A GIS Method to Assess Distance Effects on Hospitalizations

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INTRODUCTION

Access to health care includes at least two dimensions: economic access in terms of affordability, (b) and geographic access in terms of proximity to providers (Gold, 1998). The so-called inverse care law—those most in need tend to have the least access to health care services—also includes social and geographic dimensions (Hart, 1971). The geographic aspect of access suggests that everything else being equal, people tend to seek health care at a closer distance than at greater distance (Gesler and Meade, 1988). Further, people may be discouraged from seeking health care if they have to travel beyond a certain distance (Brustrom and Hunter, 2001; Parkin 1979; Williams et al 1983); otherwise, other aspects of their lives might be adversely affected (Yantzi, et al. 2001). In the Canadian context, while efforts to reduce socioeconomic barriers to access to health care have been ongoing, policies aimed at reducing physical barriers have been less persistent, especially for hospital care. The 1970s saw the construction of numerous smaller hospitals outside of larger urban centers to help address the problem of geographically unequally distributed hospitals. However, in the late 1980s and early 1990s, many small hospitals were subsequently closed as a means of cutting costs (Liu et al., 2001).

The changes evident in the policy arena reflect a lack of understanding of the role of geography in terms of accessibility, which is due, in part, to a lack of routine data collected on geographic access measurements (e.g., distance variables) and limited methodologies. While most methodological developments using distance measurements have dealt with either potential accessibility or efficient ways of allocating hospital resources (Love and Lindquist, 1995; Mayhew and Leonardi, 1982), effective engagement requires multiple linkages and several different data sources. This could prove challenging for data collection and manipulation. With the advent of geographic information systems (GIS), greater accessibility of geo-reference data from multiple sources, and renewed interests in local participation in health care planning, it is now possible to evaluate geographic accessibility based on actual distance and other geographic variables. This process also provides a mechanism whereby dialogue between geographic and socioeconomic perspectives on access to health services can begin

This paper explores methods for assessing distance effects on hospital utilization using GIS technologies. Previous studies (see Goodman and Fisher, 1997) generally find that hospitalization rates decline as distance to hospital increases. However, most of studies deal with a specific type of hospitalization (Mollsop, 1969) or specific population group (Mooney et al., 2000). In our case studies of general and avoidable hospitalizations, we examine the general patient population for all types of hospitalizations. In addition, both physical barriers and socioeconomic variables are included in the analyses. Our approach is similar to that used by Goodman and Fisher (1997), but draws on actual rather than potential distance to hospitals. In the remaining sections, we first describe the data and data manipulation procedures undertaken to construct the geographic variables. Next, we document the distance effect on hospitalizations and model it in a multivariate framework with the intent of bringing geographic and socioeconomic perspectives together. Finally, we offer some concluding remarks in terms of the methodological and substantive findings.

DATA AND SAMPLE SELECTION

Database and sample area. In the U.S., most hospital discharge data are readily available, however, if hospitals are the reference points for data analyses, we would not be able to measure hospitalization rates along distance to reflect proper at-risk population. In Canada, most people (>95%) are normally on provincial health plan, and hospitalizations data are based on resident population, and they do not have to be limited to a number of hospitals. To have an area-based approach, data for this study are drawn from the British Columbia Linked Health Data Resource (BCLHD - Chamberlayne et al., 1998) which includes, person-specific data on the utilization of publicly-funded health services, such as physician claims, acute care hospital separations, continuing care services (home-based and residential care), mental health services, pharmacare, as well as vital statistics (births and deaths). These data were also linked to 1996 Canadian Census data using various geographic indicators such as health region, local health area, census tract, census division (or subdivision), and census enumeration area. From the BCLHD, the current study relies on data available from hospital separation files for a 10% random sample of the BC population in the Capital Health Region (CHR) who were registered with the provincial health services plan from April 1, 1990 to March 31, 1998. The CHR is an area of approximately 2,317 square kilometers encompassing twelve municipalities, fifteen aboriginal communities and unincorporated territory in four electoral areas. The region, which is organized into four local health areas, is situated on the southern tip of Vancouver Island and includes the southern Gulf Islands and the provincial capital city of Victoria. The Victoria metropolitan area is the largest urban center extending to a radius of approximately fifteen kilometers from the downtown core. In 1997, the CHR served a total resident population of 334,541 people (8.4% of the total population).

