 4.8). The code 3 average response time is 3 minutes and 30 seconds more at 9 minutes and 58 seconds, based on 1,480 calls. Both code 3 and 4 averages are the highest of the three study areas.

	St. Catharines	Niagara Falls	Welland	**Total**
# of calls: code 4	6703	4021	1968	**12692**
# of calls: code 3	1480	1930	962	**6414**
Avg. Response: code 4	6:28	5:43	5:52	**6:08**
Avg. Response: code 3	9:58	8:41	8:40	**9:23**
P-value	0	0	0	
F statistic	3263.89	998.31	604.46	
% of area code 4 avg.< code 3 avg.	98	100	97	

Table 4.8: Code 4 vs. Code 3 ANOVA test results

minutes and 43 seconds, based on 4,021 calls (Table 4.8). The code 3 average response time is almost 3 minutes more at 8 minutes and 41 seconds, based on 1,930 calls. Both code 3 and 4 averages are the lowest of the three study areas.

In Welland, the code 4 average response time for the whole study area is 5 minutes and 52 seconds based on 1968 calls (Table 4.8). The code 3 average response time is 2 minutes and 48 seconds more at 8 minutes and 40 seconds, based on 962 calls. Both Welland and Niagara Falls have the same code 3 average response times.

Overall, Figure 4.9 shows how organisational factors of ambulance service delivery, such as how MOH prioritises requests for ambulance services, have a significant impact on realised geographic accessibility. In this context, the differentiation of the nature and urgency of demand, using priority codes, is fundamental to the assessment of the corresponding spatio-temporal patterns of realised response times and the evaluation of ambulance performance. For example, the analysis of priority code 3 and 4 calls together would clearly increase the variation and thereby increase spatial aggregation error, resulting in less reliable accessibility measures and surface representation. However, the methodology is limited by the fact that response times in each grid cell do not always approximate normal distributions, even after the RTVAI process filtered response time anomalies. Moreover, a large enough sample or response times should be used for ANOVA to ensure a minimum of 30 response times in each treatment are compared in each grid cell. Some of the grid cells on the peripheries of each study area did not meet this minimum requirement.

4.4 Evaluation of Tools to Help Explain Performance Indicators

After response time performance indicators are used to evaluate realised geographic accessibility, the CVFD, RTFD and STG processes are used to help explain response time anomalies and performance indicator patterns in the three study areas. As discussed in performance standards in a particular area so that deployment decisions can be better informed.

The CVFD process generates frequency distribution tables that compare the volume of calls each station answered and the average response times for those calls in any given area. Using this table it is possible to visualise the Euclidean (straight line) distances ambulances based at each station are travelling in relation to their performance levels. The distance travelled by ambulances is an important geographical factor that intervenes to either increase or decrease response time performance indicators.

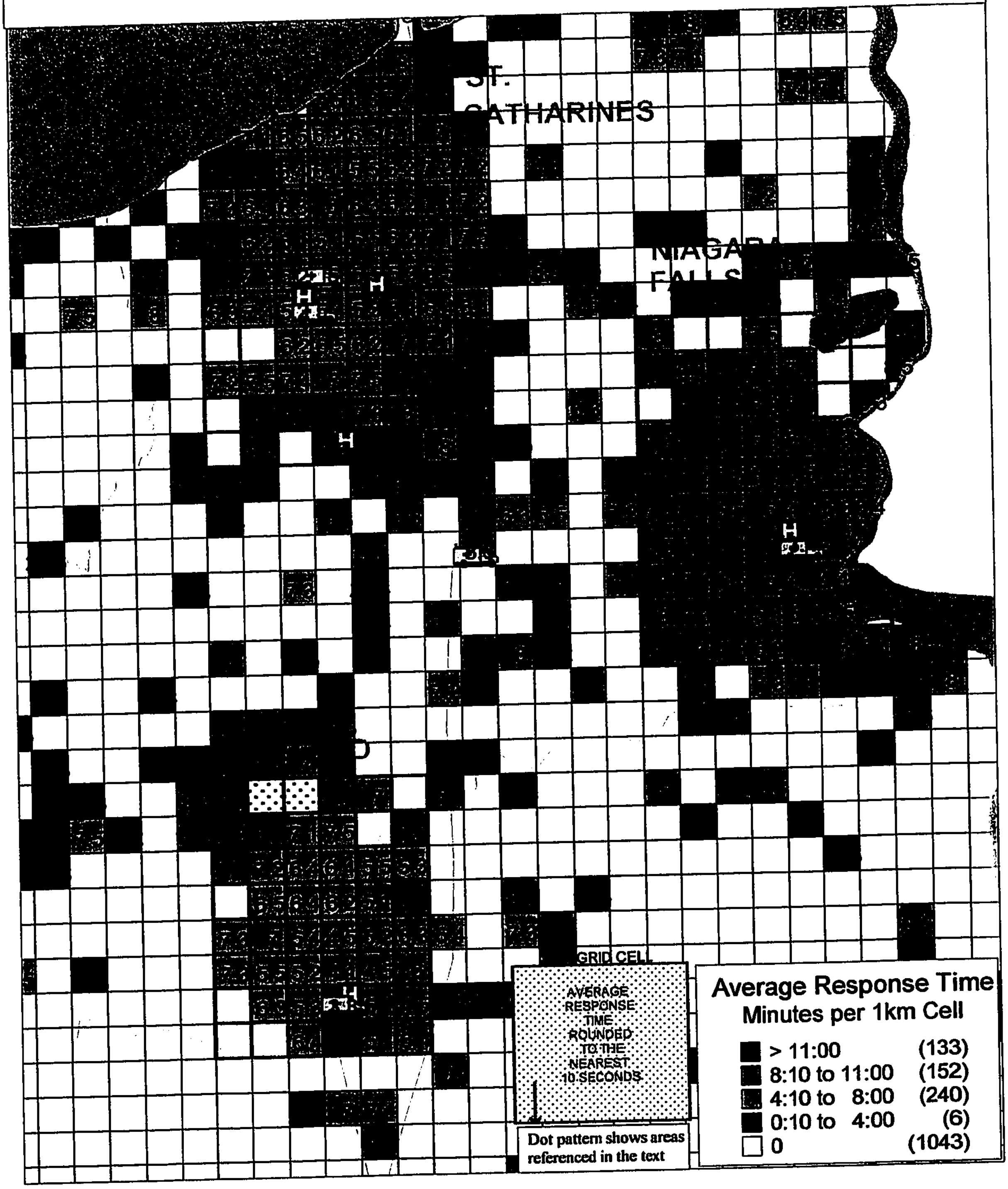
As a compliment to the CVFD process, the STG process defines *functional* catchments (territories) historically serviced by selected ambulance stations. These catchments help explain performance indicator patterns in terms of the Euclidean (straight-line) distances travelled by ambulances based at each station in relation to their performance levels and in relation to the distances and performance levels of other ambulances.

