Exploring the Intra-Urban Variations in the Relationship among Geographic Accessibility to PHC Services and Socio-demographic Factors

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ABSTRACT

In this study, we investigate the intra-urban variations in the relationships among various socio-demographic factors and geographical accessibility to primary health care (PHC) services using a local regression model. Geographic accessibility to PHC services is calculated at a local scale for two Canadian urban centers (Calgary, AB and Toronto, ON) using a three-step floating catchment area (3SFCA) method. Socio-demographic factors were derived from 2006 Canada census data. The regression analysis was performed using two different methods: 1) a single regression model for both cities together, using a regional dummy variable, and 2) separate models for each city. A similar modeling procedure was applied for both methods: first, a best Ordinary Least Squares (OLS) regression model was determined using a forward step-wise approach in SPSS software. Next, to test the spatial non-stationarity in the regression residuals, the best OLS model was repeated in ArcGIS. Further, to explore whether or not regression coefficients vary across space, we applied the geographically weighted regression (GWR) method with an adaptive spatial kernel. The GWR results exhibit the intra-urban variations in the relationships between socio-demographic factors and the accessibility score. A comparison of the GWR models demonstrates the benefit of local spatial regression in disaggregating the relationships between socio-demographic variables and the geographical accessibility to PHC services at a local scale; however, our results suggest that a more careful modeling approach is required when analysing the data with spatial effects.

Categories and Subject Descriptors

K.4.1 [**Computers and Society**]: Public Policy Issues – *computer-related health issues.*

General Terms

Measurement, Performance, Design, Verification

Keywords

Spatial non-stationarity, geographically weighted regression, urban geography, physician-to-population, geographic accessibility

1. INTRODUCTION

There are many challenges to health care delivery in urban areas. Among them is the relationship between the arrangement of primary health care facilities and the populations they are meant to serve. In this context, geographic accessibility to PHC services in association with health care needs is a critical and relatively unstudied topic. In Canada, access to health care is essential in ensuring all people receive adequate health care as near as possible to their residence [1]. Geographic access to health care in relation to population health needs (or consumers) varies across space [2]. In health geography, the multivariate regression technique is normally used to determine the association of a response variable with explanatory factors; however, with current advancements in GIS, spatial data handling, and spatial statistics, spatial regression methods are increasingly used to address methodological issues as well as the contextual aspects of spatial data analysis [3-12]. The main advantage of spatial regression, in addition to increasing the reliability of regression measures, is to explore the spatial variation between variables. This is typically achieved by focusing on certain spatial effects that normally exist in spatial data. Two types of spatial processes that can affect regression estimates are considered for regression models in geography: spatial autocorrelation and spatial non-stationarity (heterogeneity) [as discussed by 13]. Spatial autocorrelation is related to spatial dependence in regression residuals, and can often result in misleading outcomes for coefficient significance tests. Spatial non-stationarity in spatial data modeling indicates that the variance of residuals is different across the space in question. There is no practical modeling solution to address both spatial effects in a single modeling framework except for the possibility of a 'geographically weighted version of a spatial regression model' [14]. Local models have several comparative advantages over global spatial regression, these include: local regression coefficients, mappable regression parameters, and local hot-spot identification [15]. Furthermore, the process of calibrating local models can accommodate the problem of spatial dependency in regression residuals [14, 15].

In this research, we focus on local spatial regression to model geographical accessibility to PHC services in urban settings. The objective of this study was to explore the intra-urban variations of geographical accessibility to PHC services in relation to census based socio-demographic factors. Geographically weighted regression (GWR), a local spatial regression technique, was applied to estimate the regression parameters at a local scale in two urban areas: Toronto, Ontario and Calgary, Alberta. The regression analysis was performed using two different methods: 1) by means of a single regression model for both cities together using a regional dummy variable (i.e. 'Multi-City Model'), and 2) using separate models for each city.