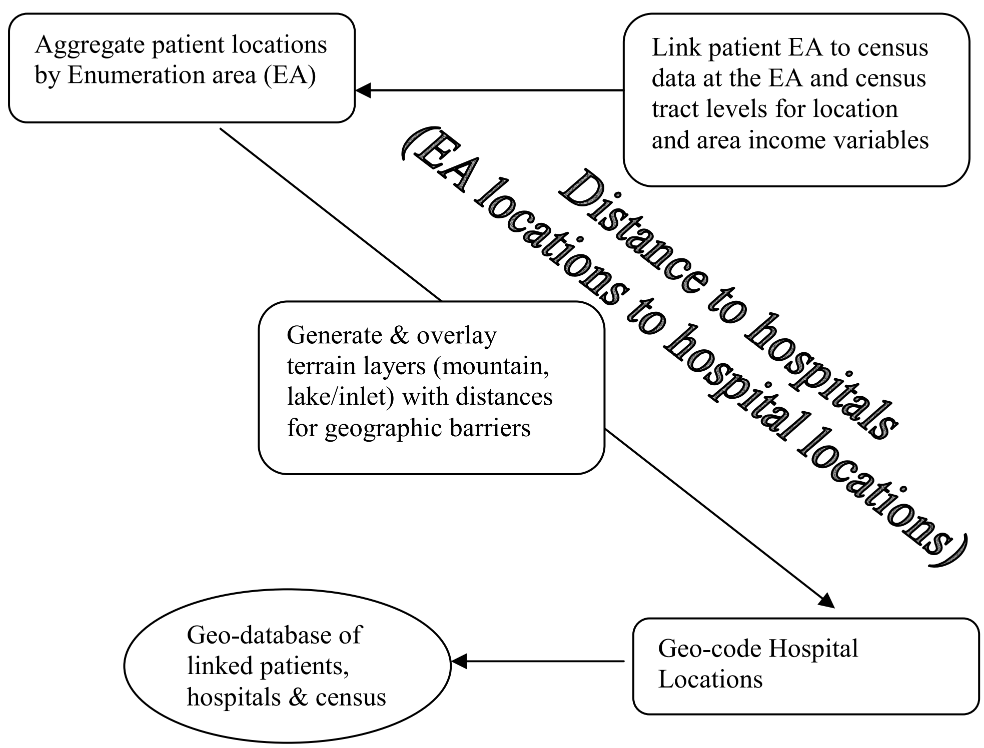
Hospital utilization. The hospital separation data include patient age-group (in five year intervals), sex, date of admission, date of separation, and the international disease codes (ICD-9) by principal and primary diagnoses for admission. To calculate hospitalization rates at the enumeration area (EA) level, we would ideally have patient registries for the entire potential patient population similar to the ones in the UK and Manitoba (Haynes, et al. 1995; Roos and Nicol 1999). These registries allow one to compare hospitalized patients to the population at-risk accurately within each geographic unit. Since they are not available in British Columbia, we rely instead on the 1996 census for these figures. This sample is restricted to those admitted during the three-year period between 1994-96 so that the patient sample is close to the 1996 census year. We use the three year (1994-96) hospital admissions as the sample basis and the 100% population counts of the 1996 census as the exposure to calculate hospital admission rates. Over the three years, the sample registered 18,947 hospital separations across 49 EAs, with each EA having about 627 residents on average. Note also that patients may be hospitalized several times during the study period, and the hospitalization rates to be calculated therefore include multiple hospitalizations during the study period with each admission being counted as a single event.

We used Weissman, Gatsonis, and Epstein's (1992) definition of avoidable hospitalizations-- conditions for which hospitalizations can be avoided if ambulatory care is provided in a timely and effective manner. There are 12 conditions included in the measure (ruptured appendix: 540.0, 540.1; asthma: 493; cellulitis: 681, 682; congestive heart: failure, 428: diabetes: 250.1, 250.2, 250.3, 251.0; gangrene: 785.4; hypokalemia: 276.8; immunizable conditions: 032, 033, 037, 072, 045, 055; malignant hypertension: 401.0, 402.0, 403.0, 404.0, 405.0, 437.2; pneumonia: 481, 482, 483, 485, 486; pyelonephritis: 590.0, 590.1, 590.8; perforated or bleeding ulcer: 531.0, 531.2, 531.4, 531.6, 532.0, 532.2, 532.4, 532.6, 533.0, 533.1, 533.2, 533.4, 533.5, 533.6). If one of the 12 conditions was identified as the principal or primary diagnosis for admission, it was coded as an avoidable hospitalization (AH=1). Admissions for other reasons were coded as AH=0. In total, there were 1185 (6.3%) avoidable hospitalizations.

