USING GEO-SPATIAL ANALYSIS FOR EFFECTIVE COMMUNITY PARAMEDICINE

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ABSTRACT

Paramedic services are developing a new model of service delivery known as community paramedicine (CP). This service delivery model seeks to build on existing paramedic skills, establish collaboration with non-traditional health care partners, and create alternative pathways for accessing care. Frequent users of paramedic services represent patients that are of particular interest to CP programs. Chapters 2 and 3 of this thesis address questions of effective delivery of these programs.

The second chapter is a spatial-temporal analysis of frequent users in Hamilton, ON. Drawing on concepts of time-geography and dynamic ambulance deployment, this analysis identifies space-time patterns in paramedic service utilization by frequent users. Data were aggregated to represent daily demand in terms of space and time. Analysis employed generalized linear mixed models that included a random slope effect for time intervals for each geographic unit. Fixed effects included distance to emergency department, proportion of residential addresses, and proportion of older adult population. Locations and times that had greater or less than expected daily demand from frequent users were identified. The findings can be used to tailor deployment of community paramedics in dual-capacity roles to address the system demand of frequent users.

The third chapter analyzes the geographic influence of CP service delivery in Renfrew County, ON. This research draws on concepts of spatial accessibility and geographic profiling to estimate spatially defined probabilities of paramedic service use by frequent users. Due to ongoing CP programs within the county, the resultant community health profiles serve as an evaluation of the benefit of these programs. The community health profiles can also be used to assess community level probabilities of patient needs for future interventions. This analysis can serve as a new way to assess spatial accessibility to health care services and identify locations with increased risk of frequent use of paramedic services.

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DECLARATION

This thesis is comprised of two articles (yet to be submitted for publication) which have been completed by Matthew Leyenaar. I, Matthew Leyenaar, am the primary author and was responsible for data analysis and writing of manuscripts.

CHAPTER 1: Introduction

Shortly after the turn of the century, Kearns & Moon (2002) presented reflections on contemporary changes in the study of health geography. Their commentary included discussion regarding distinctions between different approaches to studying the relationship between health and place. At that time they argued that health geography was developing a critical lens that may lend itself to “social justice and transformative politics.” (Kearns & Moon, 2002). They suggested that this development was a subversive alternative to the dominance of traditional approaches within the discipline, including spatial epidemiology. One of the objectives of this approach was later reflected by Fleuret and Atkinson (2007) in acknowledging the role health geography may play in promoting well-being. While Kearns & Moon (2002) presented differences between critical health geography and other traditional approaches, Rainham et al. (2010) illustrated that through inclusion of non-traditional data sources—or more specifically new and emerging data sources—the traditional approaches (as described by Kearns & Moon (2002)) may be utilized not only to understand place and health but also inform interventions to improve health in place. The concepts presented by Rainham et al. (2010) may be most clearly summarized by spatial characteristics becoming integrated into data sources and improved methodologies for their analysis. The results of such integration are dynamic models of health and place with inclusion of time and individual-level factors of interest. Within this context it is possible to analyze data in such a way as to inform change. The application of these concepts is broad and the challenges in their successful utilization numerous. This thesis serves to express both the application and challenges through investigation of frequent users of paramedic services.

Background: Paramedic services and frequent users

Data related to paramedic services offer a unique source of inquiry regarding health and place for a variety of reasons. The paramedic service delivery model is a dynamic system where units respond from various locations to emergency calls for medical assistance. The origin of responding units may be a fixed paramedic post or ambulance station, a designated stand-by location, a hospital, or any location in between depending on service demand and unit availability. The locations to which paramedics respond are even more diverse. While residential locations may be a chief origin of emergency calls, these calls may also occur in any public location from sidewalks to shopping centers. Furthermore, paramedic services abide by a variety of protocols where the closest destination for patient care may be bypassed in order that the patient may receive specialized treatment at an alternate facility. These factors considered in isolation of a single call describe a dynamic system. Add to this multiple levels of paramedic training, multiple calls occurring at the same time, call triaging based on information regarding the severity of the call type, and response units that are either traditional ambulances or single responder vehicles and the dynamic nature of the system can become overwhelming. However, in one form or another, each of these dynamic components is documented for every call that paramedics respond to.

Paramedic services function within a system that faces complex challenges and stresses. These include operating in accordance with government oversight of budget and legislation, meeting community needs including response time standards, and improving clinical outcomes for the patients they treat (Spaite et al., 1994, Meislin et al., 1999, Blackwell & Kaufman, 2001, Myers et al., 2008, Vandeventer et al., 2010). In a variety of emergency circumstances, paramedic services represent an “on-ramp” to the greater healthcare system. If the system as a whole is functioning well, the transfer of patient care from the “on-ramp” to the “freeway” is seamless. However, when the capacity of the system becomes congested, it is possible for negative feedback cycles to develop. Consider a scenario where there is a shortage of long-term care beds.

Older adults in need of long-term care are admitted to hospital thereby transferring the shortage of beds from one facility to another. In turn, hospitals accommodate patients by either reducing or altering other services (such as cancelling elective surgeries or having admitted patients accommodated in the emergency department). If admitted patients are using emergency department (ED) beds, ED over-crowding can occur and paramedic services experience offload delays. Finally, patients in the community—perhaps waiting for a long-term care bed—experience longer wait times when they call 9-1-1 for assistance. In such a scenario, strengthening effective collaboration within the system is a necessary part of addressing the complex needs of each particular system component in much the same way as increasing overall capacity may reduce system stress.

Addressing the fixed capacity of the healthcare system is complicated. The costs involved in operating a publicly funded health care service in Canada limit the system capacity. This is generally referred to as the number of available beds. But, in the case of paramedic services, the beds are mobile in ambulances so the capacity has a limited number of available units. Not surprisingly, services funded and used by the public face a perpetual drive for improved efficiency. This focus on efficiency exists throughout the health care system (Drummond, 2012). In Ontario, health care spending exceeds 40% of provincial spending (Drummond, 2012). In light of this, governments have endeavoured to present the public with some measure of value for dollars—usually in some form of publicly available report on waiting times. For paramedic services, these reports present response times (Ontario, 2015). Even though response times receive much scrutiny, the optimization of paramedic response may have more to do with the overall system of service delivery and the patients that it serves.

Through investigating the needs of patients, insights have emerged about a particular group of patients that use paramedic services on multiple occasions (Hall et al., 2014, Scott et al., 2014, Tadros et al., 2012). Findings reveal that this is a heterogeneous group (Scott et al., 2014) that may benefit from a variety of different interventions (Bigham et al., 2013). To respond to this challenge, paramedic services are developing and deploying a new model of service delivery known as community paramedicine (Bigham et al., 2013, Mason, Wardrope, & Perrin, 2003). Advances in paramedic education have resulted in new skill development—skills which can be employed outside of traditional clinical settings, thereby strengthening or enabling preventative approaches to health care (Bigham et al., 2013). Examples of this range from referrals to other health care or social services (Bigham et al., 2013) to specialized programs for patients with addictions (Dunford et al., 2006) to preventative home visits of at-risk patients (Ruest, Stitchman, & Day, 2013). In practical terms, this application of service delivery is seen as a means of helping to prevent over-crowding of emergency departments and rates of hospital admission (Drennan et al., 2014, Mason, Wardrope, & Perrin, 2003). The potential benefits, in terms of service delivery may be a significant savings of both time and money (Drennan et al., 2014). More important may be the realization of clinical benefits to patients and improved system performance.

To date, published literature on community paramedicine is scarce (see reviews by Bigham et al., 2013, and Jensen et al., 2015). Part of the reason for this is related to its relatively recent emergence as a form of service delivery. Another reason is that program development is not consistent from place to place. Often, community paramedic programs are developed to meet the needs of a specific community. This poses challenges to the generalization of research findings. While a “one-size-fits-all” approach to community paramedicine may not be realistic given the complexities of the stresses on the health care system, opportunities for innovation and collaborative approaches can present solutions to common problems. Existing literature has pointed to some of limitations regarding a lack consensus on what role community paramedics should play and how to go about measuring their success (Bigham et al., 2013). Drennan and colleagues (2014) have proposed research whereby patients receive augmented care by community paramedics with the outcome measured being number of hospitalizations. Their secondary outcome measures will include total paramedic service and primary health care team utilization, length of hospital admission where applicable, mortality, health status assessments, compliance and safety, and cost-effectiveness. Due to the challenges associated with measuring clinical outcomes, it may be more feasible to present improvements in system performance. Jensen and colleagues (2015) present a review of alternatives to dispatch and alternatives to transport for paramedic services. These alternatives are to the traditional system performance function whereby, upon receipt of an emergency call an ambulance is automatically dispatched which then initiates transportation of the patient to an emergency department. The objective behind these alternatives is that less transportation time will result in a greater capacity within the system to respond to other calls.

The idea that a patient may see a practitioner on more than one occasion is central to primary health care. However, within the context of emergency care, this is not traditionally the case. Nevertheless, this has been identified as a factor to be considered within the community paramedicine service delivery model (Scott et al., 2013). As a result of this change in perspective, it is important for service providers to identify the patients that may benefit from this type of interaction with clinicians. Specifically, these are the individuals that use paramedic services on multiple occasions, often called frequent callers or frequent users. The definition of a frequent user can vary depending on the context of the community, patients, and service provided (Doupe et al., 2012). For example, studies of emergency department utilization have considered intervals as short as 7 days (McCusker et al., 2007) to classified patients as frequent users. This is one example of how the time interval between service utilization can differentiate patient classification. Multiple classifications may exist from single use, to repeated use and frequent use, to exhaustive or super use (McCusker et al., 2007). Other time intervals have been from one to six months with the most common being one year (Scott et al., 2013). Contradictory findings regarding frequent users of emergency departments highlights the need to uniquely define what constitutes a frequent user in particular situations or settings (Doupe et al., 2012). Paramedic services can face difficulties if they consider definitions of frequent use that have been developed in other settings, such as emergency departments. Scott et al. (2013) indicate the importance of defining frequent use differently within the context of paramedic services. Even so, some research considers frequent use on the basis of particular medical or social conditions (Dunford et al., 2006). Similarly, a great deal of work has been done that focuses on older adults exclusively (Weiss, et al., 2002). These differing contexts underline the heterogeneity of frequent users as a group.

Research objectives

This thesis presents a spatial analysis of frequent users of paramedic services. It draws on spatial attributes within administrative health records to detail the places where these patients access paramedic services during emergency medical situations. Primarily, the analyses will address aspects of health and place by identifying locations where paramedic services encounter frequent users. Further information will be presented regarding the times that these encounters occur. Characteristics of these individuals will be described as well.

This research will contribute to the study of community paramedic interventions and to the understanding of frequent use of paramedic services. These contributions may serve to provide insight regarding the potential for service delivery efficiencies to be realized through community paramedic interventions. This follows the logic that addressing the needs of these individuals through alternative measures may decrease their utilization of emergency resources, thereby increasing the system's capacity to respond to non-frequent users.

Thesis structure

The complexities involved in the dynamic delivery of paramedic services married with the particular characteristics and behaviours of individuals who are frequent users require further analysis. While front line paramedics may utilize informal mechanisms to address frequent users—whether that be unstructured education of the patient or ad hoc information sharing between colleagues regarding the patient, this research seeks to formalize information that will be valuable to both front line paramedics and paramedic service administrators. Part of this information is gained through the locations where paramedics treat frequent users. This may provide insight into their level of accessibility to services. Location can also provide insight into the socio-economic status of the community in which an individual resides as well as environmental factors which may influence their health. More importantly, the analytical approaches utilized herein will translate ad hoc information sharing into evidence regarding spatial, temporal, and individual characteristics of frequent users.

To accomplish this, Chapter 2 presents a spatial-temporal analysis of frequent users of paramedic services in Hamilton, ON. This analysis is set in a city where community paramedic programming has been limited. The framework for the analysis presents the feasibility of using a service delivery model wherein community paramedics operate in dual-capacities. That is, while engaging in non-emergency community paramedicine activities they also have opportunity to be available for emergency response. The question investigates the place and time where this type of resource may be best deployed.

In Chapter 3, the spatial patterns of frequent use in Renfrew County, ON will be described. In this setting, community paramedic programs have been established since late 2008. This analysis draws on a variety of concepts to determine spatially defined probabilities of paramedic service use by frequent users. While the results are specific to the location of study, the methods of analysis employed may be adapted to other settings. The results present evidence that can serve to verify ongoing community paramedic programming and identify locations for future interventions.

The concluding chapter will summarize findings from the two investigations. While the findings of each chapter may have particular relevance to the communities that were studied, the methods used in each approach represent important contributions to spatial inquiry. Therefore, the strengths and limitations of each approach will be summarized to inform future work in this area.

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CHAPTER 2: A spatial-temporal analysis of frequent users of paramedic services in Hamilton, ON

Introduction

Transportation planning research considers questions about human activity that focus on time and location. This idea recognizes that in order to address challenges faced in the provision of goods or services, it is important to consider the mobility of the users that accesses these resources. The advent of new technologies has enabled advances in the spatial-temporal analysis of human activity-travel behaviour (Buliung & Kanarogolou, 2007) that may be applied to a wide variety of such analyses. One such application is to the provision of health care services. Expanded utilization of activity-travel behaviour analytical approaches within health research may provide new epidemiological insight (Rainham et al., 2010). This research draws on these concepts in the study of paramedic services—a mobile form of health service delivery—through consideration of time geography.

Time geography is a sub-specialty of geography that addresses questions of “where” and “when.” This field serves as the basis of activity-travel analysis. The conceptual framework for time geography was established in the work of Hagerstrand (1970). Hagerstrand (1970) used space-time prisms to illustrate individual travel patterns (see Figure 2.1, adapted by Cullen and Godson(1975)). The logic behind this was that the distance that any particular individual may travel is constrained by a) their starting location and b) the time required to travel such distance. Humans typically have fixed places of residence and employment making it possible to accomplish a great deal of analysis regarding travel behaviour. These assumptions reveal two fundamental ideas employed in activity-travel analysis: that people are mobile and that this mobility typically follows a diurnal pattern. These concepts have become central to transportation planning (Buliung & Kanarogolou, 2007). They are evident in our daily lives through morning and afternoon "rush hours," business hours of operation, and peak and off-peak availability of services. For paramedic services, these realities can inform decision makers with respect to the deployment of ambulances.

Stout (1983) devised a dynamic approach to ambulance deployment known as System Status Management (SSM). The basis for SSM followed the logic of Hagerstrand (1970) in that it acknowledged the mobility of human activity. In short, SSM presented an approach to the deployment of ambulances that recognized that calls for service happen where people are—which is not necessarily where they live. This is an important distinction when considering the provision of a mobile public service. Consideration of geographic influence on service delivery that is based on population overlooks this problem because population counts are derived from place of residence. However, Stout (1983) recognized that the spatial distribution of ambulance calls over the course of any given day varied in a way that differed from the spatial distribution of population. Furthermore, as with Hagerstrand (1970), Stout (1983) observed that this mobility was often predictable. Stout (1983) demonstrated that by understanding this trend, it was possible to forecast demands for service with information regarding both time and place. The research that has followed the respective findings of Hagerstrand (1970) and Stout (1983) continues to be applicable to the challenge of linking the mobility of the paramedic service user with the planning of paramedic service delivery.

The role and function of modern paramedic services has evolved from providing basic first aid and rapid transport when Stout (1983) developed SSM. While paramedic services continue to respond to emergency situations, their role within health care services as a whole has grown (Shah, 2006). In particular, as will be detailed further in chapter 3, patients that struggle to access adequate primary health care services are turning to paramedic services and emergency departments (Bigham et al., 2013). Furthermore, these patients may utilize paramedic services on multiple occasions (Scott et al., 2013). This presents a question as to whether or not individuals that frequently use paramedic services exhibit a different pattern of usage than non-frequent users because of differences in health-related behaviours. If they do, it will be important for paramedic services to adapt service delivery to address these needs while maintaining aspects of traditional service delivery required for emergency response. It may be possible that changing service delivery in this way will improve paramedic services system response as a whole while also improving the clinical status of these particular patients. Scott et al. (2014) have presented evidence that the most frequent of frequent users exhibit a different temporal pattern of service utilization than non-frequent users. Based on this evidence within the context of health and place, it is expected that frequent users exhibit differing spatial patterns of use. Further analytical work is needed in these areas, including identifying the appropriate means to quantify the differences and evaluation of appropriate service deployment measures.

Combining theories regarding time geography, activity-travel analysis, and system status management demonstrates a potential to redefine deployment of paramedics to reflect their changing role in health care. Paramedic services are also adapting service delivery models to changing community needs. One example of this is an enhanced service delivery model that includes using community paramedics in dual-capacity roles. Operating in a dual-capacity role means that community paramedics respond to emergencies under certain conditions while primarily focusing on delivering community paramedic programming in non-emergent settings to improve primary health care. This model of service delivery has been implemented in various forms in a number of communities (International Roundtable on Community Paramedicine (IRCP), 2014, IRCP 2015). The motivation for this approach is to add value to patient care within existing delivery model structures. The advantage of this approach is that it does not aim to initiate an alternative to transport or alternative to dispatch (Jensen, 2015), although that may occur as a secondary outcome. Rather, it builds on the existing skill set of paramedics as both emergency responders and clinicians.

Two examples of deployment of this style of service delivery model can be found in Renfrew County, ON and Winnipeg, MB (IRCP 2014, IRCP 2015). The County of Renfrew Paramedic Service (CoRPS) utilizes a Community Paramedic Response Unit (CPRU) where approximately 60% of its activity is directed at community paramedicine. The other 40% of activity is directed to responding to emergency calls (IRCP 2014). The Winnipeg Fire Paramedic Service (WFPS) has a similar method of deployment called Emergency Paramedic in the Community (EPIC). This unit is dispatched to emergency calls for patients that are known to have a community paramedic managed care plan and to locations known to be associated with frequent user utilization (primarily homeless shelters). Additionally, the paramedic assigned to the EPIC unit completes home visits and wellness checks for patients identified as being at risk of frequent usage (IRCP, 2015). Deploying community paramedics in both emergency and non-emergency capacities presents a means of increasing system capacity to treat patients while maintaining productivity, increasing collaboration, and improving efficiency. Simply put, a paramedic acting in a community paramedic role still has the training and capability to act as an emergency responder. This is an important consideration given the diversity of clinical activities that community paramedics engage in.

Objective

The purpose of this chapter is to identify space-time patterns in paramedic service utilization by frequent users. Identifying these patterns will provide information important for the deployment of community paramedics in dual-capacity roles as an enhancement to traditional service delivery. Given that both the model of service delivery and the analytical approach represent relatively new advances within their respective fields, this research presents an innovative contribution to prehospital care. Specifically, the space-time pattern of daily demand on paramedic services by frequent users will be analyzed to describe differences in daily demand by location and time of day. While controlling for other variables, it is expected that certain locations and certain times will have greater demand for services by frequent users.

Methods

Data sources

This study is a spatial-temporal analysis of frequent users of paramedic services in Hamilton, Ontario. The City of Hamilton is located at the western end of Lake Ontario and is centrally located within a region referred to as the Golden Horseshoe. It is Ontario's third largest metropolitan area. Data were obtained for analysis from the Hamilton Paramedic Service (HPS). This paramedic service provides emergency response for all 9-1-1 medical calls in the city. The paramedic service is publicly funded, receiving half of its funding from the municipality and half from the provincial government. This arrangement presents a somewhat complicated structure of administration and oversight. While the service is operated directly by the municipality, other components of service delivery are managed by the province. For example, HPS is dispatched through a Central Ambulance Communications Centre (CACC) that is operated by Ontario Ministry of Health and Long Term Care (MOHLTC). During peak hours, HPS deploys 30 ambulances and paramedic response units (PRU) staffed with either primary or advanced care paramedics (PCP or ACP). These units are posted to 19 stations throughout the city. Approximately one quarter of HPS staff are certified as advanced care paramedics. Annually, the service responds to approximately 55,000 requests for service. During the period of study, HPS began to utilize paramedics in community paramedic programs but did not specifically use these paramedics in dual-capacity roles.

Hamilton Paramedic Service provided data for calls between January 1, 2010 and December 31, 2014. Each call record included pertinent times, the medical nature of the patient's complaint as obtained by the dispatcher, the location of the call within a dispatch grid, and a unique individual identification number. Times pertinent to the call included time of ambulance notification, time of ambulance arrival on scene, and time of departure from scene. The complaints were classified by ambulance communications officers according to standardized procedures for computer aided dispatch (CAD). In Ontario, when a 9-1-1 call is received by the ambulance communication centre, the location of the call is geo-referenced within a provincially standardized grid to facilitate paramedics' ability to locate the address. Utilizing this grid for the analytical process provided an additional layer of anonymity to patient identification that may otherwise be compromised through utilization of street address or postal code forward sortation areas. The cells in the dispatch grid are one square kilometer in size. For the period of time that data were provided, HPS received 471329 calls. Excluding duplicates, calls with missing data, non-transport calls, and inter-facility transfers reduced the number of calls available for analysis to 216164.

To supplement the ambulance call data, further data were obtained regarding Hamilton's population and geography. Information regarding population characteristics was included based on dissemination areas (DA)—the smallest geographic areal unit for which data are available—from the 2011 Canadian Census. The census data of interest included number of dwellings, total population, and number of adults over the age of 65 for each DA. Geographic data were obtained from Statistics Canada regarding dissemination areas and census tracts. Other geographic data from the City of Hamilton were necessary to complete geographic analysis. This included road network data and geographic location of address points available through Hamilton's open data initiative. Finally, the geographic data for the ambulance dispatch grid were obtained from HPS.