2. DATA AND STUDY AREA

This research investigates intra-urban spatial patterns in two Canadian cities (census subdivisions 'CSDs'): Toronto and Calgary (for locator map, see Figure 1). The City of Toronto is the central part of the largest metropolitan area in Canada (the Greater Toronto Area (GTA)), with a population of 2.62 million in 2011. The city of Calgary is the third-largest municipality in Canada and the largest city in Western Canada with a population of 1.10 million. Both cities have distinct characteristics; for example, population changes from 1996 to 2011 (Toronto = 9.6%; and Calgary = 42.7%), and population density in 2011 (Toronto = 4149.5 and Calgary = 1329 persons per square kilometre)[16]. Recent developments in the field of health and urban geography have drawn attention to the need for intra-urban distribution of health care resources (such as family physicians) with respect to population health care needs. Health care need can be identified through a number of different methods, including tendency to seek regular care [17]. There are a number of benefits associated with having regular care by a family physician including prevention and treatment of common diseases and injuries; basic emergency services; referrals to and coordination with other levels of care, such as hospital and specialist care; primary mental health care, healthy child development, primary maternity care, rehabilitation services, etc. [18, 19]. It has been reported that 78.8% of the total population (75.6% male; and 82.2% female) age 12 and over in Calgary census metropolitan areas (CMAs) and 90.3% of the total population in Toronto (87.3% male; and 93.2% female) have a regular family physician[1]. In this research, we focused on the spatial distribution of primary health care resources in relation to population health care needs. An accessibility score that characterizes the ratio of population to PHC services is used as the dependent variable. A brief description of this dependent variable is as follows:

Our accessibility score is a local form of the physician-to-population ratio. In order to calculate the accessibility score, a GIS-based Three-Step Floating Catchment Area (3SFCA) method was used, which is a local measure of geographical (potential) accessibility to health care resources in urban settings [20, 21]. There are two spatial layers required to apply the 3SFCA method: 1) population at the smallest possible geographic scale (such as Dissemination Areas (DAs) or Dissemination Blocks (DBs) in Canada, Statistical Area Level 1 (SA1)[2] or Mesh Blocks[3] in Australia, Census Blocks (CB) or Block Groups (BG) in USA[4]), and 2) geographic locations of health care services/sources (such as locations of family physician clinics, dental services, etc.). In this research, DA centroids were used to represent population settings along with the geocoded locations of PHC services. In the first step of the 3SFCA, a physician-to-population ratio (R1) for each PHC practice location was calculated. For this, the number of family physicians/general practitioners at a particular PHC location was divided by the total population within its 3km road network catchment area (considered an appropriate distance to calculate local accessibility). In the second step, a sum of all R1 ratios (R2) those falls within a 3km road network catchment area from any DA centroid was assigned to a DA centroid. In the 3rd step, locally relevant neighbourhoods, as defined by the local government, are used as the units of analysis to calculate the physician-to-population ratio with a neighbourhood accessibility score being generated by aggregating the Step 2 ratios. For further details on how this variable was calculated, see [22]. For a more detailed description of the 3SFCA method, see [20, 21, 23].

The spatial patterns of the 3SFCA accessibility scores for both cities are shown in Figure 1, maps b and c. Both city maps are prepared using a quantile (Q) classification scheme with four classes (Q1: less than 0.57 physicians per 1000 people, Q2: 0.58 to 0.87, Q3: 0.88 to 1.43, and Q4: 1.44 to 4.41). Neighbourhoods with higher accessibility scores indicate comparatively better geographic accessibility to PHC services for local residents. Comparatively, the mean accessibility score of Calgary neighbourhoods (1.12 physicians per 1000 people) is higher than those in Toronto (1.05 physicians per 1000 people) as indicated in Table 1. In both cities, a typical distribution pattern can be seen (see Figure 1b and 1c) where higher scores are clustered in the core urban and downtown neighbourhoods with decreasing accessibility toward the edges of the urban areas. It should be noted that there are some limitations to accessibility estimates that may influence accessibility scores. In the 3SFCA method these include the following: physician selection criteria[5]; the procedure implemented in preparing data for analysis[6]; as well as the geocoding method applied (may carry positional errors) [24, 25].