PUTTING HEALTH DATA INTO GEOGRAPHIC CONTEXT

In this section, we develop a geo-processing procedure for contextual measurements. In order to evaluate distance effects, we first geo-coded each patient and hospital so that distance to hospital could be calculated and put into socioeconomic and geographic contexts. However, in the process of seeking hospital care, a patient must overcome socioeconomic and physical access barriers. From a socioeconomic perspective, income is an important indicator of access to care. From a geographic perspective, various physical barriers should be considered especially when the Euclidean distance is used. Some even suggest that it is not distance, but other geographic barriers that affect people's propensity for seeking health care (Kreher et al., 1995). Figure 1 provides a flow chart for various tasks in the process of modeling individual and contextual effects on hospital admission. At the first step, it is critical to review all the meta-data, so that common projection and an acceptable level of precision can be established. To assess the contextual effect of neighborhoods, we begin by linking patients' residential locations with census variables at the level of census enumeration area (EA). Next, we geo-coded each hospital location by latitude and longitude so that distance from each EA (representing patient location) to a hospital could be determined. Furthermore, given the terrain characteristics of the three health regions, getting to a hospital may be complicated by having to cross a mountain, sea, or other physical barriers. In order to represent these barriers, we generated dummy variables using various geographic data obtained digitally through BC Land Resources at the original scale of 1 to 250,000. In particular, we generated barrier themes, such as water-body, mountains and hills, and then overlaid with the distance feature. Originally, we implemented all GIS procedures in ArcInfo 8.0, and then replicate most procedures in ArcView 3.2a, a desktop GIS package, the detailed procedures reported in the following sections are based on the ArcView GIS.

Figure 1. Data manipulation for assessing distance effects



Geo-referencing patient locations. The BCLHD includes geographic identifiers from the larger health region, to mid-level census tract or census subdivision in rural areas, to the smallest unit, census enumeration area (EA), which is comparable to block group in the US census. All geographic identifiers, regardless of size, are identifiable from their respective geographic center (centroid) in latitude and longitude from the 1996 Census of the population. Thus, by linking each EA in the hospital file with the EA in the census file using the unique enumeration id, patients' residential location can be identified in terms of their respective EA centroids. These, in turn, can be used to generate a point theme.

Income variable. Census data come from the 1996 Census Profile Series, a series of tables that represent over 100 selected census variables and are presented at different geographic levels. The majority of variables are concerned with the demographic structure of the population. However, there are some income related variables indicative of the socioeconomic status of an area. While multiple indicators or a single indicator derived from multiple indicators are perhaps better alternatives to a single-item indicator for demonstration purposes, median household income was selected as a proxy measure of socioeconomic status. However, approximately 17% of the EAs have suppressed incomes in the 1996 census due to small populations and a concern for confidentiality. Even though less than half of EAs with missing incomes affect our patient sample, we decided to impute missing values using a method similar to Frohlich and Mustard (1996) that uses the geographic unit one level higher than the EA (i.e., census subdivision – CSD). Generally speaking, if income for a particular EA is missing, the average of incomes from adjacent enumeration areas is assigned to it.

To classify neighborhoods with regard to income, we initially tried to assess absolute deprivation (e.g., poverty level) at the census EA level. However, there is a lack of empirical literature in the Canadian context that compares individual and area deprivations, let alone for the province of BC. Although this in itself is an important research project, we decided to use the relative measure of four income quartiles as the basis for the classification. The lowest income quartile includes those living in an EA with average annual household income below $38,414, the second between \$38,414 and \$47,360, the third between \$47,360 and \$57,453 and the highest above \$57,453.