Data structure

Spatial data measured at differing geometries presents a challenge when attempting to establish a tangible link between data elements. Here, the comparable challenge was to establish a relationship between dissemination area population data and ambulance dispatch data which are not directly geo-referenced to census boundaries. On the one hand, some dissemination areas were much larger than dispatch cells. Conversely, the irregular geometry of the dissemination areas presented some cells that contained seemingly equal proportions of multiple dissemination areas (see Figure 2.2). To address this problem, spatial aggregation created cell blocks that were a combination of individual dispatch grid cells and grouped grid cells. When grid cells were grouped, the goal was to follow census tracts boundaries as much as possible. Census tracts are geographic units that are used by Statistics Canada in larger urban centers to aggregate dissemination areas. The centroids of the grid cells were used as the first means of creating new geographic areas. In cases where census tracts contained multiple dispatch grid cell centroids, the corresponding cells were joined into larger blocks of cells. This resulted in 1076 grid cells being aggregated into 62 blocks that were roughly the shape of the larger census tracts. The smaller census tracts either contained zero or one grid cell centroids. To cover these areas, the grid cells were used without modification. This accounted for the remaining 49 of the total 1125 grid cells. In total, 111 grouped or individual blocks of dispatch grid cells were created (see Figure 2.3).

The creation of new areal units required new estimates of census data. This was accomplished by using the centroids of the dissemination areas. This way, the characteristics of the cell blocks closely resembled those of the census tracts but allowed dissemination area data to be attributed to the corresponding block regardless of that block's origin (grouped or individual). Data for each attributed dissemination area characteristic were totaled for each corresponding block to complete the spatial aggregation process.

Temporal patterns can exist based on a variety of measures of time such as annual, seasonal, monthly, or weekly. The objective of this analysis was concerned with daily patterns of demand for service. Therefore, the twenty four hours of a day were divided into six intervals in order to evaluate daily temporal patterns. Division of a 24 hour period into multiple time intervals can be approached in a variety of ways. Here, this division sought to logically follow daily patterns of human activity while also being equal in duration. In particular, intervals attempted to best reflect daily patterns of human mobility. The time bins that were established represented midnight, overnight, morning, midday, afternoon, and evening periods. However, one day of time bins did not conform to the common 24h clock. The midnight bin commenced at 22:00, the overnight bin at 02:00, the morning bin at 06:00, and so on. This meant that the morning and afternoon bins included time periods for the traditional beginning and ending of an eight-hour workday. Together with the spatial aggregation of data, this resulted in 666 observations (6 time bins multiplied by 111 blocks) for analysis.

Analytical approach

In the most general terms, it would be possible to predict the number of frequent users of paramedic services as a proportion of non-frequent users. For example, if 25% of all calls were attributed to frequent users, it may be possible to estimate that within the provided dataset there were 54041 calls from these users (of the total of 216164 calls). The problem with this calculation is that the data were provided for calls and that frequent users call multiple times. Therefore, all that can be determined form such an estimate is that there are less than 54041 frequent users. That problem aside, it is expected that the proportion of use by frequent users would not be constant for all individuals at all times and at all locations. To address this expectation, it would be possible to predict a proportion for each location. In this case, we could produce 111 linear models of daily demand—each specific to a particular block (see Figure 2.4 as an example). Or, we could produce 6 simple regression models, one for each time interval (see Figure 2.5). The drawback of these approaches is the difficulty of comparing one model to another. It is clear that the complexities of adequately modelling the proportion of frequent users within observations measured at different space-time intervals cannot be accomplished with simple regression. This is also because some of the basic assumptions required for simple regression will not be true for any data set of this structure (Schabenberger, 2005). For instance, repeated measures based on a specific geographic location are not independent of each other. This aspect of "space" and the analysis of changes observed over geographic space can be challenging to quantify regardless of approach. Similarly, this challenge exists when observations are made at specific intervals of time. For example, measures taken at different locations during a specific interval of time are not independent of each other. The consequence of considering changes in both time and space is that these complexities are likely accentuated. Therefore, the analytical approach needs to address certain attributes of covariance between observations. A generalized linear mixed model (GLMM) is an appropriate approach that accounts for the correlation of measurements within these conditions (Rasmussen, 2004).

The appeal of a GLMM is that it considers fixed and random effects (Schabenberger, 2005). The fixed effects of the model are considered through independent variables and reflect the overall relationship between a group of independent variables and some dependent variable. The added functionality of a mixed model over a generalized linear model is found in the random effects. Random effects may be described as an accountability of subject specific parameters that are not directly measured by the fixed effect. This concept can be considered an improvement over creating 111 models for different locations (Figure 2.4) or 6 models for different time intervals (Figure 2.5) since including random effects in a GLMM provides a means to account for these differences in a single model. The analysis of space-time observations using a GLMM is beneficial because the correlations between observations that will occur as a result of measurements in both time and location can be addressed. Random effects are described as being either R-side or G-side random effects. In the approach used here, G-side random effects are included based on a known condition (as opposed to R-side effects which are associated with unknown conditions). Based on this approach and the described data structure, it is possible to consider model parameters and specification.

Model parameters and specification

The dependent variable in the model was based on counts of occurrences and did not fit a normal distribution. Therefore the model was specified to fit a Poisson distribution. In total, three models were developed, each following similar specification. The first included time as the fixed effect and random effects. The second included the addition of other fixed effects. The third included the addition of interactions between fixed effects. Data analysis was completed using the GLIMMIX procedure in SAS 9.3 (SAS Institute, Cary, NC, 2010).

A GLMM can be described through notation similar to a linear mixed model:

$$(1) \qquad \mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\gamma}$$

where values of matrix **Y** equal the independent variable values of matrix **X** multiplied by the fixed effects coefficients in matrix **β** plus the values of matrix **Z** multiplied by the random effects in matrix **γ**. In this analysis, **Y** represents the observed number of frequent users. The 666 space time observations represent the independent variable matrix **X**. Matrix **Z** contains values of 1 or 0 to indicate the presence or absence of a relationship with the G-side random effect of matrix **γ**. In this case, this relationship is between location and time interval. A GLMM was employed to model expected number of frequent users, η per number of general users and frequent users combined, C such that:

$$(2) \qquad g\left(\frac{\eta}{C}\right) = \boldsymbol{X\beta} + \boldsymbol{Z\gamma}.$$

Using the log of the combined number of frequent and general users can be substituted as an offset:

$$(3) \qquad g(\eta) = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \log\left(\boldsymbol{C}\right)$$

The dependent variable was the number of frequent users that utilized the paramedic service within observed space-time blocks. Defining what constitutes a frequent user can be complicated (as has been noted in Chapter 1). HPS has used the definition of greater than 4 ambulance transports (excluding inter-facility transfers) per year to identify frequent users. This definition was adjusted slightly in the analysis as the temporal aggregation applied herein was not annual. Instead of counting calls within a calendar year, the time interval between calls was used. When individuals used HPS greater than 4 times within a 365 day period they were classified as frequent users. If this classification occurred, all of that user's corresponding calls were added to a subset of the original dataset. Within this data subset, only the calls that occurred for the individual during the period of time where they were classified as a frequent user were contributed to the respective space-time observations. Any individual user could only appear once in any particular space-time observation. This accounted for the potential mobility of the user while maintaining a degree of independence between observations. We assume that most frequent users call at multiple times and from multiple locations—thus contributing to multiple space-time observations. This is an important assumption about the behaviour of frequent users. It may be possible—though rather unlikely—for one user to always call from the same location and at the same time of day thus contributing only one occurrence within that particular observation and exist as only one occurrence within the entire dataset. While structuring the data in this manner may present a bias towards the most frequent and most mobile frequent users, it is important to remember the context of the analysis is not focused directly on the user—but rather the service they are utilizing. Therefore, accounting for the frequent user's presence in each observed block at each observed time illustrates that user's contribution to service demand within the context of the daily spatial-temporal pattern being modelled. In order to accurately predict the influence of observations with no occurrences of the dependent variable, consideration of the number of general users within blocks was necessary. This was done through the offset term in equation 3. The number of combined users was comprised of frequent users and general users. General users were identified as individuals that did not use paramedic services more than one time per calendar year and were never classified as a frequent user. Recall that frequent users were classified as such after their fourth utilization within the period of a year. This classification could be considered to represent a continuum of usage that begins with general use, progresses to occasional use (between 2 and 4 transports within a year), and ends with classification of frequent use. Excluding occasional users resulted in a combined group with stronger independence between the two contributing parts.

Numerous studies have considered the diurnal and weekly pattern of demand on paramedic services (see Aboueljinane, Sahin and Jemai, (2013) for a recent review). With the objective of considering daily demand, time was the only fixed effect to be included in the first model. (The coefficient for time and the intercept were the only components in the β matrix in equation 3 for model 1). The value of 1 was assigned to the midnight time bin and subsequent values were assigned up until the evening time bin having a value of 6. In subsequent models the following other fixed effects were included in addition to the variable for time (increasing the size of the β matrix of equation 3). First, it was important to include a measure of spatial accessibility to services. Given that the dependent variable represented individuals who were transported by ambulance to hospital emergency departments on multiple occasions, the measure of accessibility that was included was a distance to the nearest ED. This distance was measured from the mean centre for all calls within each block to the nearest emergency department. In this way, the mean was weighted not by the individual, but by the number of occurrences. Distances were calculated using road network distances with the Network Analyst in ESRI ArcMap 10.2 (ESRI, Redlands, CA, 2013). Distances were transformed using the natural logarithm. Second, the proportion of residential addresses was calculated by taking the total number of dwellings within each block and dividing it by the total number of address points within each block. It is important to note that this meant that it was possible for proportions to exceed a value of one in certain situations. For example, in locations with multiple high density residential address points such as high-rise apartment buildings, one address point may contain multiple dwellings. Finally, the proportion of population of older adults in each block was also calculated. While some evidence is contradictory regarding the association between age and frequent use (Scott et al., 2013), including the population of older adults was considered based on the general idea of declining health in advanced age as well as differing lifestyle behaviours that result from reaching the age of retirement. The proportion of older adults was calculated by taking the total population over the age of 65 and dividing it by the total population for each block.

In the third model, two more parameters were added. By including time as an independent variable, the model controlled for the influence of time within the system as a whole. The inclusion of time was important for two other reasons. Existing evidence suggests that the influence of time as an independent variable is not linear (Cantwell et al., 2015, Ingolfsson, Erkut, & Budge, 2003). This meant that it was important to include the quadratic function of time (each interval squared) to address this behaviour. Similarly, in keeping with the work of Hagerstrand (1970) and Stout (1983), an interaction was included in the model to account for the relationship between time and residential proportion. At certain times, the number of people within a block is expected to change based on its proportion of residential (or non-residential) addresses. This allows for the link between ambulance calls and population that was created during the spatial aggregation process to be quantified. In other words, the dependent variable presents a number of frequent users within each space-time block but their presence therein may or may not be related to their place of residence.

Random effects were specified as a random slope effect for time in each model. This specification represented a G-side random effect. As such, the overall distribution of the effect is assumed to follow a normal distribution with a mean of zero and a variance of G. Another way to describe this effect would be to consider the 111 separate models of daily demand that were created as an example in Figure 2.4. There, each model of time has a different slope. By including the random slope effect, these subject-specific differences observed in the separate models are included into one single model.

Spatial calculations, analysis, and cartographic outputs were performed utilizing ArcMap. Ethics approval was obtained through the Hamilton Integrated Research Ethics Board.

Results

Within the dataset a total of 5826 utilizations by frequent users were observed. In contrast, 89390 observations of general users were included. As a global proportion, this indicates that approximately 6.1% of combined users are frequent user. However, it was expected that this proportion would vary by time and space. Table 2.1 presents this variation by time interval. It also includes model predicted expected values for each of the three models.

Model diagnostics are presented in Table 2.2 for each of the three models. The ratio of the generalized chi-square statistic to the degrees of freedom was calculated to measure dispersion of the model with values greater than one indicating over dispersion. The results indicate that the first model was slightly over dispersed. However, the second and third models were under dispersed based on the values of 0.94 and 0.9, respectively. What this reflects is a variance of residual values that is lower than the mean of residual values. The pseudo Akaike information criterion (AIC) shows decreasing values through model progression indicating improved fit as parameters were added.

The parameter estimates are presented in Table 2.3 for each of the models. In all three models, time was statistically significant with a negative coefficient. The negative coefficient is somewhat counter-intuitive suggesting that as time increases, the expected number of frequent users decreases. Some insight regarding this finding can be gained from Figure 2.5 that represents the number of frequent users predicted through simple linear regression for each time interval. In ordering slope from least to greatest, Figure 2.5 shows the midday interval (4) as having the least slope, then morning (3), then afternoon (5), then midnight (1), followed by evening (6) and morning (2) as having the greatest slope. The non-chronological ordering presents evidence of a non-linear trend associated with time. In the third model, the inclusion of time as a polynomial term and its performance illustrates findings consistent with this non-linear expectation. The coefficients for proportion of residential addresses and the interaction of this variable with time were not statistically significant. However, their behaviour is important to note. The proportion of residential addresses had a negative coefficient, indicating that as the proportion increased, the number of frequent users decreased. However, based on the coefficient of the interaction term, this relationship was mitigated by the afternoon time bin. This shows that for periods of time later in the day, an increase in residential proportion predicted an increase in frequent users. This is also consistent with the behaviour of time. Table 2.3 also shows that the coefficient for proportion of older adults was significant at alpha = 0.1 and that the other parameter estimates and model intercept were highly significant.

To visually assess the results, model predicted expected values (with confidence intervals of $\alpha=0.05$) were compared to observed values for each location. As a rule, model predicted expected values that were less than observed values were considered as being less favourable than observed values being less than expected values. This was because expected values less than observed values may have the potential to result in a systematic incapacity to address the needs of these individuals. In terms of service delivery, expected values that were greater than observed values would represent the potential of an increased capacity of community paramedics acting in dual-capacity roles to respond to more emergency calls. These results are summarized in Figure 2.6. Model predicted expected values were less than observed values in 85 of 666 observations, or in 12.8% of the space time cell blocks.

The performance of the model and the role of fixed effects are important context to frame the results regarding the random slope effect that was included for time. Insight can be gained from Figure 2.4 about the differences in the random slope effect. For example, the greatest random slope effect would be expected in the locations with the most model predicted expected values. Table 2.4 presents the covariance parameter estimates for the random slope for time in the three models. This is reflection of the distribution of the random slope effect. Recall that the random slope effect is normally distributed with a mean of zero and covariance parameter estimates found in Table 2.4. Figure 2.7 summarizes the random slope effect for each block with increasing slope effects shown in solid or lined violet and decreasing slope effects shown in solid or lined orange. Table 2.5 presents a summary of the locations that had the greatest and least random effect. Notice that the locations with greatest effect are congruent with the expectations stated earlier from the findings of Figure 2.4.

This prompted further investigation of the locations that had the highest observed values of frequent users. Table 2.6 summarizes the characteristics and model performance in these ten locations. All of these locations had random slope effect showing an increased expectation in frequent users—six of ten also appearing in Table 2.5. These characteristics are also reflected in Figures 2.8 and 2.9. These figures offer a closer view of eight of the ten locations that are found in the city centre. Added to Figure 2.8 are the measured distances to the closest emergency department for each block. Figure 2.9 presents a visual depiction of the two other location specific independent variables, residential proportion and proportion of older adults.

Discussion

A number of useful findings can be drawn from the results. The results indicate that the number of frequent users within space time blocks can be accurately predicted with a fairly high level of confidence using a

GLMM. Furthermore, the results are consistent with expectations regarding temporal patterns of daily demand by frequent users. These findings can be used to identify spatial utilization characteristics of frequent users. This means that the results can serve to inform decision makers with respect to tailoring their service delivery model to meet the daily demands of these individuals. The findings also serve to identify where utilization by frequent users differs most from non-frequent users. The objective of this space-time analysis of paramedic service utilization patterns was to inform decision makers as to the viability of deploying community paramedics in both emergency and non-emergency functions. The findings are consistent with expectations with respect to daily temporal patterns and the influence of predominantly residential neighbourhoods in ambulance deployment. Furthermore, the results present new information about the influence of other geographic characteristics and the influence of frequent users within the existing service delivery model. These findings should be contrasted with existing ambulance deployment plans to determine implications for service delivery that may be valuable to service providers.

Time

The performance of time as a fixed effect followed a non-linear pattern as expected (see Table 2.3). The daily demand pattern for paramedic services can be difficult to model, as demonstrated by Cantwell and colleagues (2015). There are a number of subtle differences that can occur based on day of week or type of complaint. The results show that, as a fixed effect, time and the square of time are both statistically significant. The coefficient for time indicates that as time interval increases, the number of frequent users decreases. But this observation reinforces the inclusion of the quadratic time variable to account for the non-linear influence of time as a fixed effect. For small values, beginning with the midnight group, the combination of the two time variables presents a decreasing number of frequent users. However, as was also seen with the interaction term for time and the proportion of residential addresses, after the afternoon time bin this trend reverses. This indicates that the influence of the midnight time bin is less than the evening time bin for the model as a whole This is consistent with the findings of Scott and colleagues (2014) regarding a temporal pattern of frequent users that occurs later in the day.

The results present a contrast of the influence of time as a random effect with its influence as a fixed effect. The purpose here was not to consider time in isolation, but rather in combination with location. The structure of the data followed processes of both spatial and temporal aggregation. While there were some limitations to this (detailed below), the overall performance was consistent with expectations. This also enabled the behaviour of time to be included as both a fixed effect and as a random slope effect. As a random effect, it is assumed that observations at midday in location X is not the same as observations at midnight in location X but that variance between the two measures is not independent. To consider this implication differently, it is evident from Figures 2.4 and 2.5 that the slopes within the respective models used to generate those plots differ based on time. Therefore, considering the random slope effect in terms of its location presents insight into locations that have higher or lower than expected numbers of frequent users (as illustrated in Figure 2.7). In general, there is not a location specific characteristic of these locations that appears consistently. For example, the locations with a positive effect do not all occur in close proximity to hospital. If this was shown, it may indicate the possibility of a variable that was not included in the model. But, the locations that displayed positive effects were a mix of urban, suburban, and rural parts of the city.

Closer inspection of the locations that had the greatest positive and negative random slope effects provides valuable information for service providers (see Table 2.5). The locations that had the greatest positive effect generally had higher numbers of general users in comparison to the locations that had the greatest negative effect. Of the top ten locations, eight had more general users than the mean number of general users of the full dataset (805.3). Based on Figure 2.7, these locations tend to be within urban core areas. This is also shown in Table 2.6. On the other hand only three of the locations that had the greatest negative random slope effect had more general users than the mean. The locations that had the greatest decreasing random slope effect were predominantly in suburban areas with a mix of urban locations. Three of the rural areas that had decreasing effects include areas of suburban growth.

One final observation with respect to the influence of the random slope effect requires further investigation. Specifically, as time increased, so too did the effect—whether that be positively or negatively. However, of all of the observations that had counts of zero frequent users 39 of 87 were during either the midnight or overnight time bins. Overall, this represents 17.6% of the observations during those time intervals (as compared to 10.8% observations having zero frequent users for all other time intervals). This is noteworthy because the model was specified to fit count data of a Poisson distribution. In these instances of zero frequent users, the model predictions may approach zero but would not become negative values. During the earlier time intervals, this restriction could be more easily accommodated by the model as opposed to during later time intervals. For the 48 observations with no frequent users later in the day, the random slope effect may have been limited. Further investigation of changes in the behaviour of time as a random effect or in combination with other effects (fixed or random) may be valuable to understand this limitation.

Location influences

Including distance to closest hospital emergency department as an independent variable was considered as a proxy measure of spatial accessibility to services. The expectation of its performance was that individuals who were further away from an emergency department would be more likely to use paramedic services to provide transportation to it. As such, it was also expected that closer proximity would decrease utilization of services. However, this was not found to be the case. There are three possible explanations for this. First, it may be plausible that individuals who become frequent users of paramedic services actively decide to reside in locations in close proximity to emergency care. However, in spite of this decision—or in direct association with it—these users still access emergency care through the utilization of paramedic services. The rationale for this decision not being based on the time required for an ambulance to respond to their location, but rather the knowledge that from the time that paramedics arrive, the time to hospital will be relatively short. Second, it may be plausible that individuals who might otherwise become frequent users but reside at a greater distance to hospital choose not utilize paramedic services because of perceptions about the time required for an ambulance to respond. In this case, these users who are at greater distance to a hospital ED determine to find other means to access care at an ED or clinic directly rather than waiting for an ambulance to respond to their need. Third, and perhaps more likely, this relationship results from an unaccounted for geographic characteristic of locations in close proximity to hospital emergency departments. Consider Figure 2.8 that shows 8 of the 10 blocks with the highest overall demand by frequent users and the classification of their random slope effect. (It is worth noting that the other two busiest blocks are located in the urban core of two smaller former municipalities—Dundas and Stoney Creek—that were amalgamated into the greater City of Hamilton). All eight of these blocks are in the lowest quartile of observed distances to hospital. Seven of the eight are within the inter-quartile range of residential proportion of address points. Six of the eight are within the inter-quartile range of proportion of population that are older adults (see Table 2.6). While the distance from the centre of these blocks to the three prominent emergency departments that serve the city is low, there are likely other characteristics that influence frequent utilization of paramedic services within these locations. The “Code Red” series has presented a number of health indicators regarding the residents that live in some of these neighbourhoods (DeLuca, Buist, & Johnston, 2012). Regardless of the influence of distance to emergency department or the potential influence of unknown factors, the fact that these locations are the busiest—both in terms of utilization of general users and frequent users—indicates that they are communities that would likely benefit from community paramedic interventions.

Further analysis is required with respect to these locations and whether or not the influence of distance is related to frequent users that are mobile from their place of residence. For example, it may be beneficial to identify differences in service utilization between frequent users who are transported from their homes from those who are transported from locations other than their homes. The results indicate that the influence of the independent variables for proportion of residential addresses and proportion of population of older adults did not prove to be statistically significant at alpha = 0.05. Nonetheless, these variables provide important insight into the predictions of frequent user utilization. Figure 2.9 illustrates the proportion of residential addresses and proportion of older adults in the same locations as were illustrated in Figure 2.8. This comparison contributes to the verification of the independence of these variables within the model. This contrast also reinforces the challenge associated with the mobility of the paramedic service user. That is, that these variables are a reflection of residential information but as has been indicated, ambulance calls occur where people are—not just where they live.