In addition, the RTFD process can help to explain how frequently and at what level of variation response times exceed standards for life-threatening calls. This process generates frequency distribution tables that compare the frequency of and variation in unique response times.

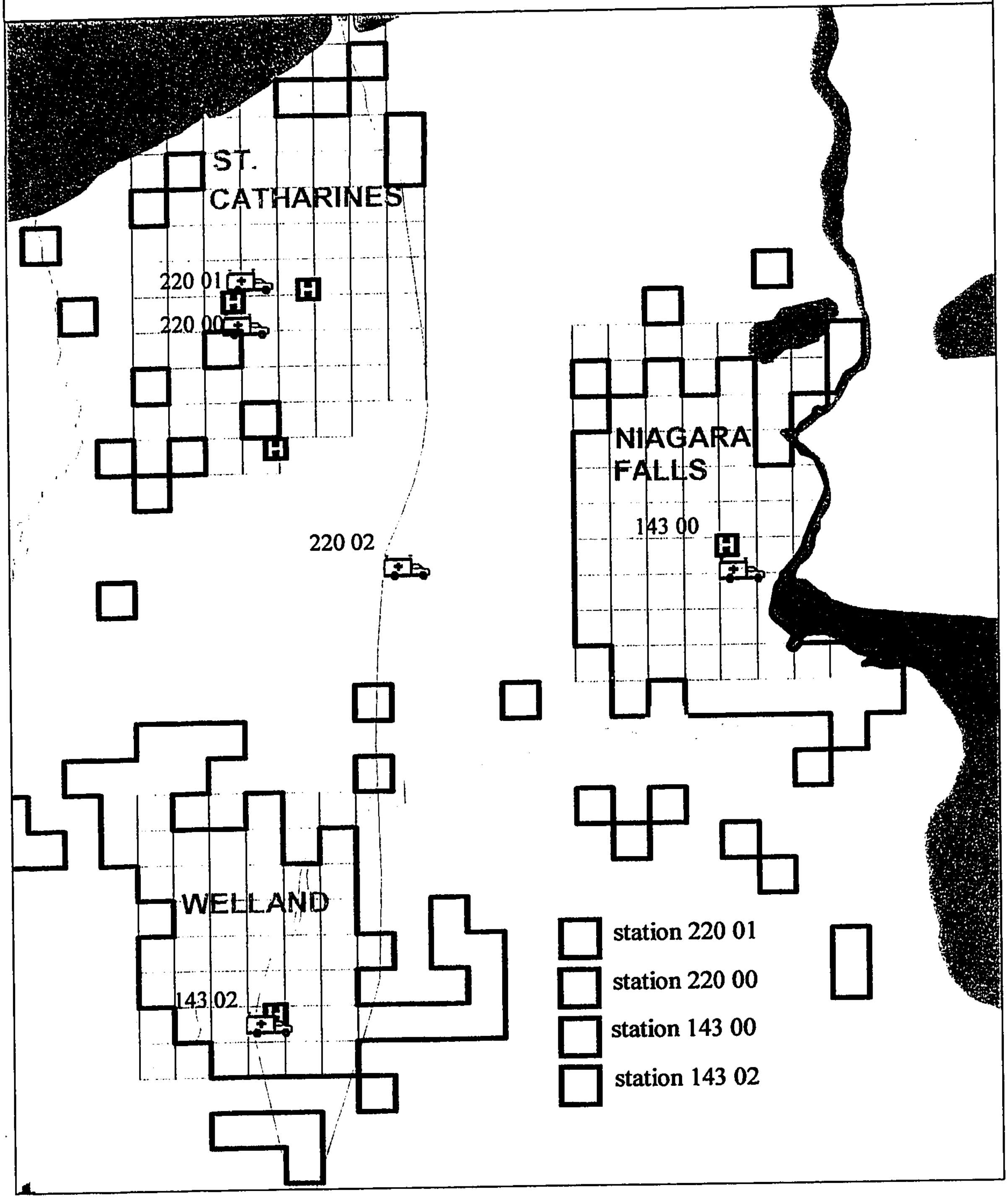
Figures 4.10 and 4.11 apply the CVFD, RTFD and STG processes to the average response time accessibility surfaces, shown in Figure 4.5, and the surrounding areas to help explain why the areas with the dotted pattern in Figure 4.10 show unsatisfactory accessibility according to both the average response time (Figure 4.5) and response time threshold (Figure 4.7) performance indicators. In the St. Catharines study area, the grid cells with the dotted pattern in Figure 4.10 represent one of the main areas showing unsatisfactory accessibility.

Figure 4.10: Average Response Time Performance ...

Without Response Times >= 2 z-scores and Single Calls in each grid cell



Where stations responded to >= 75% of calls in each grid cell



that no station responded to 75 percent or more of the calls in this area showing unsatisfactory accessibility. The catchments with a >= 75 percent response rate for St. Catharines stations 220 00 and 220 01 are represented by the red and green polygons respectively. These two catchments also indicate that the majority of the study area is similar to the dotted area where no single station responded to the 75 percent or more of the calls. This pattern can be explained by the fact that two stations, located in St. Catharines, each responded to a large enough proportion of the calls so that no individual station answered 75 percent or more of the calls in the majority of the grid cells.