In Canada, census-based socio-demographic characteristics for analyzing health disparity at local scales and to proxy for the determinants of health care needs are increasingly used in health geography [26-33]. For this study, eight census-based socio-demographic variables (i.e., derived from the 2006 Canadian census) were shortlisted based on theoretical significance and data availability [see, 34]. Table 1 below indicates some of the main characteristics of these explanatory variables (mean, as well as standard deviation (SD)) along with information on how these variables were calculated. Note that all explanatory variables were expressed as percentages with higher values indicating higher health care needs.

[1] Statistics Canada. 2013. Health Profile. Statistics Canada Catalogue No. 82-228-XWE. Ottawa. Released April 15, 2013. http://www12.statcan.gc.ca/health-sante/82-228/index.cfm?Lang=E

[2] http://www.abs.gov.au/ausstats/abs@.nsf/0/7CAFD05E79EB6F81CA257801000C64CD

[3] http://www.abs.gov.au/ausstats/abs@.nsf/mf/2074.0

[4] http://www.census.gov/geo/reference/garm.html

[5] Family Doctors, Family Physicians, General Practitioners, or Non-Specialists

[6] Excluded based on: non-geocodable addresses such as physicians having no address or having Post Office Box (P.O. Box) information only, and physicians practicing outside the municipal boundaries.

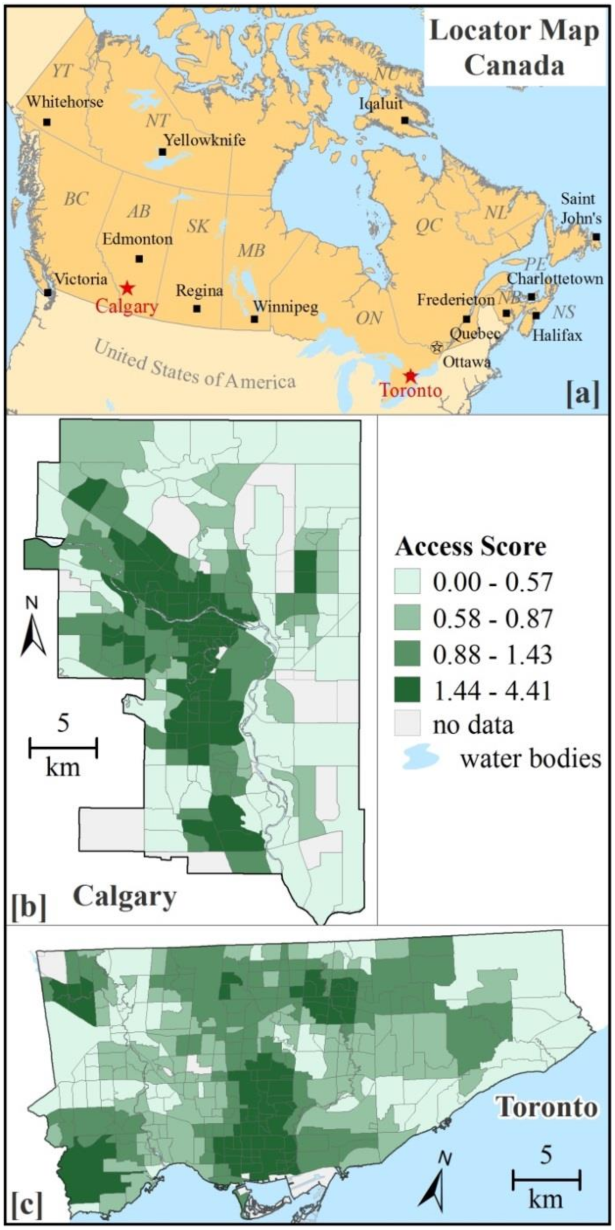

Figure 1. Study area map: a) locator map, b) Spatial distribution of the accessibility score – Calgary, c) Toronto.