The influence of the spatial characteristics within the context of this model presented important insight regarding the role of geography in frequent use. This is evident in the spatial context of the model assessment presented in Figure 2.6. Out of the 111 blocks, only five blocks had model predicted expected values that were less than observed values in three different time bins. These blocks were located in Stoney Creek and lower Hamilton. The locations with two model predicted expected values that were less than observed values are a mix of urban, suburban, and rural blocks. These findings present the basis for further investigations that seek to establish common characteristics of these locations. Determining common characteristics that contributed to under predictions in model performance would permit improved specification of the model. Examples of other possible characteristics that are geographic in nature would be tourism points, shopping centres, or locations of primary care or walk-in clinics. The later of these may present alternative measures of accessibility to health care. Other examples may be characteristics that are population based or related to socio-economic factors.

Implications for service delivery

Part of the objective of this analysis was to provide information to decision makers with respect to the deployment of paramedic services. While Figure 2.6 and Table 2.8 may be interpreted to suggest that deployment of dual-capacity community paramedics should occur in the busiest locations, this may not necessarily be the case. For example, in these situations, the problem for the deployment of community paramedics in dual capacity roles is the potential for them to be over utilized as emergency responders at the cost of preventative interventions. Adequate deployment of traditional response units may mitigate this concern. On the other hand, as these are busy locations, it may be feasible to deploy a community paramedic whose sole responsibility is preventative measures and is not available for emergency responses.

The results of this analysis affirmed previously stated expectations that were based on the work of Scott et al. (2014) that the highest demand of frequent users occurs later in the day. However, the deployment of dual-capacity paramedics strictly based on this evidence would overlook the evidence gained through the findings pertaining to the random slope effect. Specific to HPS, the implication is that these resources should be deployed in urban core areas, including the urban core of the former municipalities that joined greater Hamilton. Further consideration should be given to the feasibility of dual-capacity community paramedics in the western rural part of the city as well. Special consideration may be given to areas that have an increasing random slope effect that are surrounded by locations that have a decreasing random slope effect. Two examples of this are found in the east-central part of Hamilton Mountain (blocks 1004 and 1015).

The principle for utilizing dual-capacity community paramedics is to improve system performance as well as clinical outcomes for frequent users. By identifying patterns in space and time where their deployment may be focused, specific interventions may be tailored to the needs of the patients in those locations. This is an important consideration of using these results to support utilizing community paramedics in dual-capacity roles as it relates to the non-emergent activities that they engage in. For example, one clinical activity of community paramedics is to perform home visits of at-risk patients. The model presents insights into the timing and locations where these programs may be most beneficial through the variables of time and residential proportion.

It is worthwhile to consider the trajectory an individual may take to becoming a frequent user. If it is assumed that the general public does not utilize paramedic services on an annual basis, and if they do, that it is unlikely that they do on more than one occasion, any individual who uses paramedic services more than once may benefit from community paramedics collaborating with other clinicians in their care. These individuals may have not yet utilized paramedic services to an extent that they are classified as frequent users, but they have utilized services on more than one occasion within a calendar year. By addressing the needs of these individuals in a proactive manner, the community paramedic has the potential to contribute to improved clinical outcomes. As a result of this approach, community paramedics may reduce the strain that these users can place on the health care system. Progress of paramedic services towards this objective is reflected in the Paramedic Referral Toolkit (Ontario Association of Paramedic Chiefs, 2015). The implication for this analysis is reflected in the definition that was used to classify individuals as frequent users. The Paramedic Referral Toolkit includes reference to repeated utilization of paramedic services within 30 days—a much shorter period of evaluation than a whole year. Also noteworthy is that the definition used herein refers to transport of patients to hospital. Considering short term repeated use as well as non-transports has the potential to improve the provision of community paramedic programs. Analysis of the space-time patterns of patients that meet these criteria may yield different results than those found here.

Limitations and future work

The benefits of employing mixed modelling may be summarized through the ability to interpret Figures 2.4 and 2.5 in contrast to Figures 2.6 and 2.7. However, it is important to consider the limitations of this approach as well. First and foremost, while some findings herein may be generalized for other settings, the results pertain directly to the specific geographic setting. While this may be a drawback for the findings, it is hoped that the methods employed herein could be transferred to other settings. In such a case, consideration of the aggregation processes would need to be required. For example, with respect to deployment of services, it may be advisable to aggregate locations based on service areas of established paramedic posts or stations. Similarly, with respect to time, performing analysis based on other temporal units may present different results. Finally, as has been shown by Cantwell and colleagues (2015), modelling patterns of daily demand for paramedic services can be done using other variations on linear modelling techniques.

It is important to note two other considerations that were made in model specification. First, attempts were made to include a subject specific random effect through a random intercept (typically following a notation of γ_0). The results of these attempts were models that failed to converge. This can be interpreted that the subject specific random effect was very close to zero. Second, the use of a GLMM for repeated measures typically includes R-side random effects. The results for a model like model 3 (Tables 2.2, 2.3, and 2.4) that included R-side random effects were very similar. Due to the similar results, it was unclear how the behaviour of R-side random effects contributed to model performance. An alternative consideration based on the structure of the data presents further ambiguity with respect to the inclusion of either effect. This is because the data were aggregated into a structure that did not represent a true repeated measures model. This also could lead to an interpretation that the evening time interval (time value 6) could also act as the subject specific random intercept (time value 0). While these considerations present a degree of caution regarding the methodology, they do not undermine the results so much as they present opportunity for further improvement in model specification and potential for data restructuring.

Future work may continue to evaluate patterns of utilization by frequent users and how they differ at certain times and in certain places from the space-time patterns of non-frequent users. In particular, the results of this research indicate a need to address the implication of the mobility of individuals, their related travel-behaviour, and this relationship with health care utilization. This should draw on concepts of spatial accessibility, time geography, and health care utilization. Programs that enroll patients in care management plans may provide the necessary means for these patients to inform research regarding factors that influence their mobility. Analyzing individual level characteristics of frequent users that have utilized services from multiple locations may be an alternative means of accomplishing this.

This analysis is informative for paramedic services that are considering expansion of community paramedic programming. Future research that evaluates the effectiveness of deployment of community paramedics in dual-capacity roles may consider changes in service utilization through an observational study. Pilot models of this service delivery model should focus on the strengths of this predictive model. An evaluation of “time-on-task” measures of community paramedics deployed in dual-capacity roles may provide insight into the economic benefit of this model of service delivery. Part of an evaluation of this scope would need to address instances where a community paramedic was unable to attend an appointment due to an emergency response as well as instances where frequent users were attended to by community paramedics acting as emergency responders.

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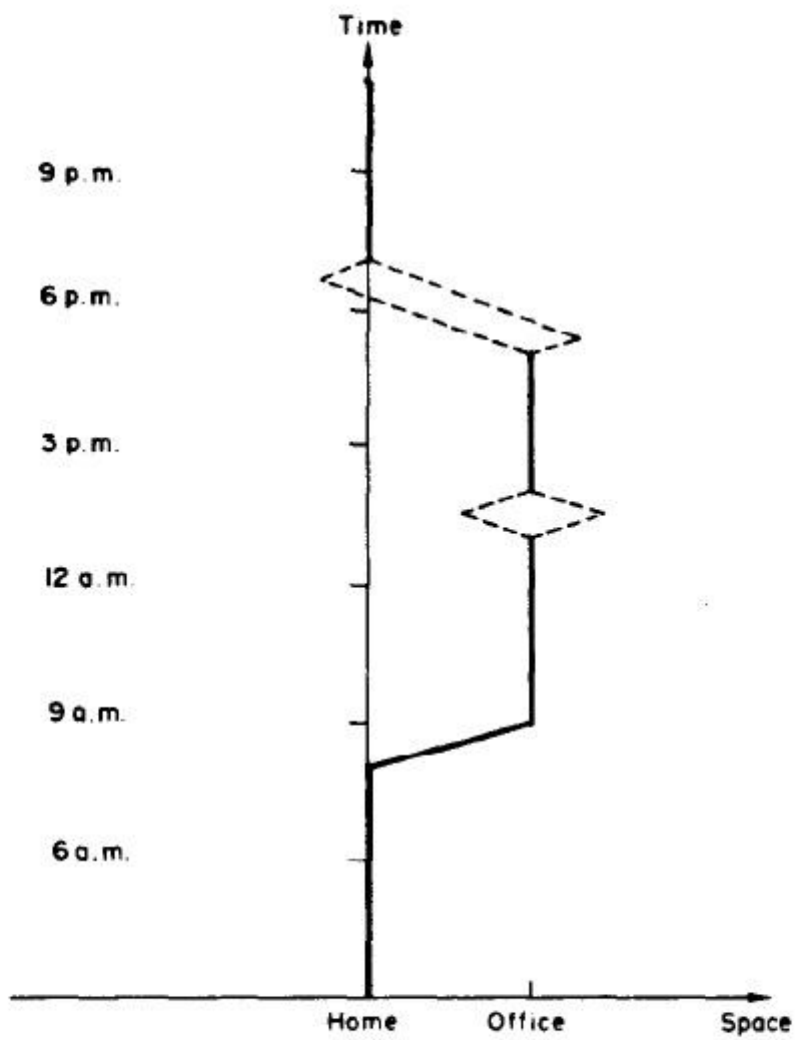

Figure 2.1: Hagerstrand's concept of space and time adapted by Cullen and Godson (1975)

Figure 2.2: Close up of grid cells, dissemination areas and census tracts.

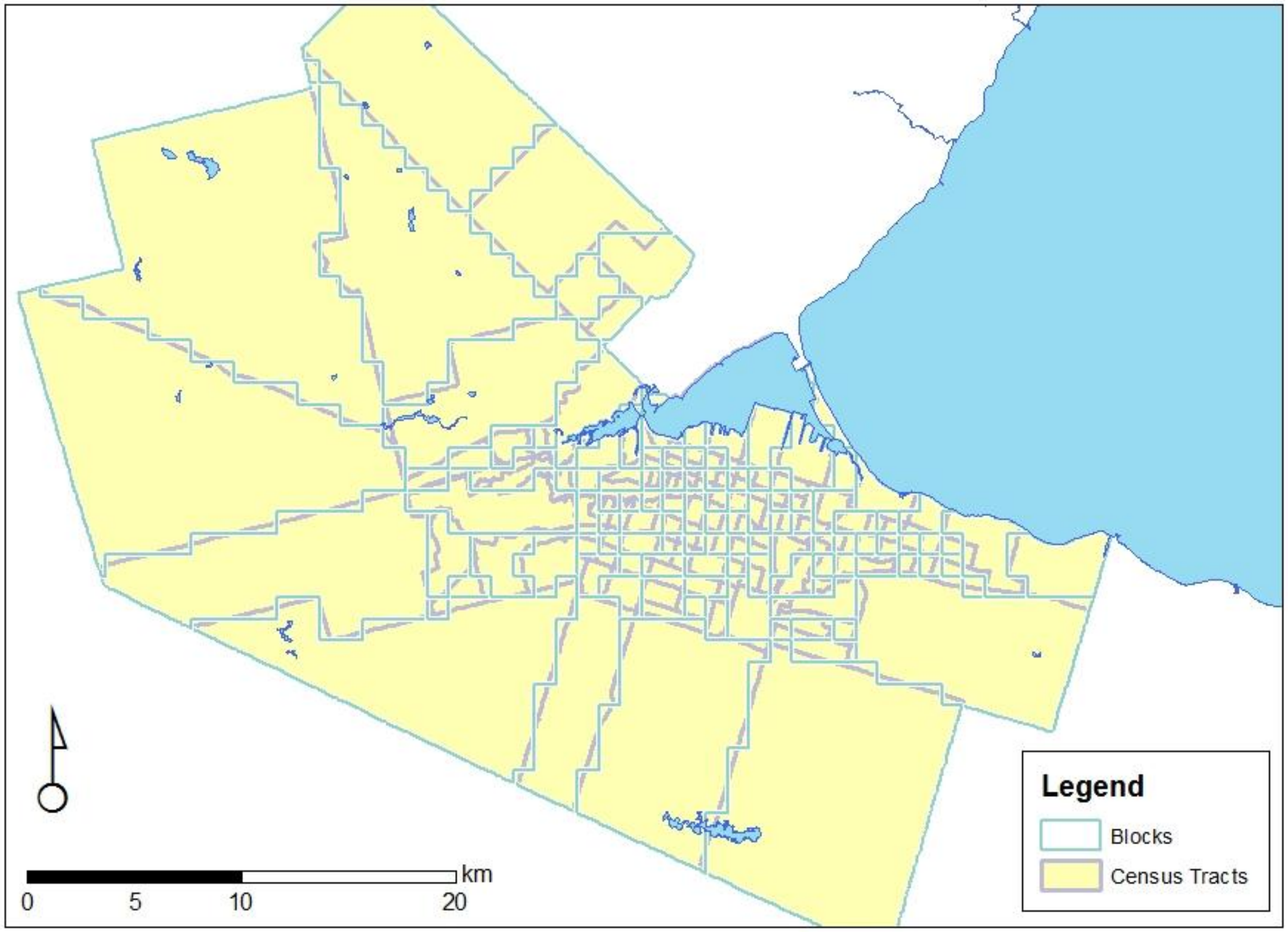

Figure 2.3: Blocks resulting from aggregation process that were used for spatial analysis.

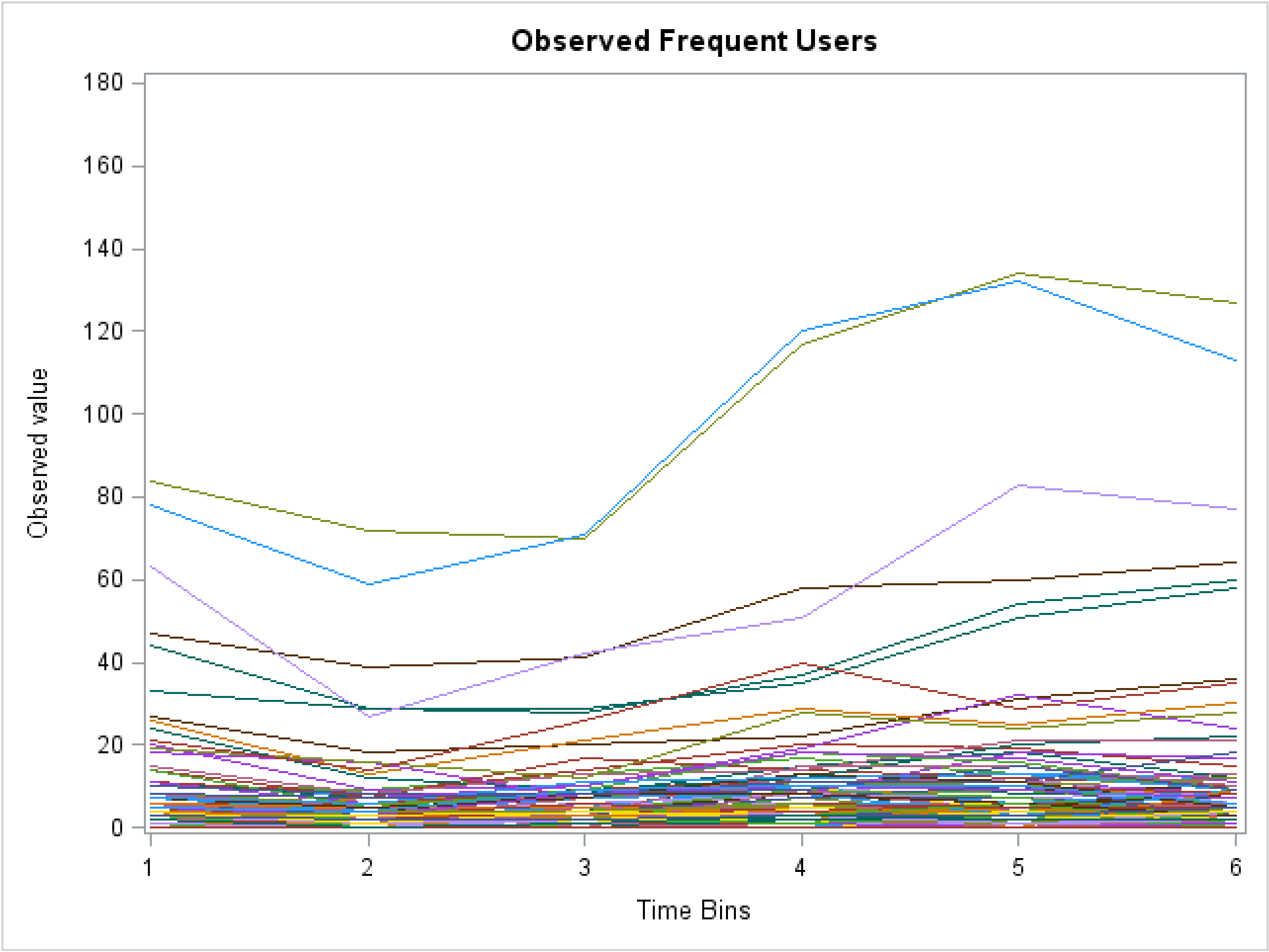

Figure 2.4: Linear graph of 111 lines, one for each blocks showing observed values of frequent users.

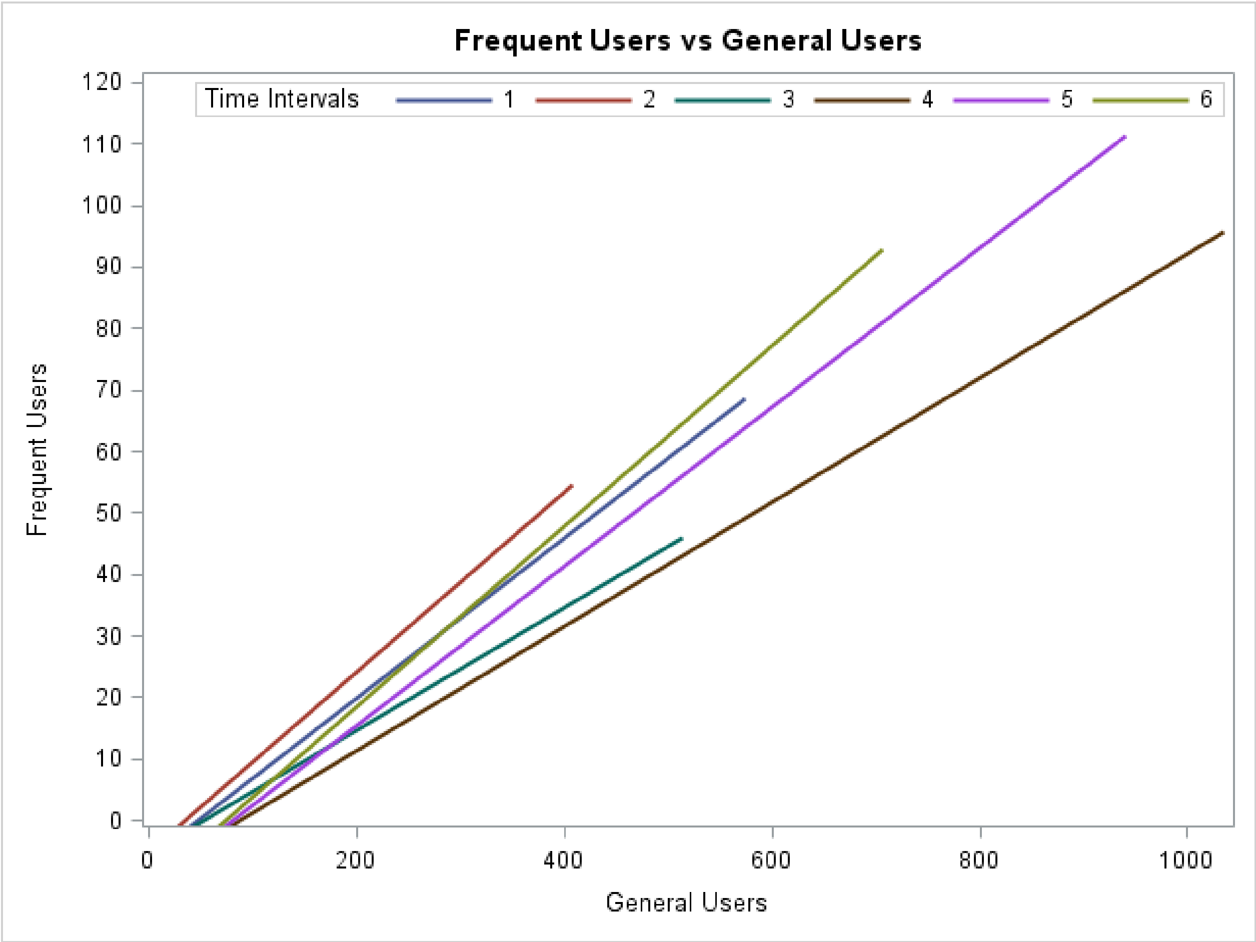

Figure 2.5: Six simple regression models, one for each time interval showing total frequent users predicted by total general users.