The CVFD table (Table 4.9) for the this area in St. Catharines, shows the frequency of calls each station answered and the average response time for those calls. The two stations in St. Catharines (220 00 and 220 01) and the station in Thorold (220 02) responded to 95 percent of the calls in this area. No single station responded to the majority of calls and each of the three stations had high average response times of between eight and nine minutes. The area is located between the three stations, all of which responded to many calls in this area with similar accessibility characteristics, (in particular 220 01 and 220 02) which do not meet MOH standards.

St. Catharines: Figure 4.10			
Station	**Number of calls**	**Percent of calls**	**Average response**
143 00	1	0.8	2:20
143 01	1	0.8	9:00
143 02	1	0.8	8:39
218 00	4	3.3	8:27
220 00	42	34.7	8:45
220 01	29	24	8:15
220 02	43	35.5	8:20

Table 4.9: CVFD table for St.Catharines

In Niagara Falls, the grid cell in the southwest corner (Figure 4.10) has the highest average response time in the study area at 10 minutes and 50 seconds. This is 2 minutes

Niagara Falls study area (Figure 4.11) shows that this is the only grid cell in the southern part of the study area where the Niagara Falls station (143 00) did not respond to 75 percent or more of the calls. The CVFD table for this grid cell (Table 4.10) shows that the Niagara Falls station (143 00) responded to 60 percent of the calls (3 out of 5 calls) in this grid cell. For these calls, the Niagara Falls station had a high average response time of 8 minutes and 15 seconds. This is 2 minutes and 35 seconds less then the overall average, and is consistent with the pattern shown for the surrounding area.

Niagara Falls: Figure 4.10			
Station	**Number of calls**	**Percent of calls**	**Average response**
143 00	3	60	8:15
143 02	1	20	9:49
220 00	1	20	19:28

Table 4.10: CVFD table for Niagara Falls

The CVFD table (Table 4.10) also shows that the St.Catharines (220 00) and Thorold (143 02) stations responded to the other two calls in the grid cell, both of which had higher response times then the average for the Niagara Falls station. The St.Catharines station in particular, which is furthest from the area, had a very poor response time of 19 minutes and 28 seconds. In this context, the RTFD table (Table 4.11) compares the frequency of and variation in unique response times in the grid cell rounded to the nearest minute. The table shows that the St.Catharines response time is 1.6 standard deviations above the average for the grid cell. This response time increases the variation in response times significantly and skews the average for the grid cell. Generally, the STG, CVFD and RTFD processes show that the unusually high average response time in the grid cell was caused by an ambulance based in St. Catharines responding to a call in the Niagara Falls study area from a considerable distance away.

Resp. time (minutes)	Number of calls	Percent of calls	z-score
6	1	20	-1
8	1	20	-0.6
10	1	20	-0.2
11	1	20	0
19	1	20	1.6

Table 4.11: RTFD table for Niagara Falls

In the Welland study area, the grid cells shown with a dotted pattern in Figure 4.10 represent the largest area with unsatisfactory accessibility. The functional catchment for the study area (Figure 4.11) shows that the Welland station (143 02) responded to 75 percent or more of the calls in this area, as well as responding to 75 percent or more of the calls in most of the study area as a whole. The CVFD table (Table 4.12) for this area shows that Welland station 143 02 responded to 91.2 percent (31 calls) of the calls with a high average response time of 9 minutes and 37 seconds. Two calls were responded to by the Port Colborne station (002 00), with an acceptable average response time of 7 minutes and 7 seconds. One call was responded to by the Thorold station (220 02) with a high response time of 9 minutes and 31 seconds.

Welland: Figure 4.10			
Station	Number of calls	Percent of calls	Average response
143 00	2	5.9	7:07
143 02	31	91.2	9:37
220 02	1	2.9	9:31

Table 4.12: CVFD table for Welland

Generally, the STG and CVFD processes show that the Welland station, which responds to a large majority of the calls in the study area, is consistently not able to respond to calls within the MOH standards in this area. Furthermore, Figure 4.4 shows that this station is not located in the area showing the highest demand for priority 4 calls, as an efficiency planning objective would require. Station 143 02 would be closer to the largest area of unsatisfactory accessibility and more centrally located within the study area efficient location would likely improve accessibility in this area as well as in study area as a whole.

The CVFD tables 4.13, 4.14 and 4.15 help explain the cause of response time anomalies represented in Figure 4.6 where a response time has a z-score of plus two or greater. The CVFD tables for all three study areas show that calls responded to by ambulances based at stations outside of each study area represent a much greater proportion of calls whose response times represent statistical anomalies than the normal variation in performance. Specifically, the CVFD table for the St.Catharines study area (Table 4.13) shows that 42.6 percent of anomaly calls were responded to by ambulances based at stations outside of St.Catharines. This proportion of anomaly calls is 27 percent greater than the 15.3 percent of non-anomaly calls that were responded to by ambulances based at stations outside St.Catharines (Figure 4.5). Similar to St. Catharines, the CVFD table for the Niagara Falls study area (Table 4.14) shows that 37.9 percent of these calls were responded to by ambulances based at stations outside Niagara Falls. In Niagara Falls this proportion of anomaly calls is 29.9 percent greater than the 8 percent of non-anomaly calls that were responded to by ambulances based at stations outside the city (Figure 4.5). Similar to the other two study areas, the CVFD table for the Welland study area (Table 4.15) shows that 35 percent of anomaly calls were responded to by ambulances based at stations outside Welland. This proportion of anomaly calls is 29.3 percent greater than the 5.7 percent of non-anomaly calls that were responded to by ambulances based at stations outside Welland (Figure 4.5). Although, a large proportion of all the anomaly calls (57.4 % in St.Catharines, 62.1% in Niagara Falls, and 65% in Welland) were responded to by ambulances based at the stations in each study area, it is likely that the ambulances responded to many of these calls from a location other then the base station. However, the data set used in this thesis does not include the information necessary to show that this is the case.