3. STATISTICAL ANALYSIS AND RESULTS

This research used both global and local regression techniques to determine the association between socio-demographic variables and the accessibility score. First, we applied a global regression method, Ordinary Least Squares (OLS), to determine the most suitable model between the accessibility score and the independent variables for both cities together. In this process, to account for regional influence in the regression estimates (cities) we introduced a regional dummy variable (a usual practice in dealing with regional differences [e.g., 9, 35-37]). Neighbourhoods with no population data were excluded in this analysis. Next, a forward step-wise regression was applied using SPSS software to determine a best Ordinary Least Squares (OLS) regression model by considering adjusted R-square values and coefficient estimates at the 5% significance level. We found that the following variables were associated with accessibility score: percentage of dwellings occupied by the owners (home owners), percentage of population 15 years and older without high school certificate, diploma or degree (no high-school), percentage of aboriginal population (aboriginal status), percentage of single parent families (lone parents), percentage of immigrants who came to Canada from 2001-2006 (immigrants), and regional variable (city dummy variable). To determine whether spatial non-stationarity is present or not in the selected multi-city OLS model, we re-ran this model in ArcGIS and found that the relationships modeled are not consistent across space (Koenker statistic = 57.68, df = 6, $p<0.001$). In order to study how these relationships vary across space as well as to address spatial non-stationarity in the global model, the use of a local spatial regression method appears to be a viable approach [12, 38-40]. We applied the geographically weighted regression (GWR) method to estimate the model coefficients for each neighbourhood. We used an adaptive spatial kernel as well as the Akaike Information Criterion (AICc) to determine the optimal number of neighbors [for more detail, see 15, 41]. The adaptive kernel incorporated 152 neighbors to estimate the multi-city model. The GWR model that estimates regression coefficients for each neighbourhood indicated a significant improvement in model fit over the multi-city OLS model. In this model, the AICc values decreased from 1011.8 to 925.1 while adjusted R-square values increased from 0.354 to 0.500. The results obtained from the multi-city OLS and multi-city GWR models (coefficient estimates and model performance indicators) are shown in Table 2. In addition, to compare the results of the multi-city GWR model (where data for both cities were analyzed together), a set of maps for all coefficients, local R-square values and the condition number are shown in Figure 2 (maps a-h).

To understand how the relationships between accessibility score and explanatory variables change, and to assess the reliability of regression measures in different settings, we built a separate regression model for Calgary and Toronto (Calgary Model and Toronto Model). The same statistical procedure as was applied above was used to determine the best OLS models for Calgary and Toronto, to test spatial non-stationarity, and the GWR model for both cities separately. The explanatory variables found to be associated with accessibility scores for each city were as follows: home owners, aboriginal status, and no high-school education in Calgary's OLS model; and home owners, lone parents, individuals living alone, recent immigrants, and no high-school education in Toronto's OLS model. It was found that the relationships modeled in both cities separately are not consistent across space (Koenker statistic = 13.90, df = 3, p =0.003; Koenker statistic = 36.89, df = 5, p =0.001 in Calgary and Toronto respectively). The GWR modeling technique with an adaptive spatial kernel was applied and the results in both cases (Calgary and Toronto models) displayed improvement in model goodness of fit (for Calgary, AICc values decreased from 455.6 to 386.1 and adjusted R-square increased from 0.450 to 0.670; for Toronto AICc values decreased from 523.7 to 460.6 and adjusted R-square increased from 0.278 to 0.426). The adaptive kernel incorporated 45 and 207 neighbors to estimate the Calgary and Toronto models respectively. The results obtained from the OLS and GWR models (coefficient estimates and model performance indicators) for Calgary and Toronto are given in Table 2 and 3 respectively. The results of GWR models for Calgary and Toronto are mapped to display the spatial patterns in local coefficient estimates and model fitting as well (Figures 3 and 4 respectively).

Table 1. List of census-based socio-demographic characteristics along-with their descriptive statistics