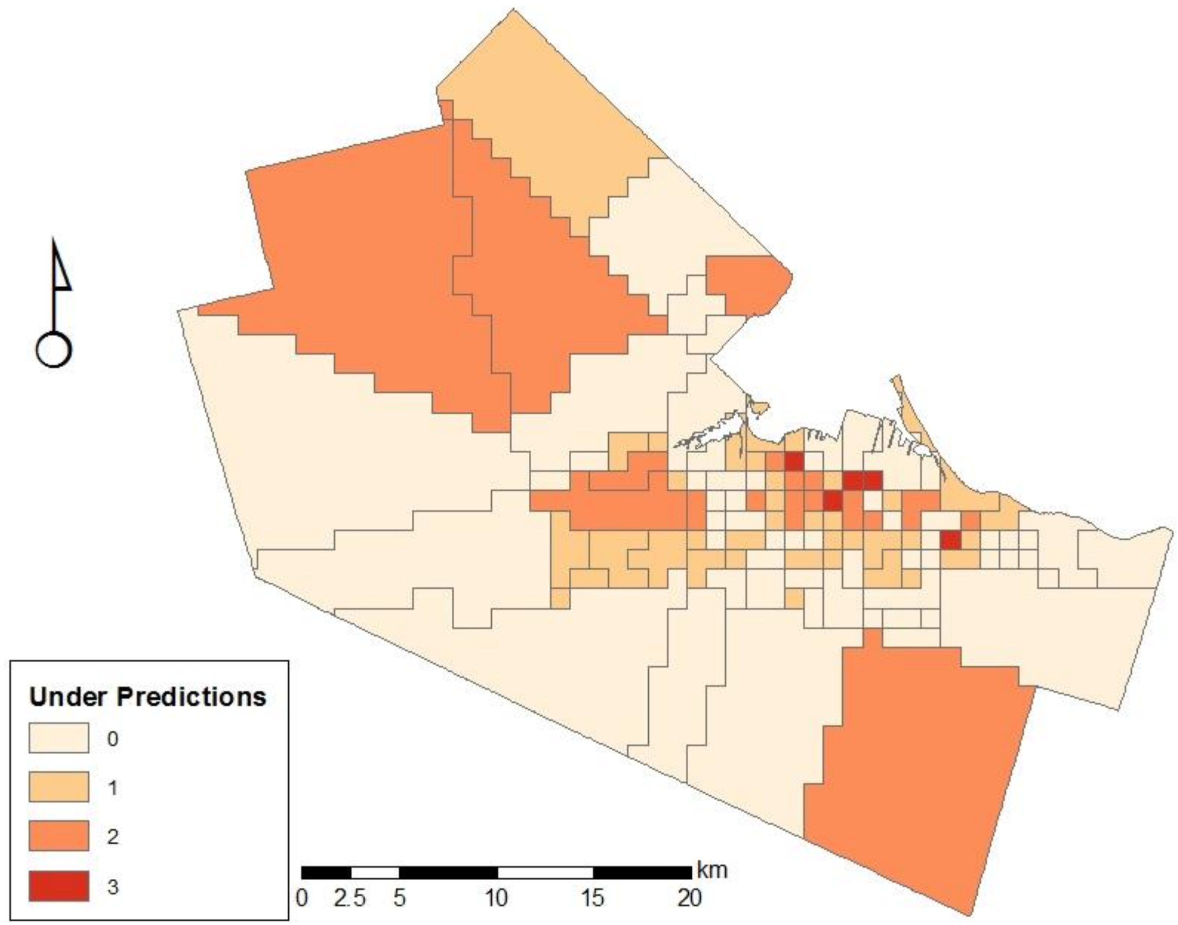

Figure 2.6: Map comparing model predicted expected values to observed number of frequent users for all time intervals.

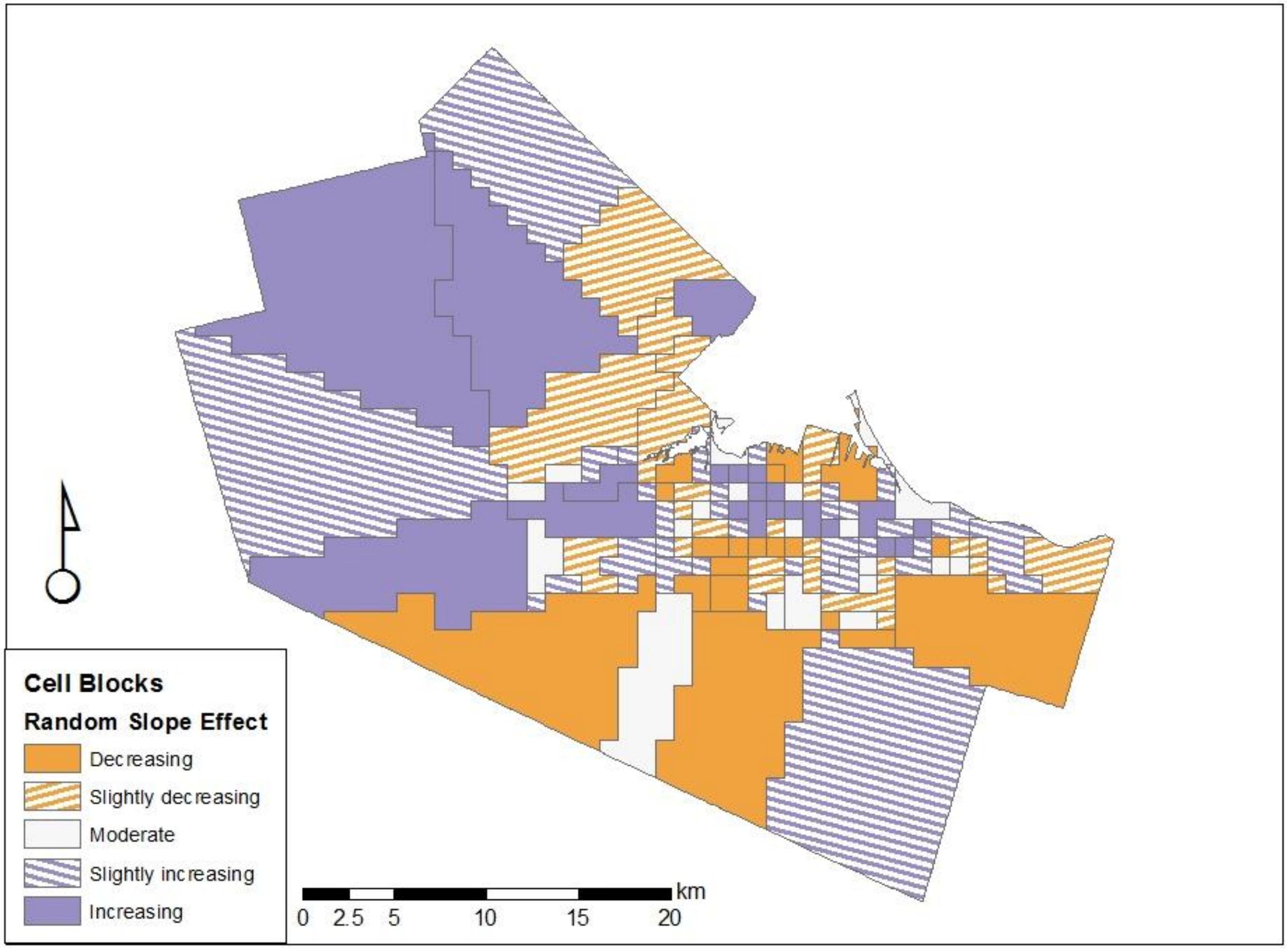

Figure 2.7: Map indicating random slope effect for each block.

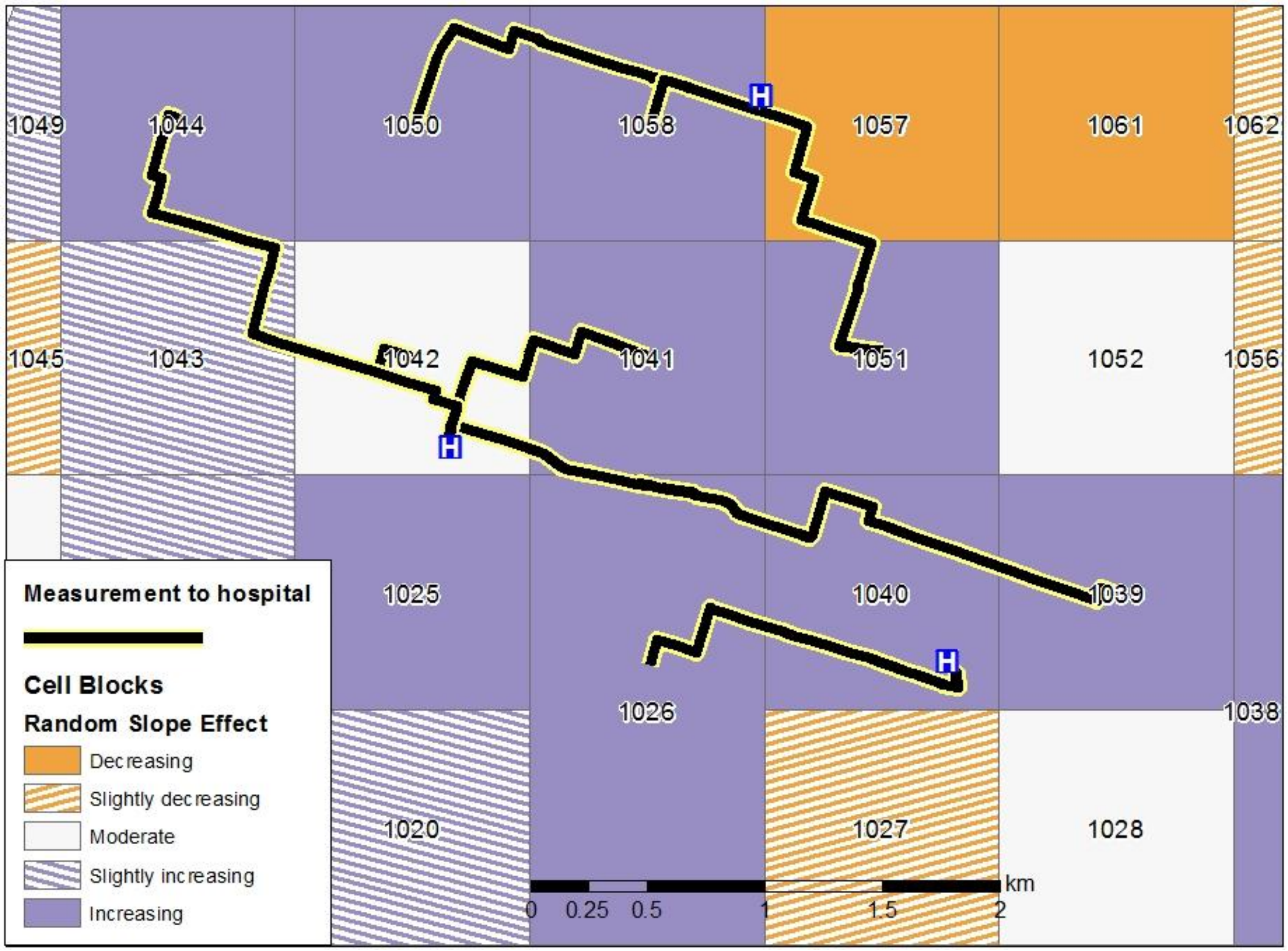

Figure 2.8: Random slope effect and distance to hospital in some of the busiest blocks.

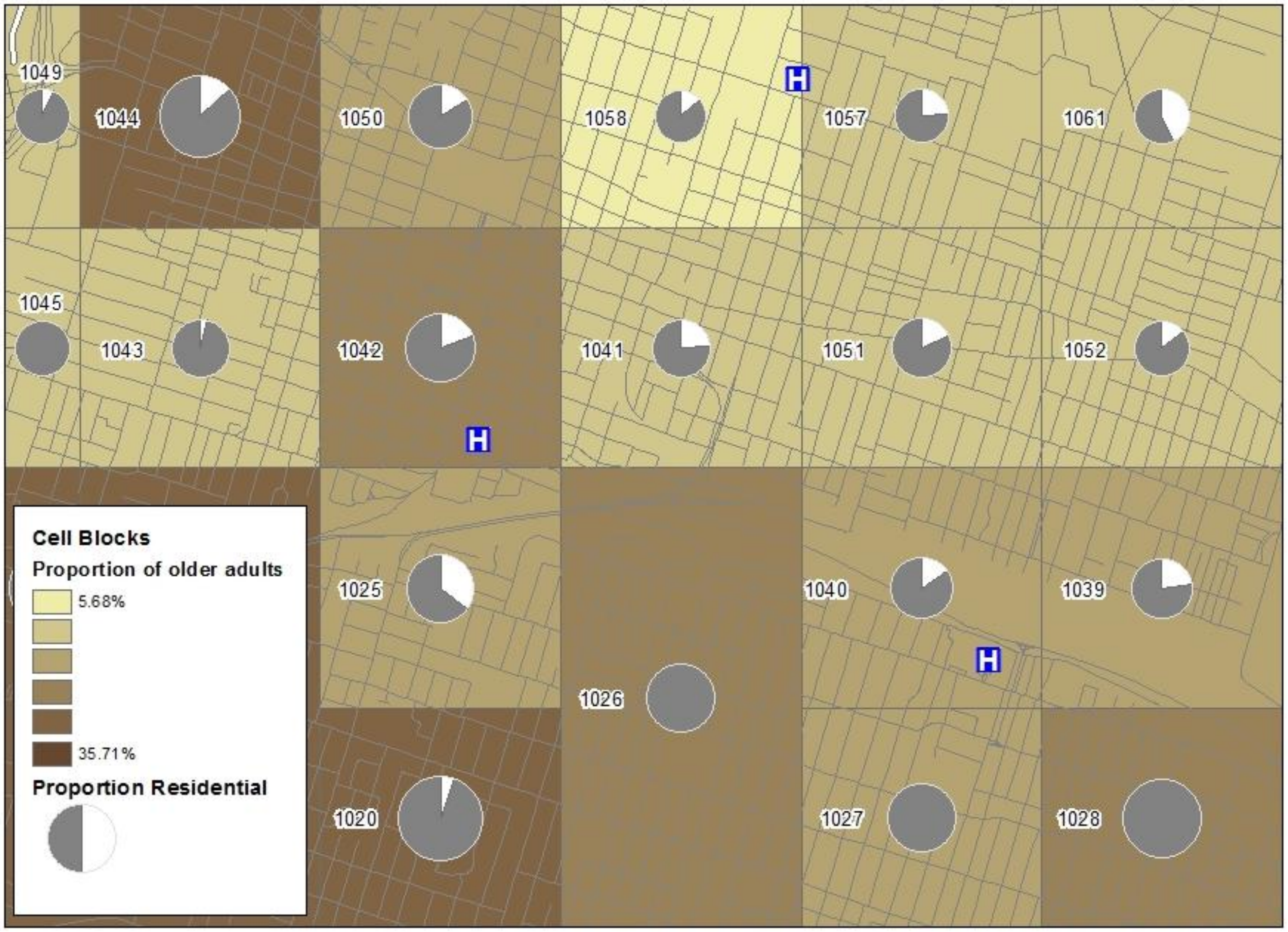

Figure 2.9: Map showing proportion of older adults and residential proportion for some of the busiest blocks.

Table 2.1: Distribution of dependent variable (expected number of frequent users) by time interval. The observed number of frequent and general users serve as reference.

Time Interval		Model 1 prediction	Model 2 prediction	Model 3 prediction	Observed frequent users	Observed general users
1	Midnight	849.07	835.28	909.54	879	11951
2	Overnight	555.94	563.14	555.37	622	8159
3	Morning	845.28	841.37	789.60	784	13805
4	Midday	1291.55	1312.69	1230.57	1153	21041
5	Afternoon	1186.97	1196.56	1175.87	1234	18346
6	Evening	1097.20	1076.96	1165.04	1154	16088
Total		5826	5826	5826	5826	89390

Table 2.2: Model diagnostics for each model.

Fit Statistics	Model 1	Model 2	Model 3
Pseudo-AIC	1353.1	1096.33	1067.56
Generalized Chi-Square	831.72	625.64	597.32
Generalized Chi-Square / DF	1.25	0.94	0.9

Table 2.3: Comparison of model parameters for fixed effects in each model including their standard error and level of significance.

Solutions for fixed effects	**Model 1**			**Model 2**			**Model 3**		
	Estimate	Standard Error	Significance	Estimate	Standard Error	Significance	Estimate	Standard Error	Significance
Intercept	-2.6441	0.03312	<.0001	1.9287	0.2698	<.0001	2.2187	0.2845	<.0001
Time Interval	-0.1465	0.01725	<.0001	-0.05322	0.01345	0.0001	-0.2784	0.0718	0.0002
Time Interval Squared							0.02456	0.005143	<.0001
Distance to Hospital (log(m))				-0.5801	0.03181	<.0001	-0.5741	0.03147	<.0001
Residential Proportion				-0.07756	0.1526	0.6116	-0.2001	0.2051	0.3295
Proportion of Older Adults				0.8319	0.522	0.1116	0.8657	0.5144	0.0929
Interaction (Time Interval * Residential Proportion)							0.05823	0.06691	0.3845

Table 2.4: Covariance parameter estimates for the random slope effect in each model.

	Model 1		**Model 2**		**Model 3**	
Subject	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Block	0.1496	0.01241	0.09105	0.008637	0.08987	0.008547

Table 2.5: Comparison of the blocks that displayed the greatest and smallest random slope effect. Smallest effects were given highest ranks as this indicated fewer expected frequent users.

	Block #	General users	Frequent users	Predicted frequent users	Prediction without random effects	Random effect rank (greatest to smallest)	Actual rate (FU/Total)
Increasing effect	1076	826	71	59.16	30.20	111	7.92%
	1065	1746	127	115.92	68.90	110	6.78%
	1050	1647	252	234.73	141.00	109	13.27%
	1040	1002	114	107.09	65.17	108	10.22%
	1039	1480	154	139.28	84.96	107	9.42%
	1026	1480	235	223.02	137.85	106	13.70%
	1041	3592	604	580.51	370.47	105	14.39%
	1107	427	18	12.20	7.74	104	4.04%
	1068	324	21	15.56	10.07	103	6.09%
	1097	2860	165	154.76	99.78	102	5.45%
Decreasing effect	1048	333	4	11.17	15.19	10	1.19%
	1078	336	2	6.70	9.74	9	0.59%
	1019	651	22	29.21	44.82	8	3.27%
	1057	868	71	81.32	124.87	7	7.56%
	1017	547	22	25.00	39.51	6	3.87%
	1070	445	1	6.45	10.60	5	0.22%
	1013	793	11	19.43	31.71	4	1.37%
	1046	1366	22	34.79	57.14	3	1.59%
	1089	833	6	14.47	25.32	2	0.72%
	1072	586	1	7.98	14.79	1	0.17%

Table 2.6: Summary of the ten busiest blocks and their relationship with the independent variables. Predicted values and rank of random effect are based on third model.

		Relationship to IQR					
Block #	**Location**	Distance to hospital	Proportion residential	Proportion of older adults	**Total observed frequent users**	**Total predicted**	**Rank of random effect**
1026	Hamilton Mountain	Above	Within	Within	235	223	106
1039	Downtown	Above	Within	Within	154	139	107
1041	Downtown	Above	Below	Within	604	581	105
1042	Downtown	Above	Within	Within	573	603	60
1044	Downtown	Above	Within	Above	144	136	99
1050	Downtown	Above	Within	Within	252	235	109
1051	Downtown	Above	Within	Within	309	298	95
1058	Downtown	Above	Within	Below	343	337	91
1065	Stoney Creek	Within	Within	Within	127	116	110
1097	Dundas	Within	Within	Above	165	155	102

CHAPTER 3: The geographic influence on community paramedicine service delivery to frequent users in the County of Renfrew, ON

Introduction

Accessibility to health care is one of the central principles of the Canada Health Act (Canada, 2015). Based on the vast geographic characteristics of Canada, this principle can present significant challenges to health care service providers and patients—particularly in rural Canada (Schuurman, Berube, & Crooks, 2010). It is within this context that rural paramedic service providers have found motivation for community paramedic programming. These programs use paramedics in non-emergency capacities to improve patients' ability to establish contact with health care practitioners. One of the first examples was the use of paramedics to improve accessibility to health care services through an expansion of their scope of practice on Long and Brier Islands, Nova Scotia (Martin-Misener et al., 2009). This example is a nationally recognized case of community paramedicine (Canada, 2011). It was a direct response to a lack of health care access resulting from the distance between patients and health care providers and the types of care available through these providers (Martin-Misener et al., 2009). This case has served as an inspiration for other paramedic services to better address the needs of their respective communities. While the needs of accessibility to services differ between communities and contexts, the ability to increase patient-clinician interaction by responding to community needs has the potential to improve patient outcomes. Structuring programs to address the specific needs of respective communities is a common practice that has been identified in reviews by Bigham et al. (2013) and Jensen et al. (2015) regarding community paramedic activities.

Poor access to health care can result from factors other than gaps in services and distance. While the case of Long and Brier Islands demonstrated that using community paramedics can improve accessibility to health care services in response to these barriers (Martin-Misener et al., 2009), the limited role paramedics have within the greater health care system means that collaboration with other health care service providers is necessary when paramedics extend their traditional scope of practice in community paramedic roles. Establishing collaboration with allied agencies that also have relationships with these patients can enable alternative pathways to access care from the traditional pathway that paramedic services provide through hospital emergency departments. This may be collaboration with non-emergency health care services, social services, or even other emergency services (Bigham et al., 2013). One of the simplest forms of collaboration can be the sharing of information between agencies. Paramedics in Ontario have started to use a standardized referral form to share patient information with Community Care Access Centres (CCACs) (Ontario Association of Paramedic Chiefs (OAPC), 2015). A crucial element of the referral tool is a section that contains assessments that have been drawn from the Paramedics assessing Elders for Independence Loss (PERIL) study (Canadian Research Information System, 2012. See Lee et al., 2007). Of particular note is the question “Has the patient called 9-1-1 in the past 30 days?” An affirmative response contributes to a higher likelihood for the patient to experience diminished well-being in the absence of a CCAC referral. The value of the referral to CCAC is a result of the time period that exists between assessments by other care givers. In the intervening time between assessments the patient’s condition may have deteriorated. Alternatively, it is possible that any similar assessment may not yet have been completed. This presents a clear strengthening of the principle of accessibility as CCAC serves the function of co-ordinating home based and community based long-term care that these patients require.