Station	Number of calls	Percent of calls	Average response
143 00	3	2.5	16:19
143 02	5	4.1	17:45
218 00	12	9.8	14:18
220 00	32	26.2	15:16
220 01	39	32	15:20
220 02	31	25.4	14:48

Table 4.13: CVFD table for St.Catharines

Niagara Falls: Figure 4.6			
Station	Number of calls	Percent of calls	Average response
143 00	54	62.1	13:08
143 01	1	1.1	10:41
143 02	7	8	12:16
218 00	16	18.4	12:07
220 00	2	2.3	11:22
220 02	7	8	13:13

Table 4.14: CVFD table for Niagara Falls

Welland: Figure 4.6			
Station	Number of calls	Percent of calls	Average response
002 00	9	22.5	13:27
143 00	1	2.5	11:06
143 02	26	65	11:43
220 01	1	2.5	14:40
220 02	3	7.5	12:54

Table 4.15: CVFD table for Welland

4.5 Summary and Discussion of Results

The objective of this thesis was to develop spatial models and methods to assist emergency health service planners and decision-makers evaluate and improve accessibility and response performance for target populations. This chapter applied the methods presented in Chapter 3 to test empirically the analytic model and GIS framework, study areas in the Regional Municipality of Niagara, for priority 4 life threatening calls, during a 2 year period from 1995 to 1996. The methodology was applied to the study areas and call data to address each of the three dimensions of response time patterns and trends. The results are summarised below.

The evaluation of realised geographic accessibility enables emergency health care service planners to assess the historical spatial distribution of supply relative to demand and to identify areas to which ambulance stations have deficient accessibility. In this context, the RVTAI model was applied to address the first dimension and thus assess the value of the independent analysis and visualisation of response time anomalies and the 'normal' variation in ambulance response times. This model provides the options to exclude calls with or without one or both types of anomaly (e.g. single calls in a grid cell and response times that have a z-score of $\geq +2.0$) from further analysis.

After the RVTAI model was applied to exclude both types of anomalies, Figures 4.3 and 4.5 showed that response time performance indicators generally improved in relation to MOH standards for all three study areas, based on response times that are more representative of consistent performance levels. Further, in St. Catharines and Niagara Falls in particular, large areas of 9 km^2 and 5 km^2 respectively changed status in terms of meeting MOH standards. In addition, a clearer and more consistent pattern of realised geographic accessibility is shown in both these study areas. Figure 4.6 showed that the distribution of response time anomalies is similar to overall demand and can therefore impact everywhere there is demand. This is especially true on the peripheries of the study areas, where demand is lowest and response time and response time variation is greatest. However, the methodology is limited by the fact that, response times in each grid cell do not always approximate normal distributions. Therefore, the number of response time anomalies filtered in each grid cell varied. In each study area as a whole 3.5 (St. Catharines) and 4.0 (Niagara Falls and Welland) percent of response time anomalies were filtered. Approximately five percent of the cases should be filtered based on normal better identify areas where ambulance response is consistently outside of the response time standard. This more accurate representation of the underlying patterns of accessibility can then help decision-makers plan service deployment in order to improve service provision efficiency and consumer equity for those areas.

The RTTPI and CARTPI models were also applied to address the second dimension of the analytic model (Figures 4.7, 4.8 and 4.9), and thus provide a complimentary set of response time performance indicators to improve the evaluation of realised geographic accessibility. The RTTPI model uses the percent of calls within a response time standard, to provide a second measure to compare with the average response time indicator's representation of performance. Figure 4.7 showed a RTTPI model accessibility surface that helps to substantiate areas of acceptable and deficient accessibility shown in the average response time accessibility surface where both models showed the same results according to their different standards. The reliability of each performance indicator is greater in areas where both models show the same results. The RTTPI model provides planners with a relative measure of accessibility that can be used effectively to help substantiate the average response time aggregate measure of accessibility, and vice-versa. Further, the RTTPI process provides planners with a equally valid performance indicator on its own, that is not affected by outlier (anomaly) response times, as averages are.

The CARTPI model provides planners with an effective measure of change in ambulance performance over space, time and by type of incident. Unlike the other two indicators, this model's results show where and when the socio-spatial differentiation (e.g. various geographical factors, socio-economic characteristics of the consumers, and organisational characteristics of the service delivery system) of actual demand (the normative need for ambulance services) is a significant factor in relation to the corresponding spatial and temporal patterns of realised response times. Specifically, in Figure 4.8 the socio-spatial differentiation of response times based on day and night areas where the day-time shift has a lower average response time than the night-time shift than vice-versa. In Figure 4.9 the socio-spatial differentiation of response times based on the nature and urgency of demand shows a significant difference and clear pattern in all three study areas in cells where priority code 4 calls have a lower average response time than priority code 3 calls. However, the methodology is limited by the fact that response times in each grid cell do not always approximate normal distributions. These same limitations restrict the RTVAI process from consistently creating more normal distributions that are required by ANOVA. Generally, these results show that by applying the CARTPI process planners can help determine the time and nature of the calls that have a significant impact on realised geographic accessibility. This process can test the hypothesis whether or not response times have, for example, significantly improved after service modification; are better on weekends than week days; are worse during rush hour than the rest of the day; or are better for life-threatening types than less serious types of calls. In this way, planners can better target when, where, and for what type of calls ambulance response performance should be improved.