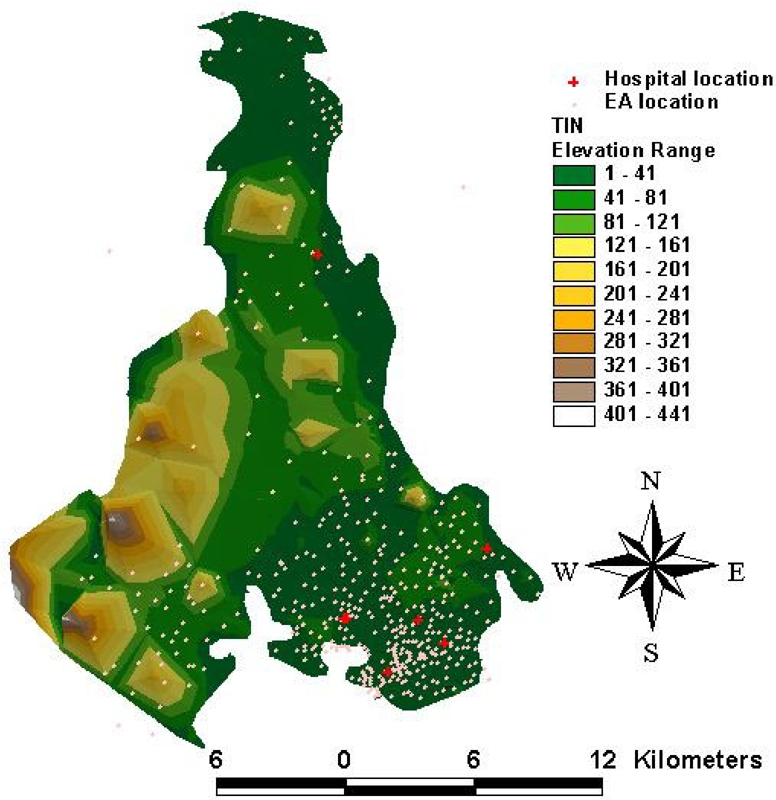
Geo-coding hospital locations. It is necessary to geo-code all the hospitals in the province as patients in the Victoria region could seek hospital care anywhere in the province. Digital hospital location files for British Columbia are available from both provincial and federal governments, however, the accuracy level is relatively poor when we selected some sample locations from these files. For this reason, we decide to geo-code each hospital location (longitudes and latitudes) from a 1:50,000 topographic map, and these coordinates were then used to generate the hospital location theme or layer. Most hospitals are clearly marked on the maps. If a map at the requested scale was not available, a map at the next level (1:100,000, or in rare instances 1:250,000) was obtained. If a hospital was not on a map, the hospital was called directly and asked to identify the nearest street intersection as its location. Using this procedure, 106 hospitals in the province were geo-coded, all of which were identifiable on a map scale of 1:250,000 or larger.

Calculating Euclidean Distance. In geographic analyses, distances to a hospital can either be potential or actual. Potential distance is hypothetical: it is assumed that patients will access a hospital based on some rational criteria (e.g., closest hospital). However, patients do not always go to the closest hospitals as demonstrated by Gesler and Meade (1988). Actual distance is based on the hospital actually used by a patient although exact travel mode (e.g., car, transit, walk) and routes may not necessarily be known. Here, we know both potential and actual hospital location for each hospitalization, However, our distance calculation is based on the actual rather than potential distance. If a patient was hospitalized twice in two different hospitals during the study period, two different measures of distance-to-hospital are calculated even though the patient lived in the same EA. Likewise, if a patient moved during the study period, the hospitalization is measured from the associated EA. We chose Euclidean distance over other distance measurements as real network distance is almost impossible to determine. For many of the study areas, patient populations are sparsely settled on mountains and islands, and the centroids of the EA may not be close to any network, not even when detailed road networks are available. Given the large geographic coverage at the provincial level, it is not feasible for us at this stage of the study to use road-network to measure distance to hospital (Love and Lindquist, 1995). It is important to note though that Euclidean distance-to-hospital is assumed to be in proportion to real network distance. Empirical evidence has shown that real network distance tends to be consistently 20-25% greater than the Euclidean distance, or half way between Euclidean and rectilinear (Manhattan) distances (Francis et al., 1992). This assumption is unlikely to affect our assessment qualitatively as we emphasize relative rather than the absolute magnitude of distance effects.