The challenges associated with accessibility to health care can differ based on the characteristics of the patients who face barriers to services. For example, improving entry to the long-term care system through paramedic referral is important for those frequent users that require it. However, while patients requiring long-term care are a specific subset of frequent users of paramedic services, developing a referral tool that can be used by paramedics operating in a geographic setting as diverse as the province of Ontario is possible when it is tailored to such a specific patient group. The review completed by Scott and colleagues (2013) describes various characteristics of patients who frequently use paramedic services. The authors assert that it is important to distinguish between frequent users of paramedic services and frequent users of emergency departments—which has been the subject of a greater amount of research. Scott et al. (2013) describe reasons for use, time of use, gender, age, ethnicity, and socioeconomic status that have been observed in existing literature. Their findings suggested that frequent users are a diverse group and that existing research has been conducted in a variety of ways (Scott et al., 2013). This suggests that, while frequent users may represent a sizeable portion of service utilization, services have attempted interventions that are directed at subsets of the frequent users group. Furthermore, in a number of places, paramedic services are operated by regional or municipal authorities leading to interventions that address the needs of frequent users within that particular place. These factors are consistent with calls for further research to assist in identifying the patients that may be best served through the forms of improved accessibility that community paramedicine can provide (Bigham et al., 2013, Jensen et al., 2015, Scott et al., 2013). However, this is difficult when community paramedic programming is established in response to frequent users with specific needs or from a specific location and leads to research findings that have limited generalizability to other settings.

A certain degree of generalizability can be drawn from the idea that certain patient characteristics may be common throughout a population that experiences diminished access to health care services. This has served as an important foundational concept in measuring spatial accessibility to health care (Neutens, 2015). Research on spatial accessibility to health care has typically focused on distances to services for populations of specific areas (Yiannakoulias, Bland, & Svenson, 2012), often using metrics based on a gravity model where accessibility is some function of distance from service providers (Crooks & Schuurman, 2012, Guagliardo, 2004). Maps of spatial accessibility indices or scores are useful for illustrating relative differences in accessibility by location. While these scores may be useful for comparing spatial accessibility in a population, they typically overlook other person-specific factors that influence accessibility such as affordability or acceptability (Neutens, 2015). Opportunities exist to further explore the influence of factors like age, gender, existing medical conditions, social support, insurability, and access to transportation in measures of spatial accessibility (Bell et al., 2013, Neutens, 2015, Paez et al., 2010). Furthermore, Paez et al. (2010) point out the distinction between the manner in which spatial accessibility measures the potential to a medical resource and the relevance of measuring actual utilization of a resource. The lack of standardized metrics in the calculation of spatial accessibility can make interpretation difficult for policy makers (Guagliardo, 2004) and limits the comparison of these scores to other settings or other periods of time.

It may be valuable to consider how predictive modelling can be included in measures of spatial accessibility. Epidemiological studies commonly use modelling processes such as logistic regression to estimate patient outcome probabilities (Steyerberg, 2009). These models also present a means of evaluating “potential” in terms of prognosis or diagnosis. If models of spatial accessibility presented the likelihood that a health care resource may be actually utilized by a population they may serve to better inform decision makers. In order to do so, measures of spatial accessibility need to undergo validation processes similar to those used on clinical predictive models. Conversely, one form of validating clinical predictive models is geographic validation. In this context, geographic validation is accomplished by either removing one of the clinical settings from the development dataset or by using data from another setting to test the models ability to generate probabilities

(Steyerberg, 2009). In either approach, the application is focused on the model's ability to accurately predict individual probabilities and therefore reflect its generalizability. It is not used to show what the model may reveal about differences between geographic settings—although it may offer this potential. In doing so, this approach to modelling would incorporate individual-level characteristics in a way that measures of spatial accessibility typically ignore.

An alternative approach to traditional spatial accessibility is to model the probability that individuals will use a health care resource. This approach presents some important similarities with geographic profiling of serial crime. Geographic profiling emerged as a technique employed in criminal investigations but has been adapted to behaviour of infectious diseases in epidemiology (Le Comber et al., 2011). The idea behind geographic profiling is that the characteristics of a serial offender have some association with locations based on patterns of human behaviour (Rossmo, 1995, Le Comber et al., 2011). The development of geographic profiling is attributed to the work of Rossmo (1987) who considered gravity models and distance decay to identify fugitive migration patterns. Rossmo (1995) later adapted geographic profiling to serial murder cases. Geographic profiling maps present a probability surface that can be used to help locate serial offenders. The value of a probability surface map is that it can present spatial data in a standardized manner (Wright, 1977). This means that the results of analysis that generates these maps can be easily interpreted—whether that is by an investigating police officer, epidemiologist, or paramedic service provider.

In order to apply the concepts of spatial accessibility and geographic profiling to community paramedic service provision, a number of adjustments in approach are required. First, community paramedicine represents a mobile service delivery model. This means that the traditional approach to assessing spatial accessibility that is concerned with the population’s ability to travel to a health resource does not apply. However, the cumulative opportunities for individuals to access services based on their location are still applicable. In applications of geographic profiling, the probability surface is typically generated based on expected patterns of human activity (Rossmo, 1995, LeComber et al., 2011) in order to help isolate one particular point of interest—the location of the serial offender. In the case of providing care to individuals through community paramedic programs, multiple frequent users are of interest to the service providers. Therefore the probability surface can indicate appropriate locations for the deployment of resources. Finally, using a predictive model as part of the approach presents an opportunity to include individual-level factors that traditional approaches overlook. This would only be reasonable with some form of validation which can also serve to improve generalizability. The very purpose of epidemiological studies is not simply to explain some phenomena, but also to guide clinicians in their decision making regarding a disease process. Considering individual and community needs through a combination of geographic profiling and measurement of spatial accessibility represents a novel approach in spatial analysis to present geographic profiles of health information that can be easily interpreted by decision makers to inform policy and delivery of services.

Objective

The objective of this analysis is to estimate spatially defined probabilities of paramedic service use by frequent users akin to the probability surface used in geographic profiling. To accomplish this, the analysis focuses on patient specific risk factors for individuals who repeatedly use paramedic services. By aggregating individual probabilities to spatially defined areas it is expected that insight into the accessibility to primary health care services within these areas will become apparent. This approach assumes that repeated use of paramedic services indicates a diminished level of accessibility to other health care services. Patients who do not have adequate access to primary or specialized health care services will repeatedly use paramedic services as a "last resort" in order to access care either through the paramedic service or at a hospital emergency department. Identifying risk factors at the individual level and aggregating them to the community level will result in community health profiles of service utilization by frequent users. Paramedic service providers of community paramedic programs can use these results to validate ongoing initiatives and prepare new interventions that may be directed at identified needs.

Methods

Analytical approach

The process used to estimate spatially defined probabilities of paramedic service use by frequent users was comprised of three parts. Using data from electronic patient call records (ePCR), patients were classified as either frequent users of paramedic services or general users. First, a model was developed using logistic regression to identify individual level risk factors that predict frequent use patients. Second, the model was tested on independent subsets of data from subsequent years in order to determine the validity of the model. Third, the resulting probabilities generated through the modelling process were aggregated to two different spatial scales to create profiles of community needs. Due to ongoing community paramedic programming within the region of study, the resultant community health profiles serve as an evaluation of the benefit of these programs in these locations. The community health profiles also can be used to assess community level probabilities of patient needs in future interventions.

Research setting

Community paramedic program development in the County of Renfrew, ON can serve as an example of a paramedic service evaluating and responding to community needs for improved accessibility (Ruest, Stitchman, & Day, 2012). The County of Renfrew is located northwest of the City of Ottawa, ON in the Ottawa River valley (see Figure 3.1). The county operates its paramedic service under the same structures as have been detailed for the City of Hamilton (see Chapter 2). In contrast to the City of Hamilton, the County of Renfrew has an area that is more than 5 times larger in size while the population is less than one fifth in size. The County of Renfrew Paramedic Service (CoRPS) responds to approximately 20,000 calls for service annually from stations in the communities of Barry's Bay, Eganville, Deep River, Petawawa, Pembroke, Renfrew, and Arnprior. Additional posts have been established in the communities of Cobden, Calabogie, and Killaloe. This total of ten paramedic posts in a county that is approximately 7700 km^2 is an example of vast distance limiting resources.

The challenges that the residents of Renfrew County experience regarding the accessibility to health care are not limited to distance. Similar to the situation in Long and Brier Islands (Martin-Misener et al., 2009), community paramedicine initiatives in the county were initiated in an attempt to directly address gaps in services that were recognized in various communities within the county. In the community of Deep River, community paramedics participate in a program called Aging at Home (Ruest, Stitchman, Day, 2012). This program was designed, in part, to respond to a shortage of long term care beds in the community. In other locations, programs were designed to respond to a shortage of primary or specialized care. Wellness Clinics, led by paramedics, were first initiated in the community of Eganville and then expanded to serve other communities (M. Ruest, personal communication, 2015). The purpose of these clinics is to provide patients with a baseline assessment of their health while also enabling and facilitating discussion regarding their overall well-being. The outcome of these consultations may include findings reported to the patient's family physician or a referral to other social service agencies that may provide patients with further assistance. Paramedics in Eganville then extended the reach of the Wellness Clinic model by engaging in an ad hoc home visit program. This program follows the guidelines established for the Wellness Clinics with assessments performed on a regular basis in the patients' homes. Other programs facilitated through community paramedics include CPR and AED education, a Heart Wise Exercise Program, and referrals to the local community care access centre (CCAC). In 2012, CoRPS began utilizing a community paramedic response unit (CPRU). This unit is deployed centrally in the county and utilized in a dual-capacity of emergency response and community paramedicine programming. The findings of Ruest, Stitcham, and Day (2012) and O'Meara, Ruest, and Stirling (2014) have presented positive outcomes from these initiatives.

Data acquisition

CoRPS provided data from 74,641 electronic patient chart records (ePCR) from 2008 through 2014. Each record represented one incident where there was contact between a paramedic and a patient. Linking the records of patients who utilized paramedic services on more than one occasion was accomplished through a unique patient identification number (PID). Other elements in the data included information on call location, distances travelled over the duration of each call, pertinent times, dispatch and return priority (including non-transports where care was rendered but the patient remained at the scene), age and gender, paramedic assessment of patient's chief complaint, paramedic assessment of patient acuity, and pertinent medical history. These elements represented fields within the ePCR that were either coded, numeric, or binary responses (check boxes). After excluding call records for transfers between medical facilities and records with missing data or invalid entries, a total of 33,418 records were included for assessment.

All individuals that used paramedic services a minimum of one time over the duration of the study period were included for evaluation in this study. Annual observations of paramedic service utilization were created for each patient by aggregating records according to the PID. In the instances where patients did not utilize paramedic services in a particular year certain assumptions regarding their status were inferred from the entry/entries during other years. For example, age was adjusted based for records before or after utilization. In the case of past medical history, it was assumed that for years prior to service usage, these individuals were healthy. Conversely, for years following service usage, it was assumed that individuals were not previously healthy. Similarly, a patient's designated primary location was thought to not change before or after utilization unless determined through subsequent utilization from a differing location. For each of the variables indicated below, rates were calculated based on number of individual utilizations. In years where an individual did not utilize paramedic services, these rates were calculated to be equal to zero.

Geographic analysis within a rural context can be challenging based on sparse numbers of observations across distance. This can present issues regarding confidentiality as well as challenges regarding the spatial distribution of data. Within the dataset, information regarding call location was related to two variables. The first was a binary indicator of whether or not the location of the call was the patient's place of residence. This variable provided information that was valuable with respect to the travel behaviour of the patient, but in and of itself was not specifically geographic as the data did not include patient address. The second piece of information was the location within a provincially standardized dispatch grid where each grid cell represents one square kilometer. (This dispatch grid was also used to geo-reference locations for the data used in Chapter 2.) To address the challenge of sparse observations in space, the geographic locations of calls were further aggregated using recursive partitioning to create a quad-tree overlay of geographic blocks. To accomplish this, all grid cells with 30 or more observations were selected to act as "seeds." The partitioning program was parameterized such that all areas of the county were included and each resultant block required a maximum of one seed. Due to the rural nature of the county, areas between seeds resulted in some blocks that contained grid cells with less than 30 observations. This required a secondary evaluation to ensure that a minimum of 30 total observations occurred in these blocks. The same recursive partitioning process was performed manually, where necessary, in these locations to meet the minimum number of observations in blocks. In the end, the results of this partitioning process were groups of grid cells in blocks of varying size that each contained a minimum of 30 observations.

Each individual ePCR record was then assigned to its corresponding quad-tree block. For individuals that had repeated paramedic service use, the quad-tree block that had the most occurrences was designated as that individual's primary location of utilization. Corresponding information regarding the quad-tree block was also attached to the ePCR records. The mean centre of all calls within each block was determined to serve as the block centroid. The centroids were used to calculate distances to paramedic posts using Network Analyst in ArcMap v10.2 (ESRI, 2013). The County of Renfrew provided the geographic data regarding the local road network. This allowed each block to be classified based on proximity to the closest paramedic post. Service areas were created based on the block centroids that were closest to each paramedic post. The distances also served to classify spatial accessibility to paramedic services as, close proximity, medium proximity, and low proximity.

Model specification

The response variable of the logistic regression was whether or not a patient was a frequent user of services and therefore eligible for community paramedic care (1=true, 0=false). The first determination of a patient meeting this criterion was made in keeping with the industry recognized standard of greater than or equal to 5 calls responded to by the paramedic service within a calendar year (Scott et al., 2013). This metric was also utilized in chapter 2 and the same method of calculating the time interval between calls was employed here. As opposed to the methods used in chapter 2, the structure of the data enabled inclusion of calls that resulted in non-transports. In addition to this criterion, a second indicator of eligibility was added; patients were classified as being frequent user if they had utilized paramedic services more than 4 times within a 365 day period or on more than one occasion within a 30 day period. If a patient did not utilize paramedic services during the year of observation, the response variable was classified as a zero.

The indicators used to inform the logistic response were as follows. Past eligibility can be a strong predictor of future eligibility. In this model, the patient's response variable was included for each of the two preceding years as an indicator of previous need. In spite of some contradictory findings in previous studies (Scott et al., 2013), age and gender were included for investigation. Each ePCR included a check box to indicate whether or not a patient was previously healthy. If at any point during the year, the paramedic recorded this as an affirmative, this value was considered for that year. Otherwise, paramedics had the option of multiple other pre-existing conditions as well as a text box for further explanation of previous medical history. For analytical purposes, only the binary response of previously healthy or not was considered. In keeping with the temporal trends evaluated in Chapter 2, the time of day values and rates of usage on weekdays were included. The same six time bins were utilized here as in Chapter 2. Clinical assessments regarding triage level and chief complaint were included as rates based on number of individual occurrences. In the case of triage level, the rate of acuity level 1 (based on the Canadian Triage Acuity Scale) was excluded as a reference rate. Complaints were grouped based on problem codes as they were entered under 10 categories on the ePCR. The preliminary model was specified to include all 10 categories of complaints. However, those identified as not being focal to existing interventions (as per Renfrew correspondence) or that were clearly not statistically significant were subsequently excluded. This meant that complaint rates for diabetic, cardiac, or respiratory problems were retained (with all others serving as reference). One exception to the complaint rate calculations was made regarding patients who had a documented final primary problem as vital signs absent (VSA). As this was assumed to be a potential indication of mortality, a dummy variable was included to indicate whether or not the patient experienced such an event. Another pertinent variable that was included was rate of refusal. This was determined based on a coded response regarding the patient's transportation status. A refusal of service indicates that paramedics assessed (and potentially treated) a patient who subsequently refused to be transported to hospital. Rates were calculated based on the number of calls where pick-up location was recorded as being the same as the individual's place of residence.

Location information was included by creating dummy variables indicating the patient's primary area of utilization as being with one of the service areas of the 10 paramedic posts. The post with the fewest observations (Calabogie) was excluded as the reference variable. If the mean center of a patient's primary quad-tree block was within 5km of a paramedic post, the location was classified as having highest proximity to service. Quad-tree block mean centres that were greater than 20km from a paramedic post were classified as having lowest proximity. Block mean centres between 5km and 20km were considered to have medium proximity. These indicators of spatial accessibility were included as dummy variables, with low proximity being excluded as reference. The model development dataset included all observations for the 2010 calendar year. Inclusion required that observations had utilization of paramedic services either during the calendar year or at some point during the previous two years (thereby enabling inclusion of past behaviour).

Diagnostics and internal validation

Models were assessed using a variety of diagnostics. Deviance and Pearson goodness-of-fit tests were applied to consider interactions and non-linear performance. The data were partitioned with the Homer Lemeshow goodness-of-fit test to assess expected values of the response variable. Concordant and discordant pairs were assessed between observations with opposing response variables. Concordant pairs represent situations where the predicted probability is higher for the observation with a response variable of 1. Discordant pairs present the reverse. Based on this assessment, the receiver operator characteristic (ROC) curve was generated to present a visual diagnostic. The ROC curve illustrates the relationship between false positive rates (specificity) and true positive rates (sensitivity). In this case, a false positive finding would be general users that were identified as frequent users and a true positive finding would be correctly identified frequent users. A minimum threshold for a ROC curve is considered to be having a slope of 1 or area under the curve (AUC) of 0.5. Further internal validation was conducted at two geographic levels. Mean predicted probabilities (and confidence intervals) were calculated at the quad-tree block and service area level. Actual probabilities were classified as being within confidence intervals, above, or below predicted probabilities at the respective geographies.

Validation against 2013 and 2014 data

The model was developed as part of the process to generate spatially defined probabilities of paramedic service use by frequent users. Therefore it was important to insure that the model performed adequately in determining individual probabilities and that the aggregation of these probabilities to the corresponding spatial units was accurate. This process was an important first step in revealing the generalizability of the model for future use.

Validation of the model was conducted using datasets for 2013 and 2014. Both validation datasets had the same structure and variables as the development dataset. Observations for patients that had utilized paramedic services in either the corresponding calendar year or at some point during the previous two years were included. Validation was performed using the coefficients of the development model to calculate predicted probabilities in the validation datasets. Concordant and discordant pairs were evaluated and ROC curves were generated. Predicted probabilities were compared to observed probabilities in patient sub-groups, within quad-tree blocks and for service areas. Mean probabilities for predictions and observations were calculated for a number of user groups by similar individual characteristics. First, each decile of predicted values was compared to actual values. Other groups included gender, previously healthy, age, refusal rate, proximity, triage level, and complaints. For the geographic validation, mean predicted values were compared to actual rates.

Data management and analysis was completed utilizing SAS 9.3 for Windows (SAS Institute, 2013). Where needed, cartographic outputs were completed using ESRI ArcMap 10.2 (ESRI, Redlands, CA, 2013). Ethics approval was obtained through the Hamilton Integrated Research Ethics Board.

Results

Model performance

The model was evaluated in terms of both its calibration (how close estimates were to observed rates) and its discrimination (how well the model identified frequent users). Given the extent to which calibration was tested through validation, particular attention was paid to the discriminatory power of the model. These results are summarized in the association of responses in Table 3.1. The analysis of concordant and discordant pairs presents adequate model performance, with the exception of the Tau-a test statistic. While Somer's D, Gamma, and c statistics evaluate only concordant and discordant pairs and ties, Tau-a considers all possible pairs. In this case, the high number of possible pairs and low number of observations resulted in a low test statistic. The ROC curve for the development dataset is shown in Figure 3.2 with an AUC of 0.876. The model calibration was first assessed with goodness-of-fit tests in terms of deviance (Deviance and Pearson statistics) and through the Hosmer-Lemeshow test. Calculating the deviance statistics test whether the model performs better at predicting frequent users than predicting them by chance while the Hosmer-Lemeshow test compares observed rates to predicted rates. The results for both tests affirm the model performance (value/DF > 0.05 for Deviance and Pearson and PR>ChiSq > 0.05 for Hosmer-Lemeshow).

Table 3.2 shows the parameter estimates and their standard error with level of significance. It also reflects parameter odds ratios (OR) and OR confidence limits. Parameters of the development model that proved not to be statistically significant included rate of weekday utilization, gender, and proximity classification. Complaints for respiratory problems were significant at $\alpha=0.05$ but diabetic and cardiac complaints were not. Age, previous classification as a frequent user, (not) previously healthy, time of day, refusal rates, triage level, and VSA were all statistically significant. A number of locations were not significant but Barry's Bay was at $\alpha=0.05$ and Eganville was at $\alpha=0.10$. Only Renfrew, Arnprior, Petawawa, and Killaloe were not significant at $\alpha=0.20$. Table 3.3 presents actual and predicted probabilities for each of the 10 paramedic post service areas. It shows that the mean predicted probabilities for each service are match observed rates (actual probabilities).

Validation

The development dataset contained 8381 observations. Of these, 305 patients were classified as frequent users of paramedic services. This represents an overall response of 3.64%. The first validation dataset contained 9433 observations with 374 frequent use patients (3.96%). The second validation dataset contained 9355 observations with 348 frequent use patients (3.72%). On an annual basis, patients that were frequent users account for approximately 10% of paramedic service users and up to 25% of all patient contacts (excluding inter-facility transfers).

Having established the explanatory model, validation was completed with the following outcomes. Table 3.4 presents a comparison of the logistic regression of the validation data sets to the development model. The test statistics are quite consistent between the development dataset and the two validation datasets. The resulting ROC curves are shown in Figures 3.3 and 3.4 with AUCs of 0.866 and 0.874 respectively. Both of these have very close resemblance to the ROC curve of the development dataset shown in Figure 3.2. Table 3.5 presents a comparison between user classification results for the three datasets. This shows consistency between the mean predicted values of the development dataset and the mean predicted values of the validation datasets.

The calibration of the model was evaluated by comparing mean predicted probabilities to observed rates (actual probabilities) for each decile of the respective dataset. This followed the concept of the Hosmer-

Lemeshow test. These results are shown in Table 3.6 and graphically in Figure 3.5. For groups that included frequent users, the observed rates were generally below predicted probabilities with the exception of the 9^{th} decile. This is indicated in Figure 3.5 as values above the line of fit (except for the 9^{th} decile). Table 3.7 presents mean predicted and actual probabilities for a number of sub-groups of paramedic service users. For complaints, refusals, and acuity groups, the datasets were divided based on whether users had rates greater than zero or equal to zero. The majority of predicted values fell within 1% of the actual probabilities. There were four patient sub-groups where predicted values differed most from observed. These were in rates on non-emergent utilization and the three pertinent chief complaints. In the development dataset a bigger difference was also observed for patients that refused transport while in the second validation dataset a bigger difference was observed in previously healthy patients.