In regard to the third dimension, the value of the CVFD, RTFD and STG models are evaluated in terms of how these models help explain response time anomalies and performance indicator patterns in the three study areas. Figures 4.10 to 4.11 and tables 4.9 to 4.12 show how the CVFD and STG models identify performance levels according to the various stations that responded to calls in areas where performance standards are not met. This allows planners to determine if unsatisfactory accessibility is caused as a result of calls that are responded to by stations other than the closest station. Once planners determine which station is responsible, the RTFD process is used to determine how pervasive the problem is in terms of the frequency and variation in response times in relation to response time standards. For example, in the case of Niagara Falls, it was determined that an unusually high average response time in the south west corner of the study area was skewed by a one poor response time belonging to an ambulance based in St. Catharines responding to a call in the area.

response time anomalies according to the various stations that responded to calls. The CVFD tables for all three study areas show that calls responded to by ambulances based at stations outside each study area represent a much greater proportion of calls whose response times represent statistical anomalies than the normal variation in performance. Generally, the CVFD model shows that when ambulances respond to calls from a location other than the closest station response time becomes a random phenomenon, often causing anomalies and response performances below those required to respond reliably to calls from demand areas.

Chapter 5

Summary and Conclusions

This chapter first reviews, in general terms, the contributions of this thesis to the current body of research on emergency ambulance service delivery. This is followed by a discussion of the contributions of the thesis in terms of the objectives stated in Chapter 1. The last section outlines directions for future work required to develop further this prototype application in the form of a more comprehensive ambulance service GIS-based Decision Support System (DSS).

5.1 Summary

The introduction of this thesis noted the fundamental importance of the accessibility, distribution and utilisation of ambulance services to the effectiveness, efficiency and equity of emergency health care service provision. However, ambulance resources are often insufficient and sometimes inefficiently and inequitably distributed in the target population, resulting in response times below those required to respond reliably to emergency calls from demand areas. In addition, the issue of improving geographic accessibility of emergency health care services to the target population is a complex spatial problem. The complexity of this problem is heightened by the fact that when ambulances are not available at the station closest to a call, response time becomes a random phenomenon, causing anomalies and considerable variation in ambulance performance.

Thus, this thesis has examined issues and models relating to the evaluation of realised geographic accessibility and its ability to account for response time variation. The goal of this work is to help plan the deployment of a limited number of ambulances in a way that maximises the number of people or calls that have ambulance services available

within a maximum time ...
technology in particular in emergency health care service deployment as a planning tool for improving the visualisation of realised geographic accessibility and assessing ambulance response performance. Specifically, the objectives of the thesis were to describe a generic model for evaluating and improving ambulance response; to develop a valid GIS-based spatio-temporal methodology that includes an easy-to-use interface to assist service deployment planners to operationalise this model; and to apply this methodology to demonstrate the usefulness of the approach presented in the thesis using empirical data. The thesis fulfilled these objectives as follows.

Chapter 2 examined issues related to assessing accessibility for emergency health-care service delivery. This chapter also provided a review of the current use of GIS technology to improve service delivery and address these issues. Further, an analytic model and GIS design framework were proposed to address analytical deficiencies in existing methodologies for assessing realised geographic accessibility.

Chapter 3 provided the research methodology used to operationalise the analytical model and GIS design framework proposed in Chapter 2. Specifically, analytic functionality to calculate and map accessibility indicators was described in terms of five processes that were operationalised together to address the three dimensions in the analytic model. Also, a design methodology and several objectives were proposed to develop a user-centred, task-based GUI as the method through which users operate the five automated processes to generate performance indicator thematic maps in a decision support environment.

In Chapter 4, the five processes of the research methodology were applied to evaluate the usefulness of the application and its approach with a case study using empirical data from the MOH. This chapter applied the methodology to three study areas in the Regional Municipality of Niagara to address each of the three dimensions of response time patterns and trends discussed in Chapter 2.

The thesis has made a contribution to current knowledge, in the areas noted above, in the following ways. The first contribution relates to the development of the analytic model and GIS design framework for assessing realised geographic accessibility. As noted in Chapter 2, the current body of related research is limited in its discussion of spatio-temporal dimensions of response time patterns and trends, including the independent analysis and visualisation of response time anomalies and the 'normal' variation in performance levels; the appropriate application of a complimentary set of response time performance indicators; and the use of tools to help explain performance indicator patterns and trends. The analytic model and GIS design framework developed provide a conceptual framework to address these analytical deficiencies in existing methodologies for assessing realised geographic accessibility.

The second contribution is the development and validation of a GIS-based application that utilises a robust and easy-to-use methodology, for improving the visualisation and analysis of ambulance response performance. As noted in Chapter 3, GIS provides emergency health service planners with a unifying framework to facilitate the development of real-world applications of geographical models and to communicate geographic patterns and trends in ambulance response performance to decision makers that would otherwise be unknown. The limitations of this methodology result from the fact that response times in each area do not always approximate normal distributions. Thus, the effectiveness of using z-scores to facilitate the independent analysis and visualisation of response time anomalies and the 'normal' variation in performance levels is limited. This independent analysis is the basis for the analytical framework. Thus, the effectiveness of other parts of the framework (e.g. ANOVA) are impacted as well.

Despite the advantages offered by the use of GIS in improving emergency response performance, existing GIS-based applications reported in the literature do not fully examine the three spatio-temporal dimensions noted earlier of response time patterns above, the integration of the proposed statistical and geographical modelling methods and outputs into GIS-based applications, that examine these spatio-temporal dimensions, historical call data can be used to assess more accurately realised geographic accessibility and ambulance response performance. Thus, the proposed methodology can have substantial benefits for managing and analysing data to produce information relevant to decision making.

5.3 Directions for Future Research

The thesis has provided several useful spatial models and methods to assist emergency health care service planners and decision-makers evaluate and improve accessibility and response performance for ambulance services. However, its focus is limited to the evaluation of realised geographic accessibility and ambulance response performances in particular using a basic set of call data attributes. In this context, it is also limited to a grid of a given spatial resolution ($1km^2$), the socio-spatial differentiation of demand by the time and the nature of a call (e.g. MOH priority codes) and the evaluation of straight-line distances. This section outlines some of the areas which require further research that can extend the spatial models and methods provided in this thesis in order to address these limitations and develop further this prototype application in the form of a more comprehensive ambulance service GIS-based DSS.