Generating geographic barriers. For simplicity, three types of barriers - steep hill, lake or inlet, and island without a hospital - were identified. Conceptually, if we treat the straight line between the EA and hospital as the Euclidean distance, then the box in the middle of Figure 1 is the barrier. If a line crosses any of the barriers, a dummy variable is assigned. First, data from a digital elevation model (DEM) were used to generate TIN (triangulated irregular network) terrain for each study region. The DEM was provided with elevation readings that included x-y coordinates comparable to the resolution of a 1:250,000 topographic-map. ArcView 3D extension was used to generate TIN from the DEM table. The resulting TIN model was identical to the TIN generated by ArcInfo. However, one needs to covert the TIN to a polygan coverage by retaining hill slop and elevation attributes. A steep hill can then be defined using a 12 percent slope or elevation difference of 200 meters or more between the highest passing elevation to either points of the distance line (EA or hospital location). If an Euclidean distance line crossed a steep hill, a dummy variable--hill crossing-- was coded one, otherwise, it was coded zero. Likewise, lake or inlet barriers were defined when a Euclidean distance line appeared across (intersect with) either one. Finally, patients living on an island without a hospital must use a ferry, thereby imposing additional constraints on travel to hospital. Figure 2 provides a graphical example of TIN with the hospital and sample locations of EA centroids for a portion of one of the three health regions studied. Using this figure, one can eyeball each EA location and identify whether or not a patient needs to cross an inlet for hospital care. Note that the map can only provide a visual impression of the relative location and general landscape, as one cannot determine which patients went to which hospitals simply from the map.

For the most part, the implementation of the above procedure is straightforward. However, there is also a need to convert digital sources of different projections to the same projection system. The UTM-N9 was used to realign the road network, one or two reference layers from different UTM zones to UTM-N9, and several digital layers (DEM, Lakes, coastal lines) of the Albere conformal project to the UTM. The key in Arcview is to convert all layers to longitude and latitude, and then re-project them to the desired projection system. Although new variables can be easily added through linkage of tables with a common field, or though spatial joining (e.g., map overlay), careful documentation is needed along the way. Without this documentation, it is very easy to lose track of the level of geography (e.g., census tract, EA) from which new variables are derived. The final step is to attach the new variables to each patient identifier, along with their respective hospital records. This is discussed in the following section.

Figure 2. Patient (EA) and hospital locations in Victoria, BC



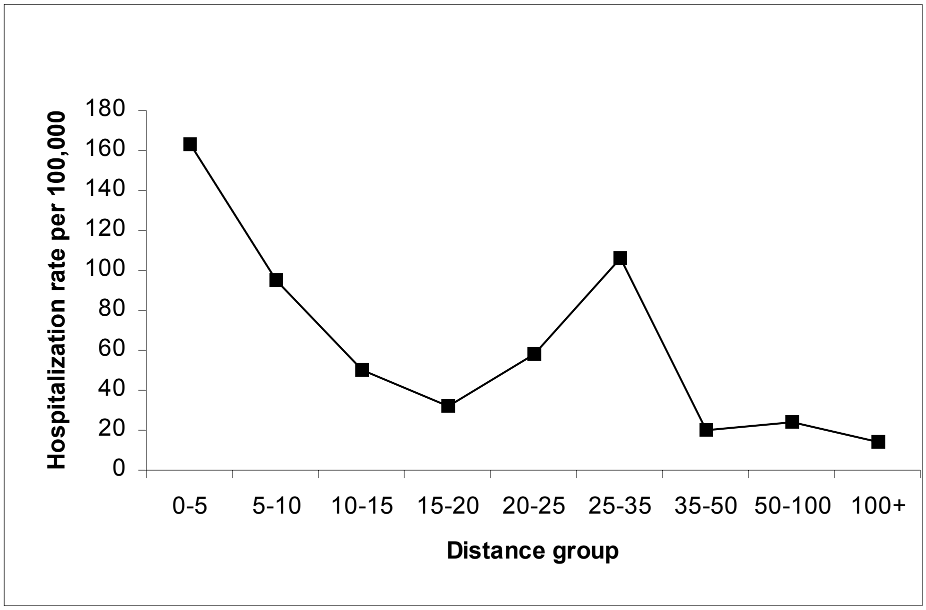
ANALYZING DISTANCE EFFECTS ON HOSPITALIZATIONS

In this section, we analyze hospitalizations in the context of socioeconomic condition of neighborhood and geographic accessibility. We first provide some descriptive pictures on hospitalizations and then model income and distance effects under a multivariate framework. At the descriptive level, we use EA total population as the exposure to derive hospitalization rates for several distance-to-hospital ranges (Pappas et al, 1997). Rate-based multivariate analyses, however, require either population-based survey or aggregate analytical models (e.g., Poisson regressions). Neither of these are appropriate in this particular case, as we do not have an at-risk population (exposure) that corresponds to patient level variables (e.g., age, sex, income). For this reason, we adopt logistic regression for the multivariate analysis.