Geographic validation was completed within quad-tree blocks and within paramedic post service areas. In the case of the quad-tree blocks, validation was not evaluated in instances where there were fewer than 30 total users. Figures 3.6, 3.7, and 3.8 present maps indicating the difference between mean predicted values and observed values for quad-tree blocks. While 75 of the 125 blocks had sufficient numbers of observations in at least one dataset, only 65 could be compared across all three datasets. In the development dataset, 45 of the 68 blocks evaluated had observed rates that fell within mean predicted upper and lower confidence values. Sixteen blocks had observed values lower than predicted values at the lower confidence interval. Seven blocks were under predicted with the upper confidence interval being less than the observed rate. Table 3.8 presents the actual and mean predicted values for each of the 10 paramedic post service areas. In the validation data sets, the greatest absolute difference between mean predicted and observed probabilities was 1.4%.

Probability surfaces

With the various evaluations of model performance and testing presented, it is possible to evaluate the predicted probabilities. Figure 3.9 presents the predicted probabilities of the model for the geographic blocks. These results provide further details to the findings presented in Table 3.8. However areas with higher predicted probabilities near Barry's Bay (in the west), Eganville (central), and Cobden (east-central) are evident. In Figures 3.10 and 3.11, predicted probabilities for the validation datasets are presented. It is important to contrast these predictions with the observed rates (as referenced either in Table 3.8 or through Figures 3.7

and 3.8). While predicted probabilities appear high in Eganville and Cobden areas, observed rates were shown to be less than predicted in a number of these blocks. Conversely, the rise in observed rates seen in Renfrew (south-east) and Petawawa (central-northwest) are not reflected in increased predicted probabilities.

Discussion

The objective of this analysis was to estimate spatially defined probabilities of paramedic service use by frequent users. These findings are applicable to improving access to health care services through community paramedic programming. Logistic regression was used to develop an explanatory model of individual characteristics that predicted frequent use patients who may benefit from improved accessibility offered through community paramedic programming. This model was validated in a variety of ways. Resulting probabilities were then aggregated to spatial groups in order to evaluate ongoing interventions as well as locations that may benefit from improvements in accessibility to health care services. At the individual level, the results presented important information regarding factors that are influential in patients at risk of becoming frequent users of paramedic services. The results are consistent with other findings regarding some of the clinical factors that influence frequent use (Scott et al., 2013, Jensen et al., 2015, Bigham et al., 2014). With respect to geographic factors, the results reinforce expectations that differing needs exist from place to place. Furthermore, the approach taken herein presents a means of forecasting future demand for community paramedic services.

The changes in actual rates of service use by frequent users from year to year are important to consider aside from the insights that are offered through the logistic regression. First, it is important to realize the distinction between the rates as they have been calculated herein for analysis and rates as they apply to the patients that paramedics have contact with on a daily basis. Recall that the sample contains all individuals who utilized paramedic services at any point during the representative year or either of the two preceding years. It may be assumed that the majority of individuals who utilize paramedic services do so on one occasion only. Therefore the actual percentage of frequent use patients within one year may be estimated by dividing the number of general use patients by three. For example, in the development dataset, 8076 users were not classified as frequent use patients over the three year period. But, as the frequent users are repeated users of paramedic services and frequent usage in past years is a significant predictor, it can be assumed that close to 305 users were frequent users in each year from which the dataset was collected. Therefore, a more representative probability of frequent use patients in terms of paramedic contacts would be 305/(8076/3) = 11.33%. In other words, this suggests that for every ten patients that a paramedic sees, approximately one is likely to be at risk of being a frequent user. That being said, the change in the numbers of frequent use patients (Table 3.8) in each service area is an important observation. Of the ten service areas, two presented a decline in rates in the two validation datasets in comparison to the development dataset. Three others presented increases in actual probabilities. One service area varied very little while the remaining four displayed more variability between measurements. Of particular interest here are the communities of Deep River and Eganville. In 2010, 16 patients were enrolled in the Aging at Home program in Deep River (M. Ruest, personal communication, 2015). It is unknown whether the 15 patients identified as frequent use patients in the development dataset coincided with these patients. However, in 2014, the program had grown in enrollment to 35 patients (M. Ruest, personal communication, 2015). Meanwhile, the number of frequent use patients identified in the validation dataset for 2014 was 9. In Eganville, similar results are seen. While the number of frequent use patients did not change greatly over time, the total number of paramedic service users increased thereby resulting in a drop of observed probabilities. These findings can serve to further validate other findings (Ruest, Stitchman, & Day, 2012) regarding the positive influence these initiatives have had.

Implications for service delivery and future work

The model developed and tested herein has the potential to be used as a tool to identify frequent use patients for community paramedic follow-up and care. This can have various implications for paramedic service delivery. If one were to consider only Figures 3.10 and 3.11, it would appear that interventions should be designed for Barry's Bay, Eganville, Cobden, Arnprior (extreme south-east), and Pembroke. However it is important to contrast Figure 3.10 with 3.8 and Figure 3.11 with 3.9. This reveals the challenges to modelling that occurred in areas with ongoing interventions and the changing needs within the various communities being served. Table 3.8 indicates relatively significant increases in the number of frequent use patients identified in the communities of Petawawa and Renfrew. These communities were not recipients of targeted community paramedic programming during the period of study. However, it is expected that further investigation would reveal new factors influencing accessibility to services that exist within these communities as well. This example of dynamic conditions within the study population is important when contrasted with the significant variables presented in Table 3.2. By reducing the independent variables in the model to the communities and those that present significant odds ratios it is possible to present a refined picture of patients at risk. Specifically, this results in highest risk for patients who refuse transport from their place of residence in the communities of Cobden, Barry's Bay, or Pembroke with a respiratory chief complaint. Making such a determination of risk presents the opportunity to develop new interventions that may respond to the needs of these patients.

One of the goals of community paramedicine is to improve accessibility to services for patients. The results may serve to validate the pro-active and engaging model of paramedic service delivery that has been developed in the County of Renfrew. The approach taken herein may inform decision makers with respect to future deployment of community paramedics that seek to build stronger community relationships between paramedic practitioners and service users. Future work may include the development of a forecasting tool—either short or long term—that may better direct the deployment of these resources. At the individual level, it may be possible to develop screening tools that are customized to particular communities to better facilitate recognition of patients who are at risk of becoming frequent users of paramedic services.

In the cases of Long and Brier Islands and the County of Renfrew, community paramedicine was employed as a direct response to the needs of patients who were lacking access to other health care services. In other contexts, improving accessibility may take the form of addressing the needs of patients for whom care needs to be more comprehensive. Within either context, creating measures to assess patient accessibility to care is an important first step in targeting interventions that can improve accessibility.

Limitations

It is essential that the concept of ecological fallacy be addressed in the interpretation of findings. Through the validation process, a variety of sub-groups were used to test the validity of the model. Of particular concern are situations where predicted probabilities in one particular group did not translate into higher (or lower) paramedic service utilization by frequent users. For example, in validating deciles of risk, one frequent use patient was identified in the second decile of the second validation dataset (see Table 3.6). The predicted probability of this user being a frequent use patient was low—but it was not nil. In other words, the model presents a risk that any patient may be identified as a frequent use patient. Conversely, the potential exists for a patient’s risk to be high but for that patient to never display the pattern of usage that would render her to be a frequent use patient. This is an important consideration given that the differences in the mean probabilities between the general user and the frequent user (see Table 3.5) are not great. As the results are being applied to an evaluation of locations, statements regarding the characteristics of risk within particular locations need to be measured. The differences in mean predicted probabilities and actual probabilities between geographic areas are not very large (see Table 3.8).

This research was conducted through a retrospective review of administrative records. Therefore, it is important to note the unknown potential for error based on excluded records and documentation errors. Furthermore, the elements utilized from the dataset were those that lent themselves to direct analysis. Cross-referencing elements documented between records for the same individual was not conducted. Doing so could have presented a more complete picture of patients' health care needs. The ePCR that the data were obtained from was the Ontario Ambulance Call Report (ACR) form. This form is designed as a "one-size-fits-all" sort of document that can be used for all types of contact that paramedics have with patients. In fact, paramedics are required to complete a new ACR for each event. As such, paramedics do not have access to a record of patient encounters in the way that other health care practitioners do. Enabling such structure of patient documentation would facilitate improved research—not to mention the ability to improve paramedics' ability to provide care.

One of the challenges observed in the results of this evaluation may have resulted from the structure of the data collection. Specifically, this limitation may have directly influenced results with respect to whether or not the pick-up location was indicated as being the patient's place of residence. In terms of structure of the ePCR, it is anticipated that this check box would be utilized by paramedics as it would auto-fill another field within the ePCR. However, it is possible that paramedics systematically did not utilize it based on this redundancy. This finding merits further investigation. If patients that may benefit from community paramedic care have higher rates of being picked up at places other than their place of residence, the idea of performing home visits by community paramedics may need to be reconsidered. Alternatively, it may be plausible that the influence of a non-frequent user who was picked-up at home (rendering a home pick-up rate of 1) may be more predictive than the frequent user who was picked up four out of five times at home (rendering a home pick-up rate of 0.8). As was indicated in Chapter 2, this characteristic represents one of the challenges associated with the mobility of paramedic service users.

Another limitation associated with the data source has to do with censoring of the data. Records were not investigated with respect to date of birth, pronouncement of death, or patient's address. These represent right and left censoring—entry into the dataset after the start date from which the data were taken or exit from the dataset before the end date. That is, patients who experienced a vital signs absent event had an attribute that was a statistically significant factor in the explanatory model. Furthermore, it may be possible to further investigate the details within the data to determine if the patient outcome following the event was death to enable left-censoring such that said patient would cease to be a frequent user upon death. Another challenge with regards to censoring occurred where infants received patient care. For patients under the age of two, it would not be possible for them to have been identified as being frequent users three years prior to the year of analysis—a problem of right-censoring. This is an important consideration given the findings of Broxterman et al. (2000) regarding repeated use of paramedic services by pediatric patients. For children under the age of 3, those that were one year old represented a higher percentage of repeated use than any one age up to 14 years old. But other limitations around this issue are also pertinent to consider. For example, patients that were not residents of the County of Renfrew, but utilized paramedic services while visiting the county would have been included in the datasets. Here, further investigation of patients' home address could have allowed these records to be excluded. This was not done here for reasons of patient confidentiality. The implication of this is that the model application of presenting findings regarding the communities in the county infers that the data is comprised of individuals who reside there. While this is very likely to be true of the frequent use patients, excluding non-residents from the data may alter probabilities. Even though the VSA even may not have significantly accounted for the challenges around censoring, its inclusion showed significant predictive influence. This finding can be interpreted to be consistent with other findings regarding the complexities of the comorbidities of these patients (Scott et al., 2013). Having unmet home care needs presents likelihood for individuals to experience negative emotional states (Turcotte, 2014) that can result in further deterioration. Other evidence has shown that highest rates of health care service utilization occur during the years preceding death (Barnato et al., 2004).

A notable limitation may be with respect to the influence of rates of refusal of transport. Existing policies and procedures enable a structure of operation wherein paramedics are expected to transport all patients who call 9-1-1 to the emergency department. Community paramedicine changes the dynamic of this structure in that it can facilitate a patient-practitioner relationship more commonly found in other health care services. The concept of building an ongoing relationship with a patient is not considered within the traditional paramedic service delivery model. (This is also related to issues of patient documentation mentioned above). However, if a paramedic has a pre-existing relationship with a patient, it may be more plausible that this could influence decisions regarding patient transport to hospital. As such, this would be reflected in rates of refusal. Furthermore, in the case of CoRPS where the service has taken a pro-active and community focused approach to service delivery, it may be possible for more patient-practitioner relationships to exist than in other settings. Limited research has been conducted regarding paramedic determination regarding necessity of care (Hauswald, 2002, DeJean, 2013). Studies that investigate the paramedic-patient relationship and its influence on care decisions may address the rates of refusal—particularly within the context of community paramedicine and community paramedics acting in dual-capacity roles. Research that accounts for refusal rate within the context to alternative delivery models (as detailed in the review by Jensen et al., 2015), is also needed.

Finally, it is important to discuss the role of generalizability with respect to these findings. It was mentioned in the introduction to this research that a limitation of many studies on community paramedicine is the generalizability of their findings. The introduction also detailed difficulties in the generalizability of some measures of spatial accessibility. The design of this research presented methodology that attempted to address these limitations. Going forward, it will be important for the methods and model developed herein to be tested in another setting. With respect to the model parameters, many may remain the same in another setting with exception of the specific dummy variables that represented paramedic service areas. Testing this approach in another setting will present a means to compare probabilities of patients becoming frequent users in different places. Future work may also evaluate how these results have been used to inform decision makers in these different places with respect to the design and implementation of community paramedic programs as a result of this generalization.

Conclusion

This research identified determinants of frequent use of paramedic services by patients in combination with analysis of the geographic setting attributed to these patients. This resulted in a model that may be used to predict patient risk factors for becoming a frequent user and community health profiles that may be used to inform service providers with respect to community based interventions. While a great deal of the results are specific to the location of study, the methods of analysis employed as well as the specification of the model may be adapted to other settings. Future work may consider other variables as measures of patient accessibility. The findings of this analysis can be used to validate the performance of community paramedic programming in Renfrew County.

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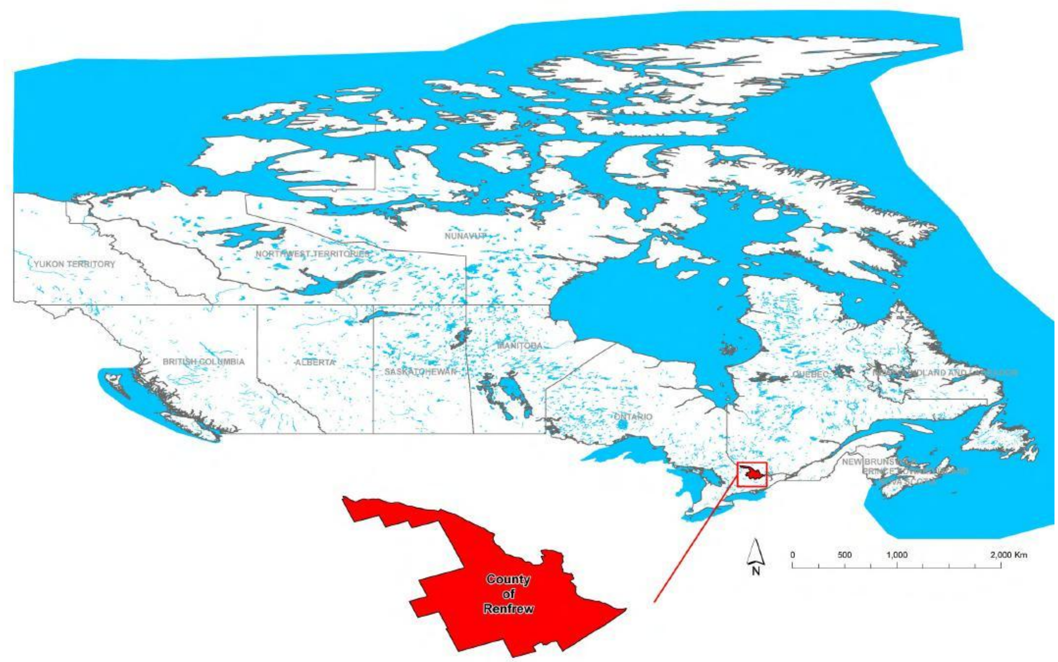

Figure 3.1: Location of the County of Renfrew in Canada (source: countyofrenfrew.on.ca)

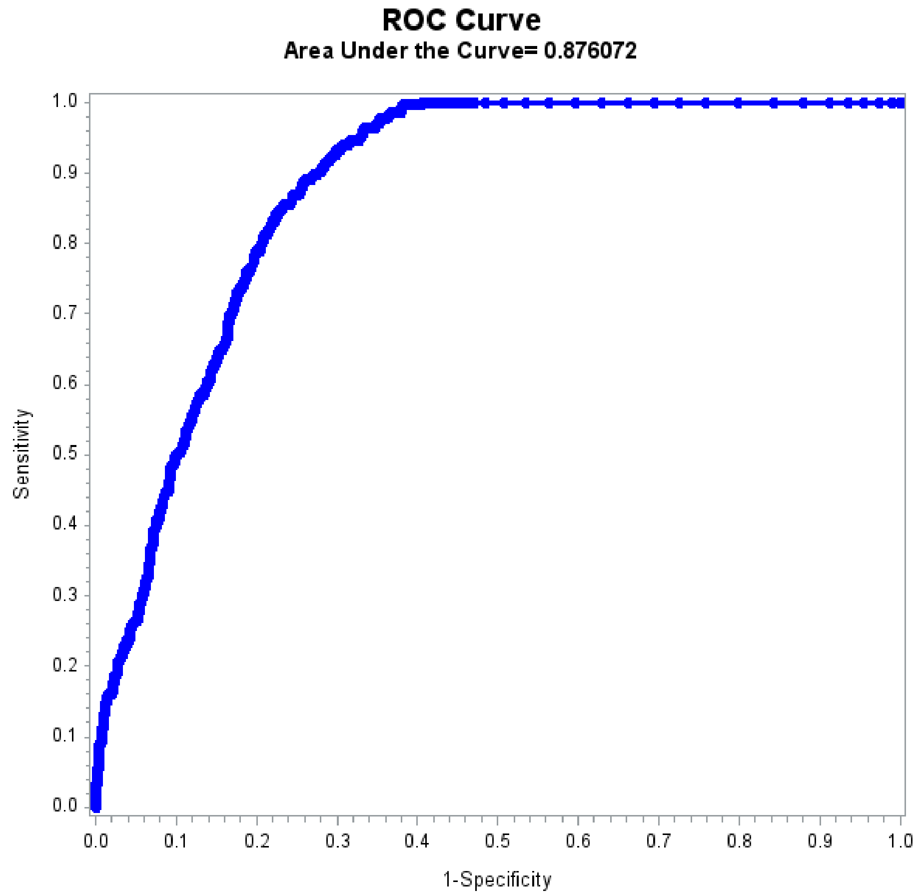

Figure 3.2: Receiver operating characteristic (ROC) curve for the development model.

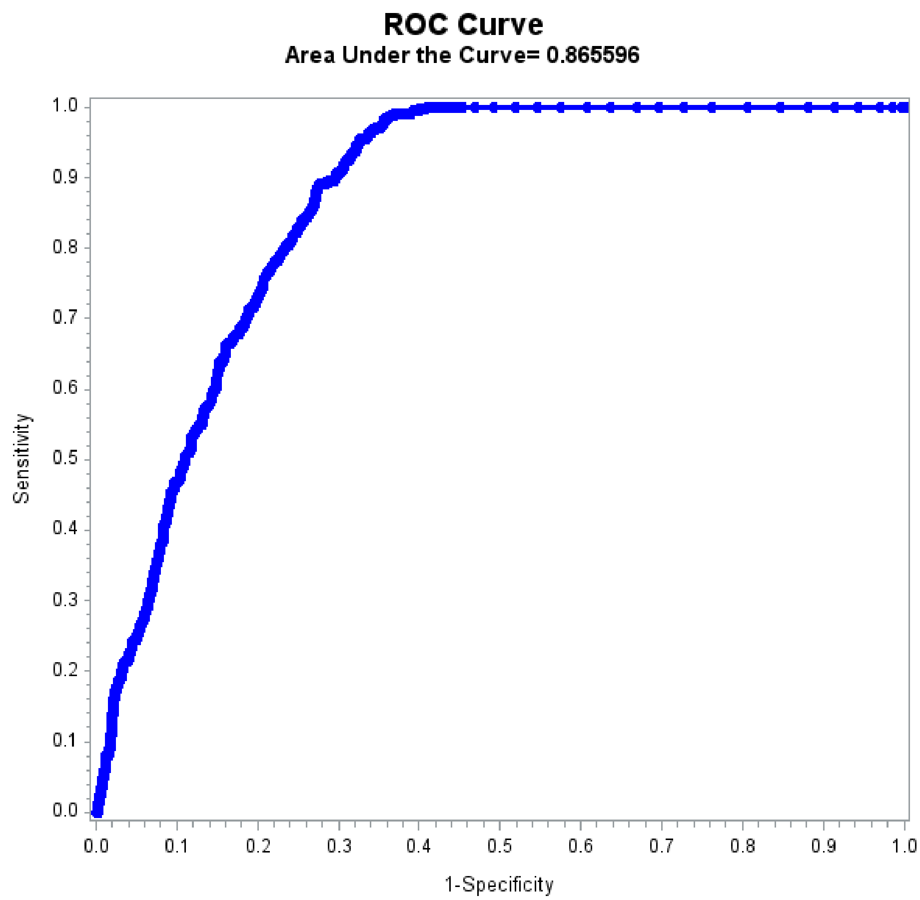

Figure 3.3: ROC curve for the first validation dataset.