In the data set used in this thesis, a grid of given spatial resolution ($1km^2$) is predefined for all ambulance call data by the MOH and the call data are geo-referenced to the grid cell centroid. However, a GIS-based DSS should include methods to determine an aggregation scheme with an appropriate grid-cell size based on acceptable aggregation error bounds [Bowerman, 1997]. In general, it is possible to calculate worst-case error bounds for accessibility measures because ambulance services record street addresses for individual calls so that calls can be geo-referenced to individual point locations. In order to determine an appropriate grid-cell size, a model can be developed to generate a spatial be used to address match the call locations that are used to calculate aggregate accessibility measures to a street network or property database (see Chapter 3). Then using geo-referenced point call locations, worst-case error bounds for accessibility measures can be computed. The average distance of the location of individual calls to the centroid of the grid cell represents an upper bound for the maximum aggregation error. The lower bound on the aggregation error is the negative of the upper bound. These methods are important in order to control the effects of spatial aggregation error.

A GIS-based DSS should also include methods for the socio-spatial differentiation of actual demand and especially the potential need for ambulance services. These methods can be used to measure the relative importance of organisational factors and socio-demographic characteristics of consumers in relation to the corresponding spatial and temporal patterns of realised and potential geographic accessibility. As noted in Chapter 2, the spatio-temporal characteristics of demand can be explained by socio-demographic variables (e.g. population density, population age, income), land use variables (e.g. land values and land use mix) and activity variables (e.g. traffic volume) although it is difficult to isolate the influence of any one factor. In this context, a statistical model can be developed to calculate and compare the number of calls with specified characteristics that are expected in an area (potential demand) with the number of calls that actually took place with the same characteristics (realised demand). This would allow the evaluation of accessibility to be enhanced by modelling differential accessibility of the potential for individual use behaviour in relation to a surrogate measure of need.

Further, measures of potential geographic accessibility can be incorporated into the analytic model and the GIS framework to compare respectively the optimal solution to ambulance service location and response performance, to the existing system. This would allow the evaluation of accessibility to be enhanced by modelling the potential for individual use behaviour in relation to a surrogate measure of need that accounts for the variation in actual response times. Specifically, the development of appropriate contribute to the emergency vehicle response planning process by determining the location configuration of facilities to reduce distance deterrence, and by determining the allocation of resources to increase service capacity.

These optimisation models attempt to address the fact that ambulances are often not available to respond to a call from the closest station by measuring the portion of time that an ambulance is out on calls. For example, this type of model could determine the optimal ambulance station configuration and resource allocation for a fixed number of stations and ambulances from a selected set of candidate facility sites chosen by a prior analysis. The model can use a single line road network to compute the shortest expected response time for each grid cell, based on testing alternative routes, between each candidate facility and each grid cell centroid. The response time calculation should ideally include impedance factors, maintained as attributes of the road network database, such as left/right turns, traffic lights, stop signs, speed limits, construction, seasonal conditions and time of day traffic flow. The calculation of expected response times based on network distances and impedance factors, not straight-line distances, can provide a more reliable accessibility measure for determining which grid cells and the related population counts are within a specified response time standard with the stated reliability. Such models, provide "what if" analysis, to hypothesise a number of alternative configurations for comparison that determine the location configuration of facilities to reduce distance deterrence, and determine the allocation of resources to increase service capacity.

In addition to location-allocation analysis, methods for "what if" analysis should provide the ability to calculate and compare the spatial distribution of expected response times based on alternative spatial distributions of potential need, land use variables and street network variables in relation to alternative ambulance deployment configurations. In a GIS-based DSS the evaluation of accessibility should include the ability to model accessibility based on potential changes to the various geographical, socio-demographic, and organisational factors that influence the accessibility and utilisation of emergency order to help plan service deployment based on demographic projections for various planning periods. It is also important to compare different land use scenarios in order to help plan service deployment based on anticipated land-use changes outlined in planning documents. Further, it is important to compare potential changes to attributes of the road network (e.g. new roads, left/right turns, traffic lights, stop signs, speed limits, construction, seasonal conditions and time of day traffic flow) in order to calculate a more reliable measure of expected response time under various potential road network configurations. Similar to location-allocation analysis, this model can use a single line road network and impedance factors to compute the shortest expected response time for each grid cell between each ambulance location and each grid cell centroid. In this way, "what if" analysis can be used to generate a number of alternative configurations for comparison and to provide a benchmark to help plan service deployment based on the evaluation or realised geographic accessibility.

A GIS-based DSS should also be able to effectively manage the various scenarios and alternative configurations that it produces using "what if" analysis as well as current and historical data. It is important to have the ability to save scenarios for future analysis and comparison in order to enumerate the relative costs and benefits for each alternative configuration. A scenario-based approach can be used in such a system to store the results of multiple analyses in a single scenario file with meta-data (data describing data) describing the scenario parameters. In this way, planners can open and regenerate previously saved scenarios containing multiple analyses for comparison. Such a scenario-based approach can form the basis of a more comprehensive ambulance service GIS-based DSS. This type of system can have substantial benefits for managing and analysing data to produce information relevant to decision making and in simulating the effects of different planning decisions.