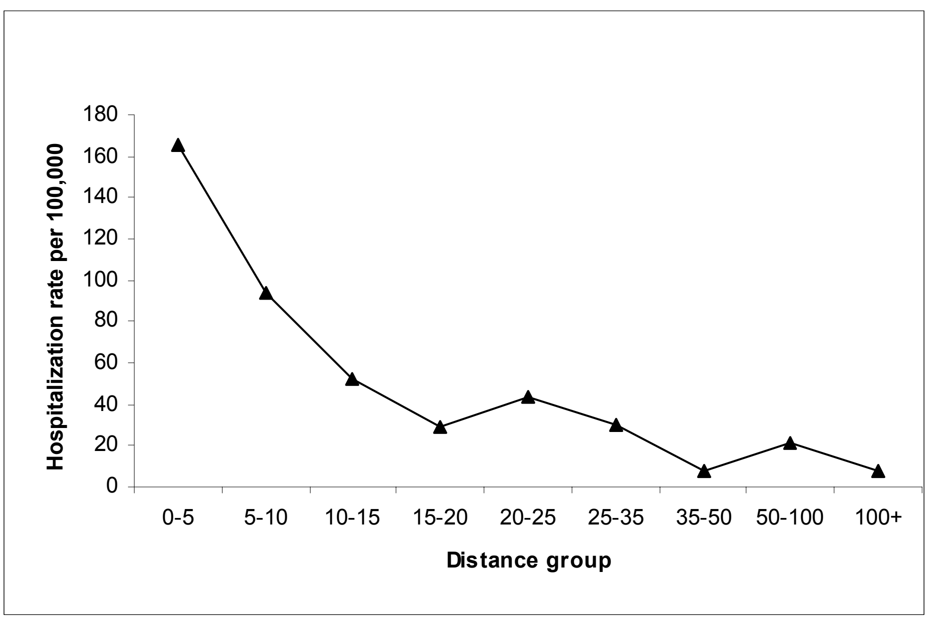
Descriptive analysis of overall hospitalizations. From a population health perspective, hospitalization rates should be more or less evenly distributed if patient populations are distributed evenly across geographic space. The degree to which rates vary across different geographic dimensions reflects level of accessibility from a provider's point of view, and ability and willingness to travel from a patient's point of view. Figure 3a shows the three-year average (1994-96) hospitalization rate according to distance-to-hospital. Overall, the hospitalization rate declines as distance increases with a reverse trend and small peak around 20 to 35 km. It seems that residents located near a hospital are either sicker or more willing to seek hospital care than residents at greater distance. Given the magnitude of the difference, this pattern is likely to persist even when potential confounding factors, such as age, sex, and income, are introduced into the model.

Figure 3. Three year average (94-96) hospitalization rates per 100,000 by distance group in Capital Health Region in British Columbia, Canada.

a. Overall rates including all communities



b. Adjusted rates excluding satellite communities



To determine why there are small peaks of hospitalization rates between 25-35 km, it is important to understand local geography. As noted earlier, the primary urban area for Victoria is within 15 kilometers to the city center. A community located 25 kilometers beyond an urban center often represents a separate catchment area rather than a continuous suburb to the urban core. For example, Sooke, which does not have a hospital, is a town (population approximately 3,000) located approximately 30 kilometers from Victoria and is separated by hills and forest. While 20-30 kilometers may not be overly burdensome to go to a hospital, it may not be particularly convenient either. Therefore, even though there is no co-payment associated with hospital care, people in these communities may not be as likely to access hospital care as those who live closer by.

In the migration literature, neutral migration rates are used to describe a region with an average propensity of in and out-migration (Liaw, 1990). Borrowing from this concept, we may want to try to determine a hospitalization rate when the distance effect is neutralized (i.e. potential convenient hospital shoppers (patients) are deterred by travel distance and cost). If there are sizeable communities located 20-35 kilometers away from a major urban center and hospitals, the average hospitalization rates among these communities may provide a reference point for a "reasonable" hospitalization rate with neutralized distance effects (Imbens and Angrist, 1994). For convenience, we label them 'satellite communities', and operationally define them as those with populations above 2,500 which are either located on an island without any hospitals, or are communities from 20 to 30 km away from a major urban center and separated by farms, mountains or water bodies. Indeed, if we delete observations from these communities, the local peaks in Figure 3a become negligible (Figure 3b).