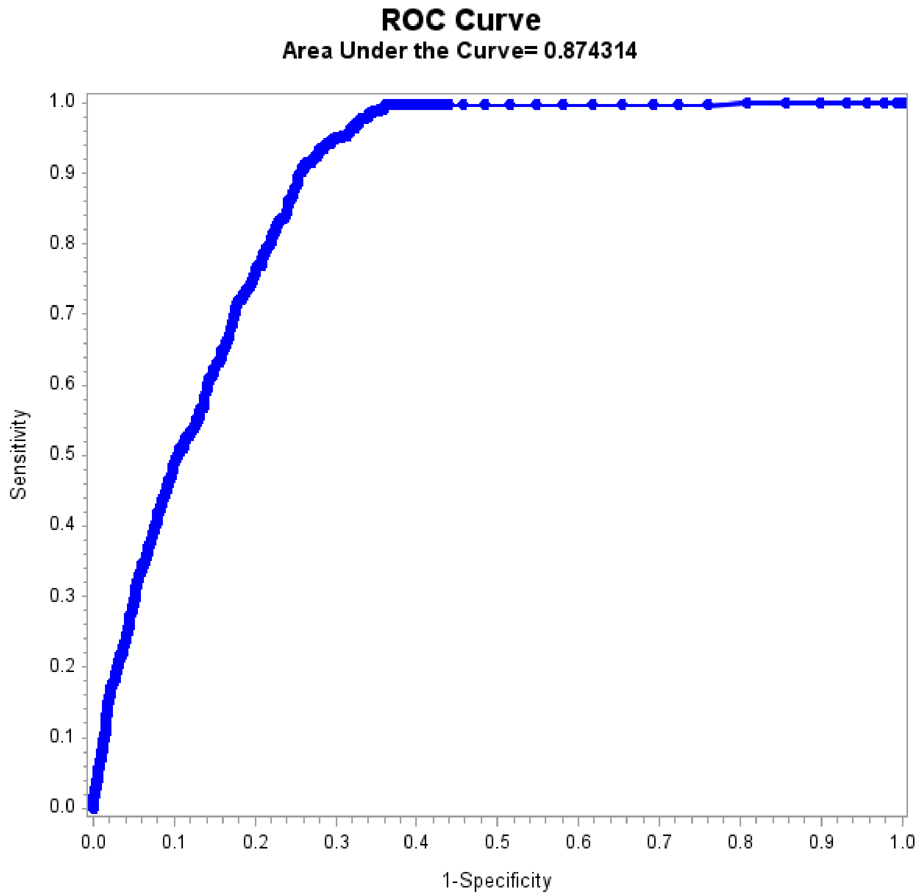

Figure 3.4: ROC curve for the second validation dataset.

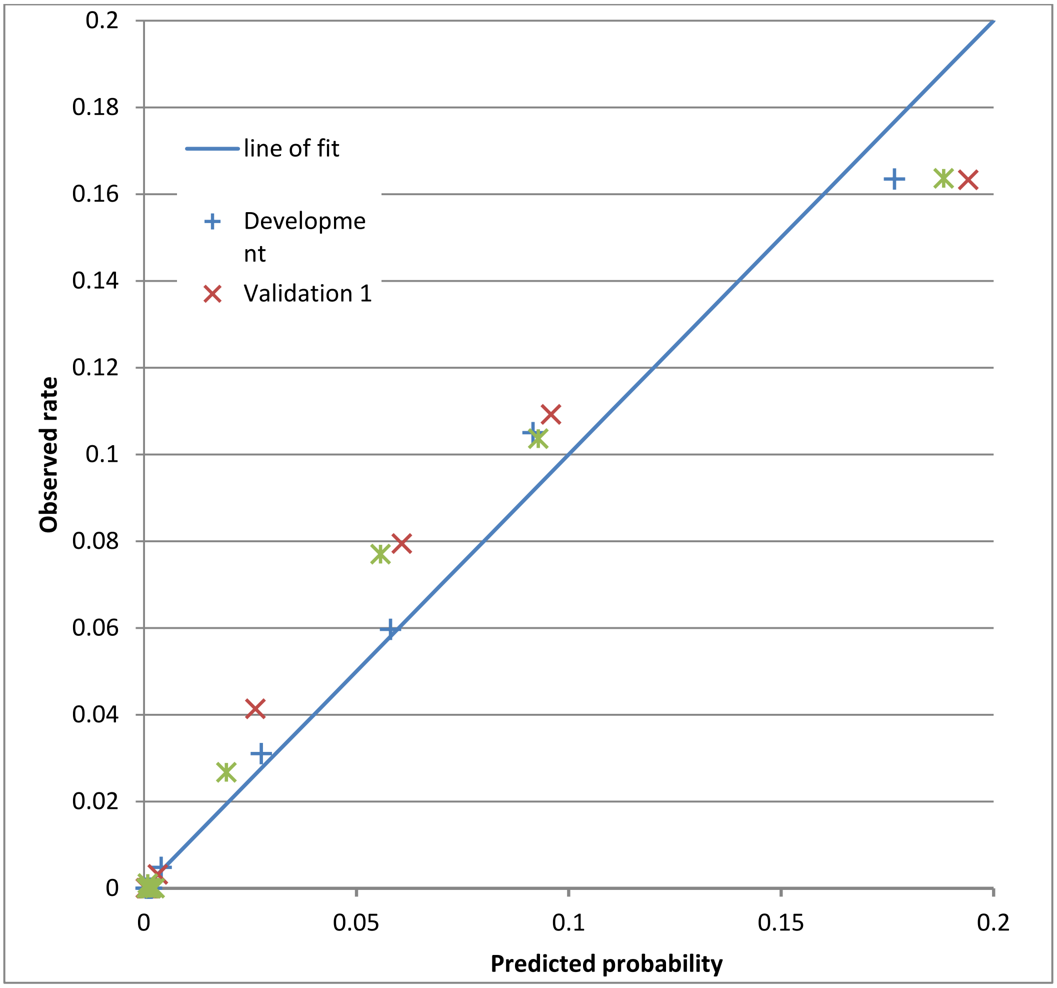

Figure 3.5: A visual evaluation of model calibration. Mean predicted probabilities are plotted against observed rates for deciles of predicted probability for each dataset.

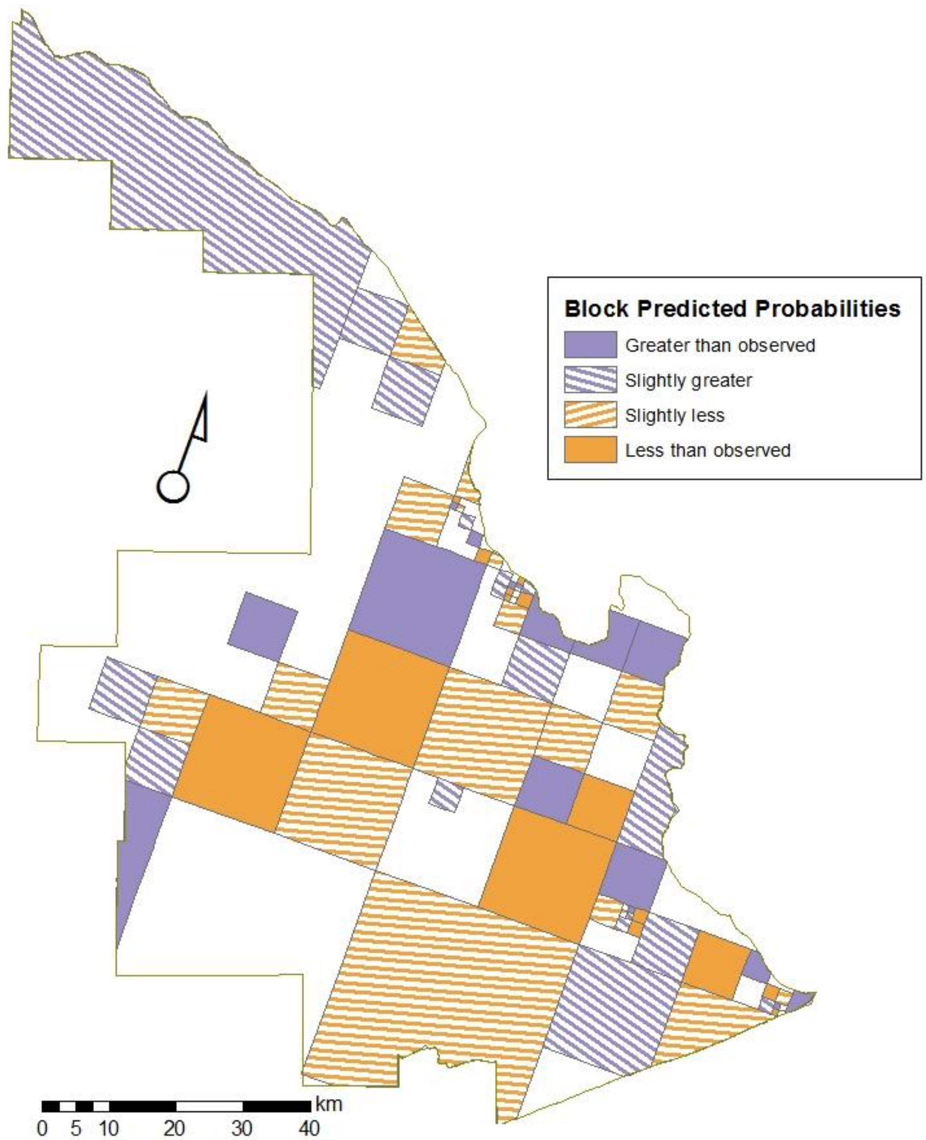

Figure 3.6: Map depicting differences between predicted probabilities and observed rates (slight differences are +/- 1.5%) for development model.

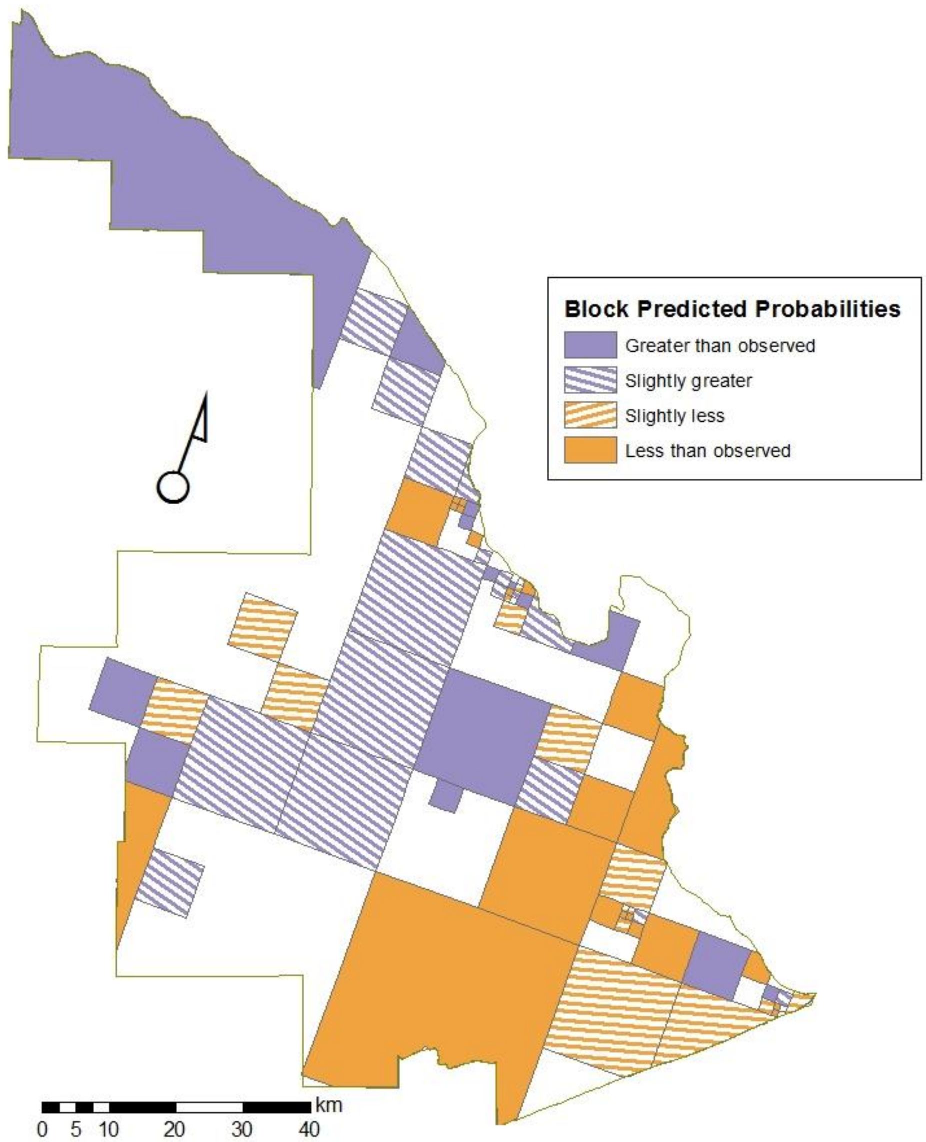

Figure 3.7: Map depicting differences between predicted probabilities and observed rates (slight differences are +/- 1.5%) for first validation dataset.

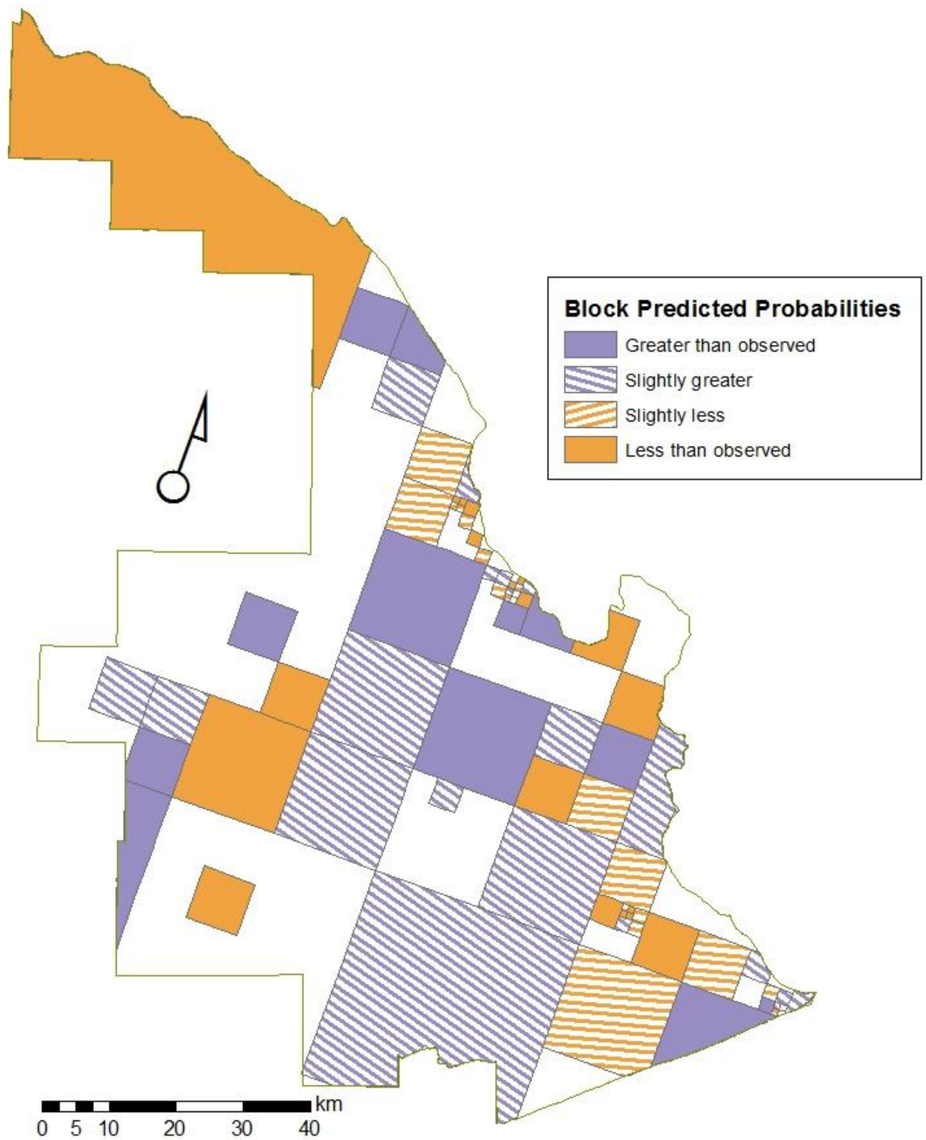

Figure 3.8: Map depicting differences between predicted probabilities and observed rates (slight differences are +/- 1.5%) for second validation dataset.

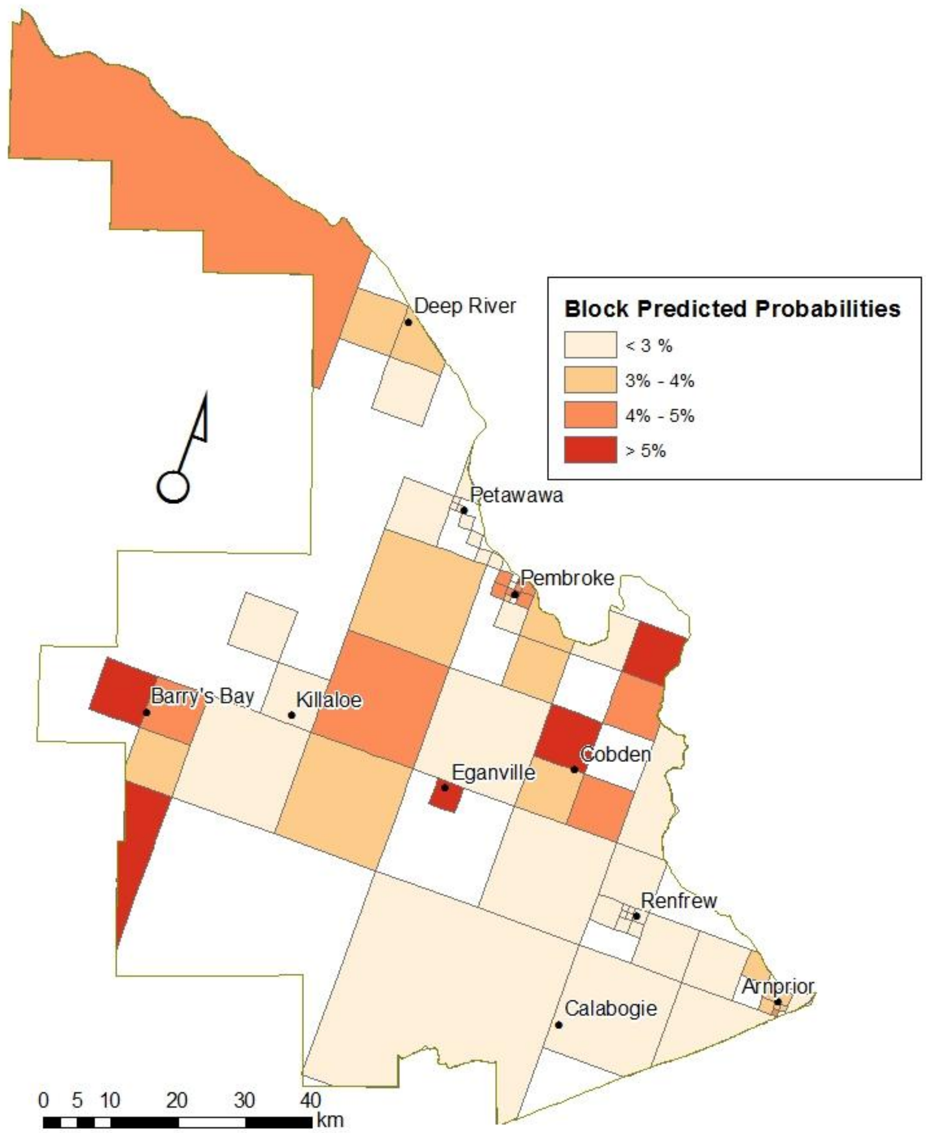

Figure 3.9: Map depicting predicted probabilities for the development dataset.

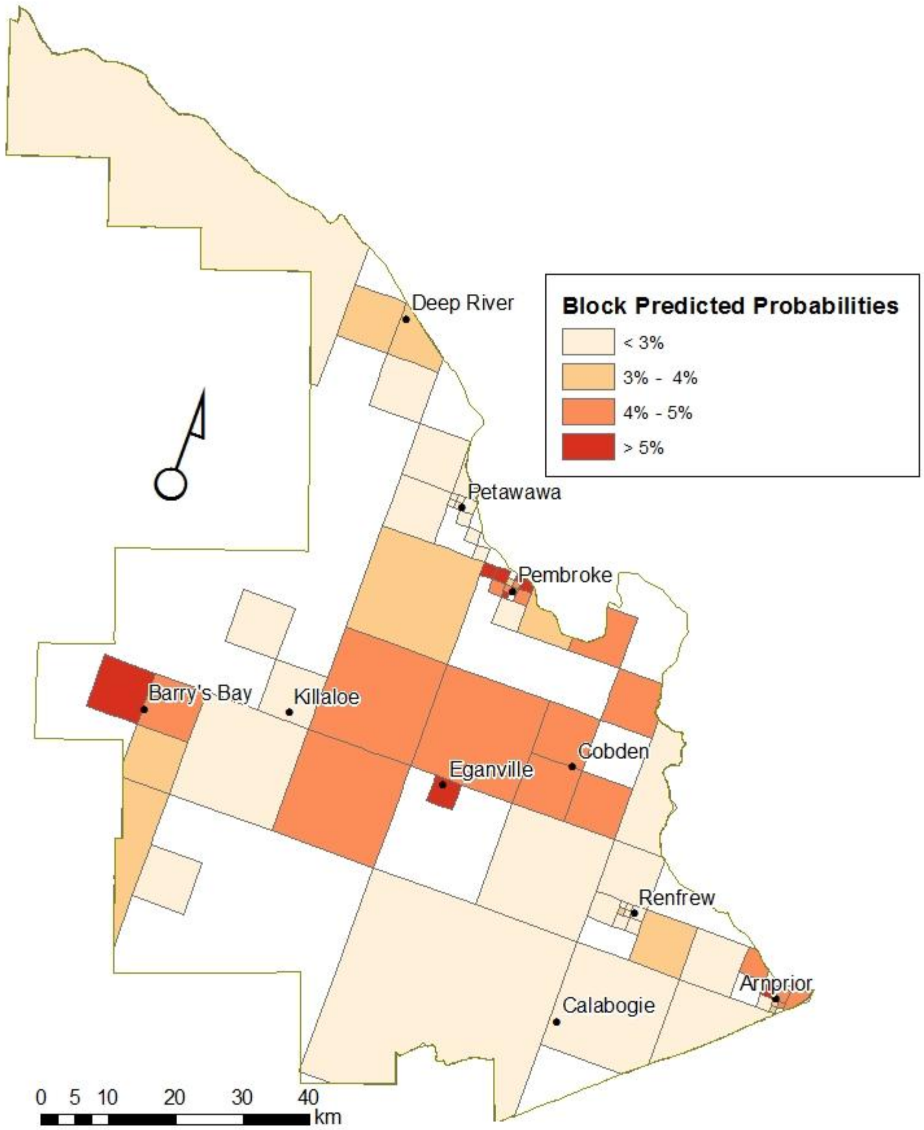

Figure 3.10: Map depicting predicted probabilities for the first validation dataset.