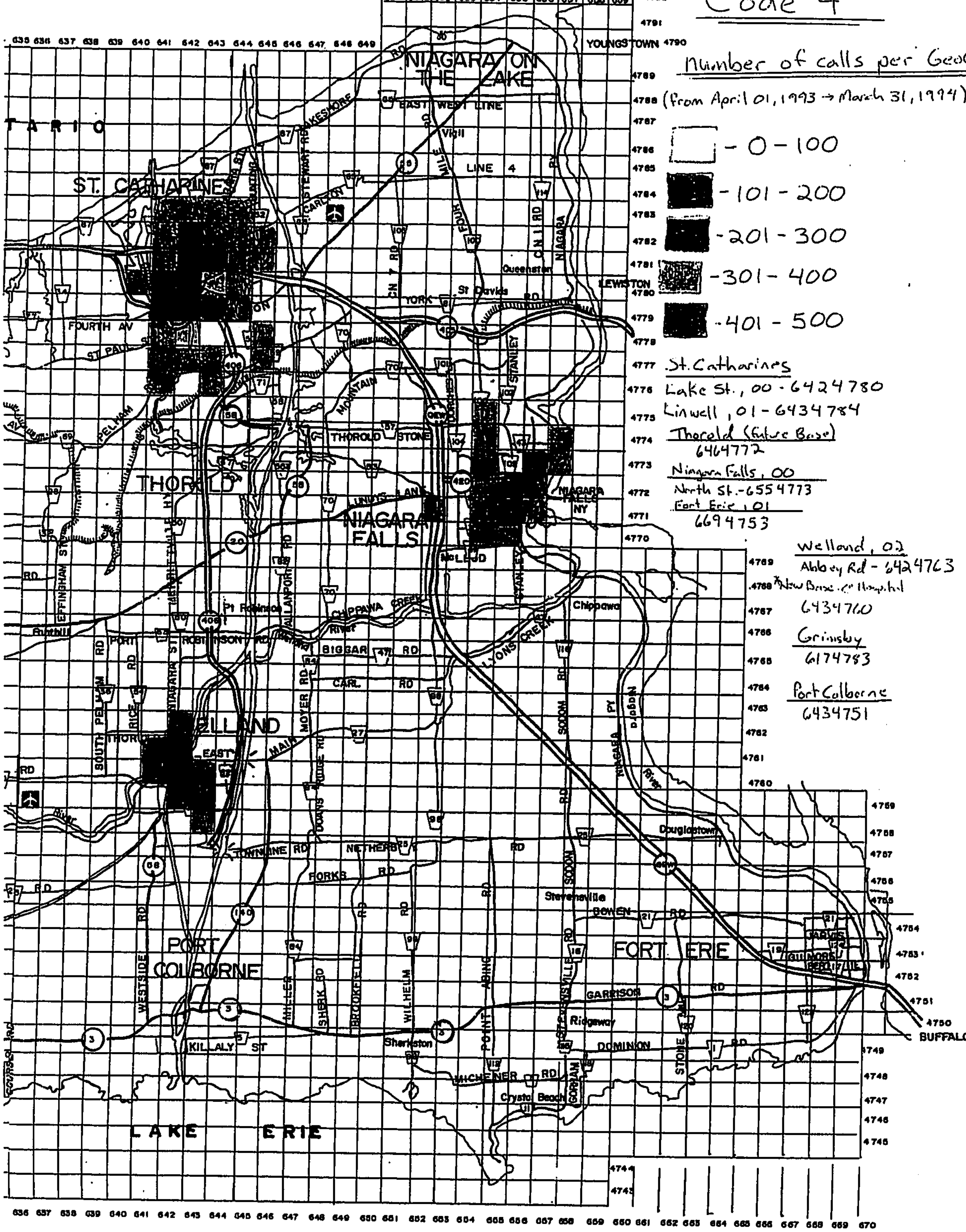
Appendix A: Sample Geoplot Reports

Code 4

Number of calls per GeoCod

(from April 01, 1993 → March 31, 1994)

- 0 – 100
- 101 – 200
- 201 – 300
- 301 – 400
- 401 – 500



St. Catharines

Lake St., 00 - 6424780

Linwell, 01 - 6434784

Thorold (future Base)