The influence of satellite communities on hospitalization rates provides an important clue for multivariate modeling. In urban geography, it is known that population density around an urban center is inversely related to distance from the urban center. If there are satellite cities located within 20 kilometers of a major center, a small peak will be evident in the urban density function around 20 km. Since the amenity that a hospital provides only takes effect when people suffer some fairly serious illness or injury, we suspect that living fairly close to a hospital induces greater propensity for going to a hospital, and living relatively far from a hospital deters some necessary hospital care. Satellite communities represent a more or less median distance range to hospital, therefore, a reasonable hospitalization rate in terms of neutralized distance effect. If we take this reasoning seriously, we can compare satellite communities with all other communities. However, subsequent comparisons between satellite and other communities found little differences (e.g., sex, income). The only exception to this is the distribution of the elderly population, with satellite communities having a greater proportion of elders (56% versus 53%). This difference, however, is not sufficient to generate a substantial difference in terms of hospitalizations.

Multivariate analysis of avoidable hospitalizations. From the previous case study, it was determined that satellite communities appear to be "outliers", and if we can control for them, the overall hospitalization rates display an inverse relationship to distance-to-hospital. Based on this finding and the fact that more than 94% of hospitalizations are unavoidable, we can compare avoidable and other hospitalizations treating other hospitalizations as known and “normal” following distance decay while explicitly controlling for satellite communities. Under the logistic regression framework, the dependent variable is the likelihood of having an avoidable hospitalization versus an unavoidable hospitalization. We run three nested logistic regression models (Table 1) starting with a simple model (model 1) controlling for age, and sex, while looking at the distance effects. In model 2, socioeconomic variables are introduced in to see if some of the distance effects can be explained by income gradients along with distance to hospital. Finally, in model 3, a number of physical barriers are added to shed some light on the overall geographic determinants of avoidable hospitalization.

Evidently, age effects are markedly different: compared to those 35-55 years of age, those in both younger and older age groups are more likely to experience an avoidable hospitalizations. In addition, males are more likely than females to have an avoidable hospitalization. Further, we find that avoidable hospitalizations generally decline with distance for the first few distance categories, and then fluctuate somewhat for the further distance categories. Compared to the 0-5km distance category, being 5-10 kilometers from the hospital reduces the odds of avoidable hospitalization by 0.758, while being an additional 5 km further away reduces the odds still further to 0.671. Since the total hospitalization rate follows a distance decay curve, avoidable hospitalizations seem to have a steeper curve, although not quite as smooth as all other hospitalizations. Controlling for satellite communities, the local peak originally found around 20 km loses statistical significance. However, the lowest avoidable hospitalization rate appears in the 35-50 kilometer category rather than in the further distance categories as was evident with regard to overall hospitalization rates.

Although the introduction of the income variable, has little impact on the distance effects (Model 2) the results are consistent with general expectation. Patients from the two lowest income groups are approximately 1.25 times as likely to be hospitalized for avoidable conditions as those in the highest income group. For those in the second highest income group, there is no significant difference from the highest income group in terms of avoidable hospitalization.

Finally, we introduce in model 3 two physical barriers: inlet/lake and mountain crossings generated from GIS operations. Relatively speaking, crossing an inlet or lake does not have significant effect. However, crossing a mountain or hill increases the likelihood of an avoidable hospitalization. To interpret these effects, we also need to consider distance and local geography. For instance, people from many distance communities need to cross a steep hill to get to the hospital. When the hill crossings are included, they not only increase the likelihood of an avoidable hospitalization but also, reduce odds for the last few distance categories (e.g., 50-10). Thus, steep hill crossings may take away some of the distance effects from farther distance categories.

Table 1. Logistic Regression for Avoidable Hospitalization

Control variables	Odds-ratio	Odds-ratio	Odds-ratio
Old (35-55 referent)	2.870**	2.849**	2.878**
Young (35-55 referent)	1.438**	1.429**	1.439**
Sex (male referent)	0.741**	0.735**	0.735**
satellite communities	1.197**	1.206**	1.177**
Distance (0-5 km referent)			
5-10	0.758**	0.805**	0.792**
10-15	0.671**	0.727**	0.709**
15-20	0.921	0.944	0.92
20-25	0.687**	0.732	0.737**
25-35	0.536**	0.540**	0.505**
35-50	0.751**	0.749**	0.727**
50-100	0.761**	0.797**	0.752**
100+	0.926	0.953	0.924
Socioeconomic			
lower 25% (top 25% referent)		1.296**	1.321**
mid-low 25% (top 25% referent)		1.246**	1.258**
mid-up 25% (top 25% referent)		1.106	1.101
physical barriers			
Lake/inlet crossing			0.923
Hill crossing			1.164**