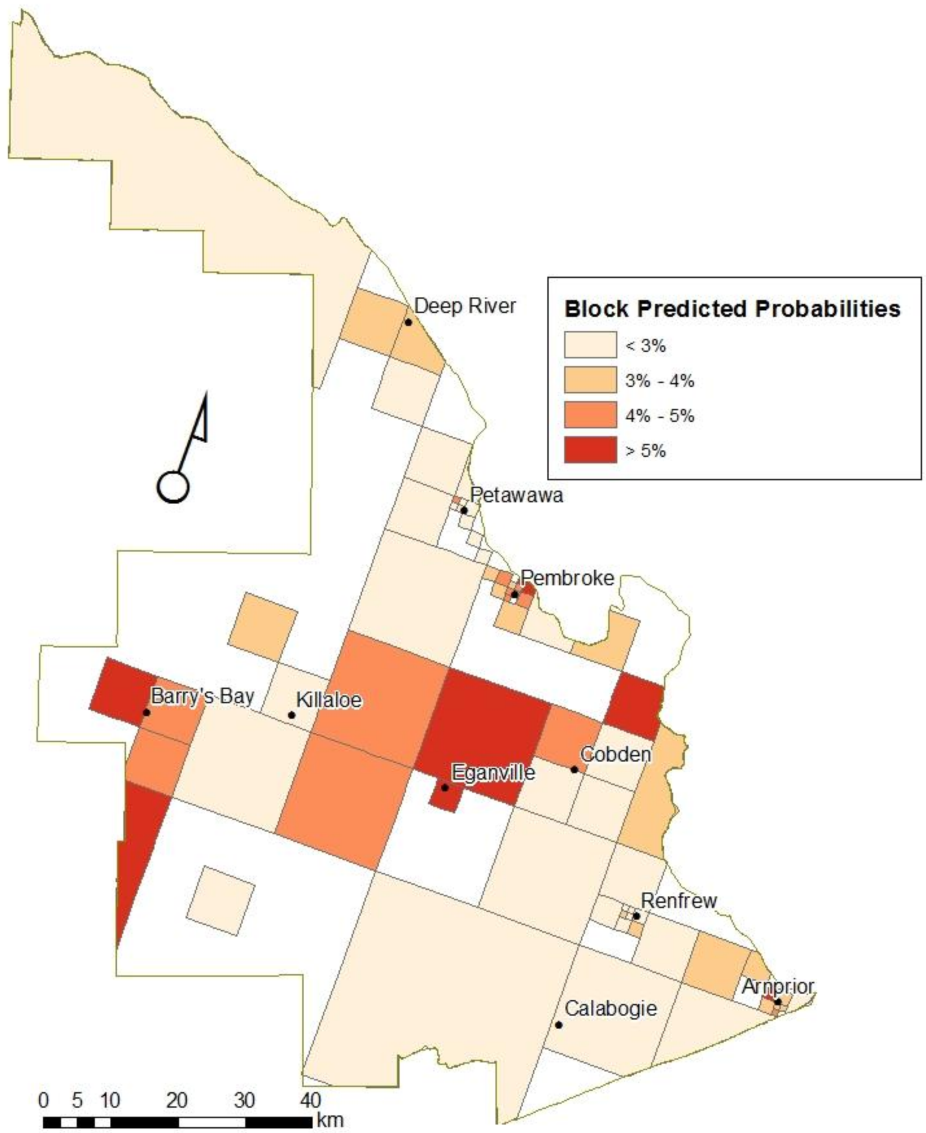

Figure 3.11: Map depicting predicted probabilities for the second validation dataset.

Table 3. 1: Summary of logistic regression diagnostic tests for development model.

Goodness-of-Fit	**Value**	**PR >ChiSq**	**Value/DF**
Deviance	1951.39	1	0.3302
Pearson	4078.28	1	0.6901
Hosmer Lemeshow	8.403	0.3951	
Association of Responses	**Value**		
Percent Concordant	87.4		
Percent Discordant	12.2		
Somer's D	0.752		
Gamma	0.755		
Tau-a	0.053		
c	0.876		

Table 3. 2: Summary of independent variables including coefficient estimate, standard error, level of significance, and odds ratios with confidence limits

Effect	Estimate	Standard Error	Pr > ChiSq	Odds Ratio	95% Wald Confidence Limits	
Intercept	-8.2671	0.9167	<.0001			
Eligible previous year	0.8472	0.2483	0.0006	2.333	1.434	3.796
Eligible two years prior	1.1307	0.2099	<.0001	3.098	2.053	4.674
Previously healthy	-0.8633	0.3633	0.0175	0.422	0.207	0.86
Age	0.00873	0.00354	0.0136	1.009	1.002	1.016
Female	0.072	0.1276	0.5725	1.075	0.837	1.38
Rate of use on weekdays	0.0218	0.1525	0.8862	1.022	0.758	1.378
Overnight rate of use				1.0		
Midnight rate of use	0.7668	0.3857	0.0468	2.153	1.011	4.585
Morning rate of use	1.0009	0.3484	0.0041	2.721	1.374	5.386
Midday rate of use	0.8601	0.3434	0.0123	2.363	1.206	4.632
Afternoon rate of use	0.7971	0.3533	0.024	2.219	1.11	4.435
Evening rate of use	0.8358	0.3609	0.0206	2.307	1.137	4.679
Home Pick-up Rate	-0.6316	0.2056	0.0021	0.532	0.355	0.796
Level 1 triage rate				1.0		
Level 2 triage rate	3.2593	0.4889	<.0001	26.032	9.985	67.869
Level 3 triage rate	3.2488	0.4639	<.0001	25.758	10.377	63.939
Level 4 triage rate	3.6221	0.4753	<.0001	37.415	14.739	94.974
Level 5 triage rate	3.8546	0.5109	<.0001	47.209	17.344	128.501

Effect	Estimate	Standard Error	Pr > ChiSq	Odds Ratio	95% Wald Confidence Limits	3.543
Rate of cardiac complaints	0.3122	0.278	0.2614	1.366	0.792	2.356
Rate of respiratory complaints	0.4737	0.2355	0.0443	1.606	1.012	2.548
Rate of other complaints				1.0		
VSA event	2.3087	0.5846	<.0001	10.062	3.199	31.643
Rate of refusal of transport	1.2823	0.4458	0.004	3.605	1.504	8.637
Calabogie service area				1.0		
Renfrew service area	0.5562	0.75	0.4583	1.744	0.401	7.585
Barry's Bay service area	1.6004	0.7549	0.034	4.955	1.128	21.758
Arnprior service area	0.9072	0.7432	0.2222	2.477	0.577	10.632
Petawawa service area	0.6381	0.7777	0.4119	1.893	0.412	8.691
Eganville service area	1.4331	0.7487	0.0556	4.192	0.966	18.184
Deep River service area	1.1303	0.7759	0.1452	3.096	0.677	14.168
Killaloe service area	0.739	0.8447	0.3817	2.094	0.4	10.963
Cobden service area	1.2	0.7565	0.1127	3.32	0.754	14.625
Pembroke service area	1.1875	0.7297	0.1037	3.279	0.785	13.703
Close proximity to post	-0.00652	0.3903	0.9867	0.994	0.462	2.135
Medium proximity to post	-0.1112	0.3956	0.7785	0.895	0.412	1.943
Distant proximity to post				1.0		

Table 3. 3: Observed and predicted rates of frequent use for each paramedic post service area

Service area	Total users	Total frequent users	Mean predicted probability	Mean predicted lower confidence level	Mean predicted upper confidence level	Observed rates
Arnprior	1094	38	3.47%	1.94%	6.01%	3.47%
Barry's Bay	462	27	5.84%	3.21%	10.11%	5.84%
Calabogie	224	2	0.89%	0.20%	3.70%	0.89%
Cobden	548	23	4.20%	2.22%	7.61%	4.20%
Deep River	426	15	3.52%	1.68%	7.08%	3.52%
Eganville	717	31	4.32%	2.37%	7.58%	4.32%
Killaloe	238	6	2.52%	0.95%	6.17%	2.52%
Pembroke	2797	123	4.40%	2.70%	6.99%	4.40%
Petawawa	721	13	1.80%	0.85%	3.74%	1.80%
Renfrew	1154	27	2.34%	1.24%	4.33%	2.34%
Total	**8381**	**305**				**3.64%**

Table 3. 4: Summary of model discrimination for each model.

	Development	Validation 1	Validation 2
Association of Responses	**Value**	**Value**	**Value**
Percent Concordant	87.4	86.6	87.4
Percent Discordant	12.2	13.4	12.6
c	0.876	0.879	0.889
Somers’ D	0.752	0.732	0.748

Table 3. 5: Summary of model predicted probabilities for each user group.

	Development	Validation 1	Validation 2
Patient groups	**Mean predicted probability**	**Mean predicted probability**	**Mean predicted probability**
General user	3.27%	3.50%	3.28%
Frequent user	13.35%	12.49%	13.10%
Overall	3.64%	3.96%	3.72%

Table 3. 6: Based on the Hosmer-Lemeshow test, this table displays model calibration for each decile in the respective datasets.

Decile	Development				Validation 1				Validation 2			
	n	**Freq. users**	**Mean predicted probability**	**Observed rates**	**n**	**Freq. users**	**Mean predicted probability**	**Observe d rates**	**n**	**Freq. users**	**Mean predicted probability**	**Observed rates**
0	835	0	0.05%	0.00%	943	0	0.05%	0.00%	935	0	0.06%	0.00%
1	837	0	0.09%	0.00%	940	0	0.08%	0.00%	935	1	0.09%	0.11%
2	841	0	0.12%	0.00%	947	0	0.11%	0.00%	936	0	0.12%	0.00%
3	841	0	0.15%	0.00%	943	0	0.14%	0.00%	934	0	0.14%	0.00%
4	841	0	0.18%	0.00%	943	0	0.18%	0.00%	936	0	0.17%	0.00%
5	834	4	0.41%	0.48%	944	3	0.33%	0.32%	937	0	0.25%	0.00%
6	838	26	2.76%	3.10%	943	39	2.63%	4.14%	936	25	1.94%	2.67%
7	838	50	5.81%	5.97%	944	75	6.07%	7.94%	935	72	5.57%	7.70%
8	838	88	9.16%	10.50%	943	103	9.58%	10.92%	936	97	9.29%	10.36%
9	838	137	17.67%	16.35%	943	154	19.41%	16.33%	935	153	18.83%	16.36%

Table 3. 7: Summary of model calibration based on patient sub-groups. (Bold values indicate difference greater than +/- 1%)

	Development		Validation 1		Validation 2	
Classification	**Mean predicted probability**	**Observed rates**	**Mean predicted probability**	**Observed rates**	**Mean predicted probability**	**Observed rates**
Male	3.26%	3.26%	3.49%	3.30%	3.41%	3.66%
Female	3.95%	3.95%	4.16%	4.52%	3.85%	3.77%
Younger	2.41%	2.42%	2.49%	2.41%	2.45%	2.35%
Older	4.64%	4.63%	4.89%	5.15%	4.54%	4.75%
Not previously healthy	3.88%	3.88%	4.26%	4.33%	3.68%	3.66%
Previously healthy	1.19%	1.19%	1.07%	1.43%	2.87%	**5.08%**
Emergent utilization	2.49%	1.65%	2.26%	1.69%	2.25%	1.69%
Non-emergent utilization	11.69%	**17.52%**	13.30%	**17.44%**	13.16%	**17.50%**
Low or medium proximity	3.11%	3.11%	3.30%	3.17%	3.17%	2.64%
High proximity	3.89%	3.89%	4.12%	4.34%	3.87%	4.24%
No diabetic complaints	3.55%	3.50%	3.78%	3.76%	3.56%	3.59%
Diabetic complaints	12.55%	**17.65%**	13.84%	**29.33%**	15.00%	**20.83%**
No cardiac complaints	3.37%	3.11%	3.64%	3.45%	3.46%	3.32%
Cardiac complaints	10.25%	**16.62%**	10.15%	**18.73%**	10.95%	**19.07%**
No respiratory complaints	3.31%	3.04%	3.56%	3.48%	3.34%	3.09%
Respiratory complaints	12.18%	**19.17%**	12.40%	**17.81%**	12.99%	**23.13%**
No refusals	3.51%	3.38%	3.35%	3.46%	3.18%	3.29%
Refused transport	12.66%	**22.61%**	20.58%	20.73%	20.04%	18.92%

Table 3. 8: Summary of observed and predicted rates for each service area

	Development				Validation 1				Validation 2			
Service area	**n**	**Freq. users**	**Mean predicted probability**	**Observed rates**	**n**	**Freq. users**	**Mean predicted probability**	**Observed rates**	**n**	**Freq. users**	**Mean predicted probability**	**Observed rates**
Arnprior	1094	38	3.47%	3.47%	1206	56	3.60%	4.64%	1155	34	3.42%	2.94%
Barry's Bay	462	27	5.84%	5.84%	517	20	5.19%	3.87%	497	24	5.97%	4.83%
Calabogie	224	2	0.89%	0.89%	255	6	1.07%	2.35%	280	4	0.91%	1.43%
Cobden	548	23	4.20%	4.20%	600	35	4.42%	5.83%	583	27	3.99%	4.63%
Deep River	426	15	3.52%	3.52%	459	9	2.86%	1.96%	429	9	3.32%	2.10%
Eganville	717	31	4.32%	4.32%	801	31	5.16%	3.87%	817	28	4.87%	3.43%
Killaloe	238	6	2.52%	2.52%	295	7	2.30%	2.37%	295	11	2.51%	3.73%
Pembroke	2797	123	4.40%	4.40%	3109	131	4.84%	4.21%	3057	134	4.38%	4.38%
Petawawa	721	13	1.80%	1.80%	894	28	2.06%	3.13%	937	31	2.14%	3.31%
Renfrew	1154	27	2.34%	2.34%	1297	51	2.64%	3.93%	1305	46	2.35%	3.52%

CHAPTER 4: Conclusion

Community paramedic providers may realize improved effectiveness of their programming based on the findings included in this thesis. The geo-spatial analysis applied to paramedic service utilization by frequent users may enable service administrators to make informed decisions regarding the deployment of community paramedics. The interventions carried out by these paramedics may result in decreased system demand by frequent users, thereby increasing the capacity for response to non-frequent users requiring medical assistance in emergency situations. Furthermore, this research provides important contributions to spatial inquiry that may be adapted to other subjects within the discipline.

Summary of Chapters 2 & 3

The second chapter considered questions of where and when frequent users were transported to emergency departments by paramedic services in Hamilton, ON. The study used generalized linear mixed models (GLMM) to model space-time patterns of daily demand by these individuals. The analysis considered the utilization patterns of these users within the context of service delivery rather than attempting to explain individual behaviours of use. This means that the results should be contrasted with existing deployment of emergency resources to identify locations best suited for future community paramedic interventions. These potential locations were revealed through the specification of the random slope effect for time intervals. Other important findings about the context of service demand by frequent users were revealed through the specification of fixed effects. While the performance of variables representing time, proportion of older population, and proportion of residential addresses met expectations, the distance to emergency departments (ED) performed differently than expected. The expectation was borne out of findings regarding the low acuity of complaints by frequent users (Scott et al., 2013). This was interpreted such that individuals who lived in close proximity to an ED would use alternatives to paramedic services to access emergency care. However, the results revealed an increased use of paramedic services by frequent users who were in close proximity to emergency departments. Plausible explanations were detailed in the discussion of chapter two which may form the basis of future work. Specifically, it will be important to identify whether or not other factors may be influencing increases in service demand by frequent users in close proximity to emergency departments. While trends in service demand may change monthly, seasonally, or annually, the analysis in chapter two considered temporal changes within a 24h period. The purpose for this was based on the 24/7 service delivery model that emergency services provide. Also, it may be more feasible to tailor staffing patterns to specific daily patterns as opposed to larger increments of time. The analysis evaluated locations where an alternative service delivery model could be employed most effectively.

The third chapter considered questions of whom and where frequent users were in Renfrew County, ON. Facilitated by a more detailed dataset, the definition of frequent users from chapter two was expanded to include patients who received care but were not transported from scene and patients who called repeatedly within a short interval of time (30 days) but not necessarily five or more times within a year. This was an important alteration as community paramedic programming has been well established within the county and because interventions seek to address the needs of frequent users proactively (before a year has passed yielding multiple transports to ED). While the approach taken in chapter three drew on concepts of spatial accessibility, some alterations to these concepts were developed. Specifically, while spatial accessibility measures potential access of a population to a service provider, here the data revealed actual access through records of patient use of a mobile service. Spatial accessibility measures can be difficult to interpret or generalize. Therefore, measures of community need were determined by aggregating spatially defined estimates of individual risk of becoming a frequent user. These estimates were derived from a logistic regression model. The results were probability surfaces similar to those developed through geographic profiling that may inform decision makers with respect to the deployment of services. The results from chapter three presented evidence of successful community paramedic programming within specific communities in Renfrew County. While these results are specific to the county, the novel approach used in the analysis presents an opportunity for generalizability to other settings. Specifically, the probability surfaces that were generated could be replicated for other paramedic services.

Research implications

In both chapters, the results can be used by the respective service providers as they continue to evolve their provision of community paramedic programming. The greater implications of this thesis may lie in the methodologies employed in both chapters.

The analytical approach taken in chapter two was introduced by illustrating that using a model to predict the system demand by frequent users could be achieved through a variety of methods. One example was to create a unique linear model for each geographic area. This example was presented in Figure 2.4 to illustrate the difficulty encountered in interpreting such a method—particularly with respect to spatial distribution of any identified trends. Alternatively, simple regression was used to predict the number of frequent users based on the number of general users for different intervals of time (see Figure 2.5). Again, this presented difficulties in identifying the implications of specific geographies at specific times. By using a GLMM approach, the difficulties in comparing times and locations of results was addressed. Furthermore the model quantified the covariance in space-time use by frequent users (see Table 2.4).

Chapter three presented a novel approach to generating probability surfaces that reflected community estimates of risk for paramedic service users repeatedly calling for assistance. The methods used built on concepts used in other studies of health geography and epidemiology. Considering the role of geographic validation in health care studies with a explicitly spatial perspective in an important research contribution achieved through this research. By mapping and analysing geographic variation in predicted risks, it is possible to produce probability surfaces that may inform decision makers in a more meaningful way than outcomes that measure spatial accessibility. This approach, as well as the approach taken in chapter two, represents new terrain in health geography that is directly motivated by improving the provision of healthcare services—not simply understanding certain health phenomena. This ideal seeks to provide the right intervention for the right patient in the right place at the right time.

More work is required to validate the methodology used in the novel approaches employed in this research. In this regard, it is important to note that while the existing literature regarding subjects of community paramedicine and frequent users of paramedic services is scarce, the methodology used herein may be applied to other subjects of health geography. In fact, more testing would be encouraged in other subjects where the interaction between client and service provider is dependent on the behaviours of each party. With respect to paramedic services, this interaction is fundamental to deployment planning. This means that more research is needed on deployment plans that include both traditional response units and community paramedics acting in dual capacities.

Research limitations

The strengths of this research are not without their limitations. It is important to recognize the limited impact that community paramedicine may offer. In this regard, it is important to consider the role of paramedicine as a whole within the greater health care sector. Future work should consider the demand that frequent users of paramedic services place on the health care system as a whole. This may offer important insight with respect to the importance of community paramedicine. In chapter three, a scenario was described that illustrated the potential for a negative feedback cycle to exist within a health care system that was over-burdened. This scenario can offer an important perspective on motivating research. To use a different health care metaphor, there are times where a band-aid helps to heal a wound. At other times, a band-aid may simply mask a wound that requires greater attention. In other words, research regarding the effectiveness of community paramedic interventions should consider broader implications of service delivery and health care utilization. Ultimately, the goal of clinical interventions should not be limited to meeting the needs of frequent users, but also to prevent individuals from becoming frequent users. The logical suggestion that interventions addressing frequent use provide benefits to non-frequent users by increasing system capacity needs to be tested.

Finally, this thesis did not evaluate either economic or clinical advantages that may be attained through community paramedicine. Studies that factor in potential cost-savings obtained through either patient care management that reduces emergency responses by paramedics or transports to emergency departments should be considered. Studies that address the clinical outcomes that may result from community paramedicine interventions continue to be developed (See Drennan et al., 2014 as an example). A key consideration of these investigations needs to be the generalizability of their results.

Final remarks

This thesis is an example of applied research to a relatively overlooked area of study using new and emerging technologies. Traditional provision of paramedic service is associated with an ambulance racing down a busy street with lights flashing and sirens blaring. As such, research that has sought to optimize delivery of paramedic services has investigated deployment largely from a reactive perspective. While the traditional service delivery model is not likely to disappear anytime soon, this research contributes evidence that can be considered to have a pro-active perspective. In the end, it may be possible that promoting effective community paramedicine may yield service delivery optimization of a different form.

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Scott, J., Strickland, A. P., Warner, K., & Dawson, P. (2013). Frequent callers to and users of emergency medical systems: a systematic review. *Emergency Medicine Journal*, emermed-2013.