6464772

Niagara Falls, 00

North St. - 6554773

Fort Erie, 01

6694753

Welland, 02

Abbey Rd - 6424763

*New Base @ Hospital

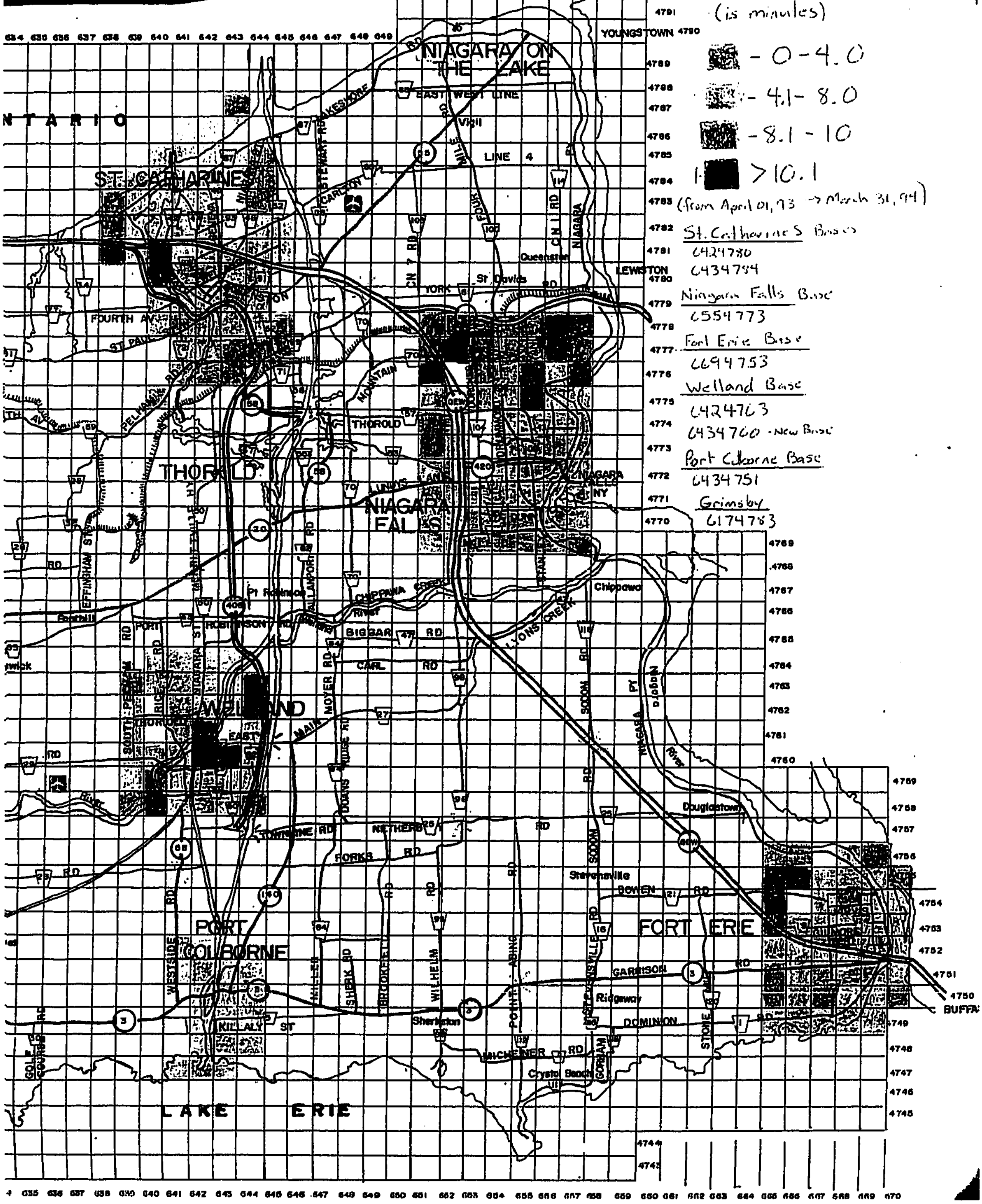
6434760

Grimsby

6174783

Port Colborne

6434751


(is minutes)
- 0-4.0
- 4.1- 8.0
- 8.1 - 10
>10.1
(from April 01, 93 -> March 31, 94)
St. Catharines Bases
6424780
6434754
Niagara Falls Base
6554773
Fort Erie Base
6694753
Welland Base
6424763
6434760 - New Base
Port Colborne Base
6434751
Grimsby
6174783
ONTARIO
NIAGARA ON THE LAKE
YOUNGSTOWN
ST. CATHARINES
THOROLD
NIAGARA FALLS
WELLAND
PORT COLBORNE
FORT ERIE
LAKE ERIE
LEWISTON
Queenston
St Davids
Chippawa
Stevensville
Ridgeway
Sherkston
Crystal Beach
Douglastown
BUFFALO

Appendix B: Acronyms

ANOVA - Analysis of Variance

AVL - Automatic Vehicle Location

CACC - Central Ambulance Communication Centre

CAD - Computer-Aided Dispatch

CARTPI - Change in Average Response Time Performance Indicator Process

CVFD - Call Volume Frequency Distribution Process

DBMS - Database Management System

DFD - Data Flow Diagram

DSS - Decision Support System

EHS - Emergency Health Services Branch

EMS - Emergency Medical Service

GIS - Geographic Information System

GPS - Global Positioning Systems

GSR - Geoplot Standard Report

GUI - Graphical User Interface

HCI - Human-computer Interaction

LAS - London Ambulance Service

MALP - Maximum Availability Location Problem

MAUP - Modifiable Areal Unit Problem

MCLP - Maximal Covering Location Problem

MOH - Ontario Ministry of Health

RC - Redundant Coverage Model

RTFD - Response Time Frequency Distribution Process

RTVAI - Response Time Variation & Anomaly Identification Process

RTTPI - Response Time Threshold Performance Indicator Process

SQL - Structured Query Language

STG - Service Territory Generation Process

UTM - Universal Transverse Mercator

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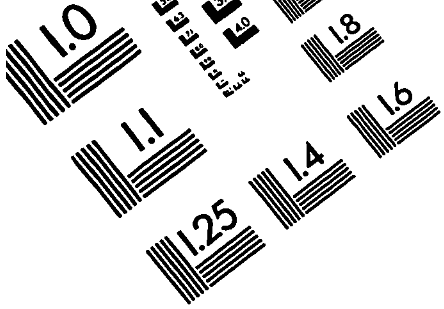

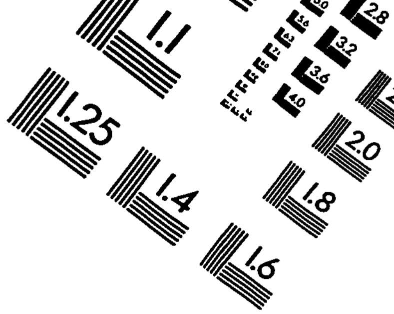

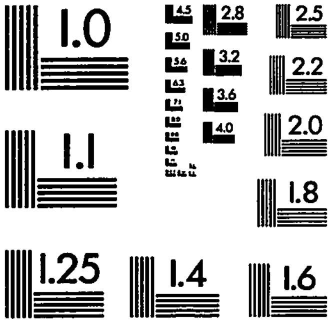

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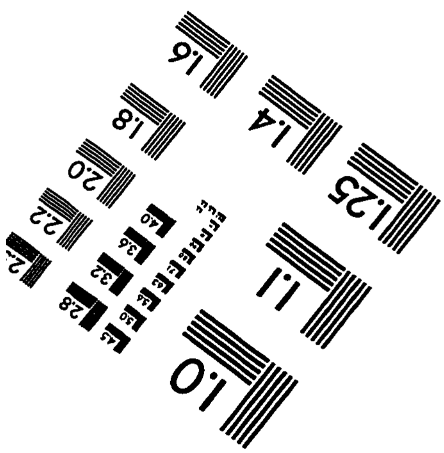

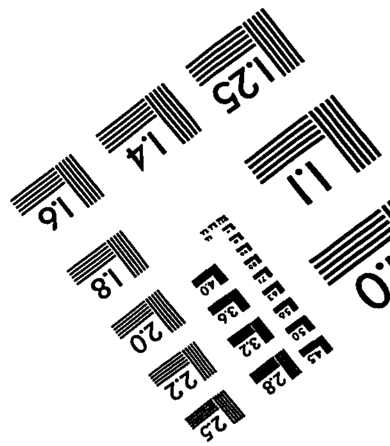

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