Note:
* and ** indicate the significant levels of 0.05 and 0.01 respectively

CONCLUSIONS AND DISCUSSIONS

In this paper, we developed a GIS procedure to generate variables for modeling distance-to-hospital in geographic and socioeconomic contexts. Since individual-level SES variables were not available, we created a socioeconomic context by linking census data with individual patient data. In addition, we believe that physical barriers, such as lakes, inlets, mountains, hills, and islands will complicate simple Euclidean distance measures, and should somehow be accounted for. To this end, we introduced a number of variables reflecting several layers of physical features, and let them intersect with distance-to-hospital. We believe that new insight can be gained by creating and incorporating physical barriers into access to care measures.

Through careful examination of local conditions, we unraveled “neutral hospitalization rates” represented by satellite communities. These rates tend to be slightly below the regional average. When we simply plotted hospitalization rates along distance to hospital, we observed a small peak on the distance decay curves. When we controlled for the impact of residence in satellite communities, the overall hospitalization rates had an inverse relationship with distance-to-hospital. This finding is robust when additional control variables are included. However, it is hard to imagine that people will find a hospital attractive enough to prompt them to go more often, as is the case with regard to regular shopping (Pellegrini, Fotheringham, and Lin 1997). In a health care system without gate fees, distance-to-hospital may be an obvious deterrent to hospital care either because one is less able or willing to travel the required distance or because referrals by physicians for those living far away from a hospital are less frequently given (Mellsop, 1969). A well-defined neutral hospitalization rate could serve as a yardstick for assessing the consequences of the distance effect on hospitalizations. If satellite communities and communities near a hospital tend to have similar health outcomes while differing substantially in hospitalization rates, then we can perhaps conclude that living close to a hospital may encourage utilization of hospital resources.

We found that avoidable hospitalizations generally follow similar variations in distance to the non-avoidable hospitalizations with slightly greater distance deterrent effects for 5-10 and 10-15 km categories. Consistent with previous literature (Laditka and Johnston, 1999; Pappas et al., 1997), low income patients are more likely to be hospitalized for avoidable conditions. We also confirmed that the income effect influences different dimensions to those affected by the distance effect, since the inclusion of income variables does little to change the distance effects. Finally, to demonstrate the use of physical barrier variables, we included crossing hills, lakes or inlets. The inclusion of these variables not only changed some distance effects, but also offered some insight into avoidable hospitalizations. For instance, crossing hills or mountains significantly increases the likelihood of having an avoidable hospitalization. Since we know that the majority of villages or small communities in mountain areas or on islands often lack of primary and ambulatory care services, it is expected to see a greater likelihood of avoidable hospitalization (Casanova and Starfield, 1995).

There are several limitations to this study. First, the simplicity of Euclidean distance comes with some compromises. We assume that the Euclidean distance to a hospital is in proportion to the true network distance to the hospital. Even though we included additional physical barriers to correct the measurement, we should only interpret distance effects in relative terms. If a health region intends to quantify distance effects for planning purposes, it is important to gauge the absolute magnitude of the distance effects, or at least convert Euclidean distance effects into network distance effects. In this situation, we will have to resort to more accurate network distance measurements to calibrate the distance effect (Mayhew and Leonardi, 1982;

Hansen and Schwab, 1987). Second, we did not include the hospital context in our design, which could be an important omission. A complete conceptualization of distance-to-hospital should bring individual characteristics, neighborhood characteristics, travel conditions, and hospital characteristics into the same modeling framework. Finally, since we did not have a complete roster of all those registered with the Medical Services Plan, we had to rely on census data to generate the population figures necessary to calculate hospitalization rates. This limited our level of confidence in the hospitalization rates for small areas. Despite these limitations, the study represents an important step in understanding the integration of geographic and socioeconomic approaches to health services accessibility. Methodologically, the use of the GIS to generate contextual variables for both socioeconomic and physical environments has expanded GIS applications, and has helped to generate new hypotheses (e.g., neutral hospitalization rate). Substantively, it explicitly confirms the two aspects of the inverse of health care law that work simultaneously: those with lower socioeconomic status and those living in greater distance to hospitals tend to be less likely to access hospital care. Even though the study is based on Canadian data, the methods can be applied to any regions, especially mountainous areas such as West Virginia. Further studies are needed to disentangle various distance decay effects in relation to other health care services, and their planning implications for new and existing hospital locations in relation to other health facilities.

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