Variables	Definition	Both Cities		Calgary		Toronto	
		Mean (%)	SD	Mean (%)	SD	Mean (%)	SD
Access score	Physician-to-1000 population ratio at neighbourhood calculated using 3SFCA method (3km network buffers)	1.11	0.80	1.21	0.98	1.05	0.64
Aboriginal status	Percentage of aboriginal population	1.24	1.76	2.53	2.20	0.41	0.45
Home Owners	Percent of dwellings occupied by the owners	65.22	22.27	73.19	21.76	60.10	21.08
Lone Parents	Percentage of single parent families	17.33	7.97	14.84	7.85	18.93	7.64
Living alone	Percentage of population 65 years of age and over living alone	3.36	2.91	2.84	3.42	3.69	2.48
No high-school	Percentage of population 15 years and older without high school certificate, diploma or degree	18.62	9.41	17.27	8.11	19.49	10.08
High needs	Percentage of following population groups: children with ages 0-4, seniors with ages above 65, and women with ages 15-44)	41.38	4.87	39.72	5.67	42.45	3.92
Recent Immigrants	Percent of immigrants who came to Canada from 2001-2006	7.78	6.44	5.07	3.98	9.52	7.09
Unemployment	Percentage of population age of 15 years & over in the labour force unemployed	5.89	2.72	3.97	1.75	7.12	2.52

Table 2. Results of regression model of accessibility score (Multi-city model): comparative summary of OLS and GWR models.

Variables	OLS coefficients		GWR coefficients							
	B	SE	Mean	SD	Min	Q1	Median	Q3	Max	Range
Intercept	3.85***	0.181	2.901	1.414	0.295	1.421	3.324	3.923	5.538	5.243
Home Owners	-0.023***	0.002	-0.016	0.012	-0.039	-0.025	-0.019	-0.005	0.004	0.044
Lone Parents	-0.02***	0.005	-0.012	0.012	-0.036	-0.022	-0.013	-0.001	0.012	0.048
Aboriginal status	-0.089***	0.022	-0.073	0.060	-0.177	-0.116	-0.085	-0.040	0.139	0.316
Recent Immigrants	-0.019***	0.005	0.001	0.020	-0.050	-0.015	0.006	0.017	0.030	0.080
No High-school	-0.018***	0.004	-0.021	0.014	-0.050	-0.032	-0.021	-0.008	0.015	0.065
Toronto (regional)	-0.453***	0.081								
Multiple R-squared	0.361		0.553							
Adjusted R-squared	0.354		0.500							
AICc	1022.100		915.500							

***p<0.001

Table 3. Results of regression model of accessibility score (Calgary model): comparative summary of OLS and GWR models

Variables	OLS coefficients		GWR coefficients							
	β	SE	Mean	SD	Min	Q1	Median	Q3	Max	Range
Intercept	4.18***	0.234	3.316	1.609	0.029	2.038	2.917	4.421	6.991	6.962
Home Owners	-0.028***	0.003	-0.022	0.013	-0.062	-0.028	-0.018	-0.015	0.001	0.063
No High-school	-0.036***	0.007	-0.005	0.055	-0.127	-0.036	-0.013	0.014	0.134	0.261
Aboriginal status	-0.104***	0.029	-0.119	0.103	-0.454	-0.183	-0.084	-0.054	0.092	0.545
Multiple R-squared	0.458		0.753							
Adjusted R-squared	0.450		0.672							
AICc	455.6		386.1							

***p<0.001

Table 4. Results of regression model of accessibility score (Toronto model): comparative summary of OLS and GWR models

Variables	OLS coefficients		GWR coefficients							
	B	SE	Mean	SD	Min	Q1	Median	Q3	Max	Range
Intercept	3.08***	0.222	2.51	0.86	0.87	1.75	2.35	3.47	3.81	2.943
Home Owners	-0.018***	0.002	-0.01	0.01	-0.03	-0.02	-0.01	-0.01	0.00	0.026
Lone Parents	-0.021***	0.006	-0.01	0.01	-0.03	-0.02	-0.01	0.00	0.00	0.037
Living Alone	-0.031*	0.013	-0.02	0.01	-0.04	-0.02	-0.02	-0.01	0.00	0.041
Recent Immigrants	-0.015**	0.005	-0.01	0.02	-0.04	-0.03	-0.01	0.01	0.02	0.061
No High-school	-0.015***	0.004	-0.02	0.01	-0.04	-0.02	-0.02	-0.01	-0.01	0.036
Multiple R-squared	0.290		0.471							
Adjusted R-squared	0.278		0.426							
AICc	523.700		460.600							

***p<0.001; **p<0.01; *p<0.05

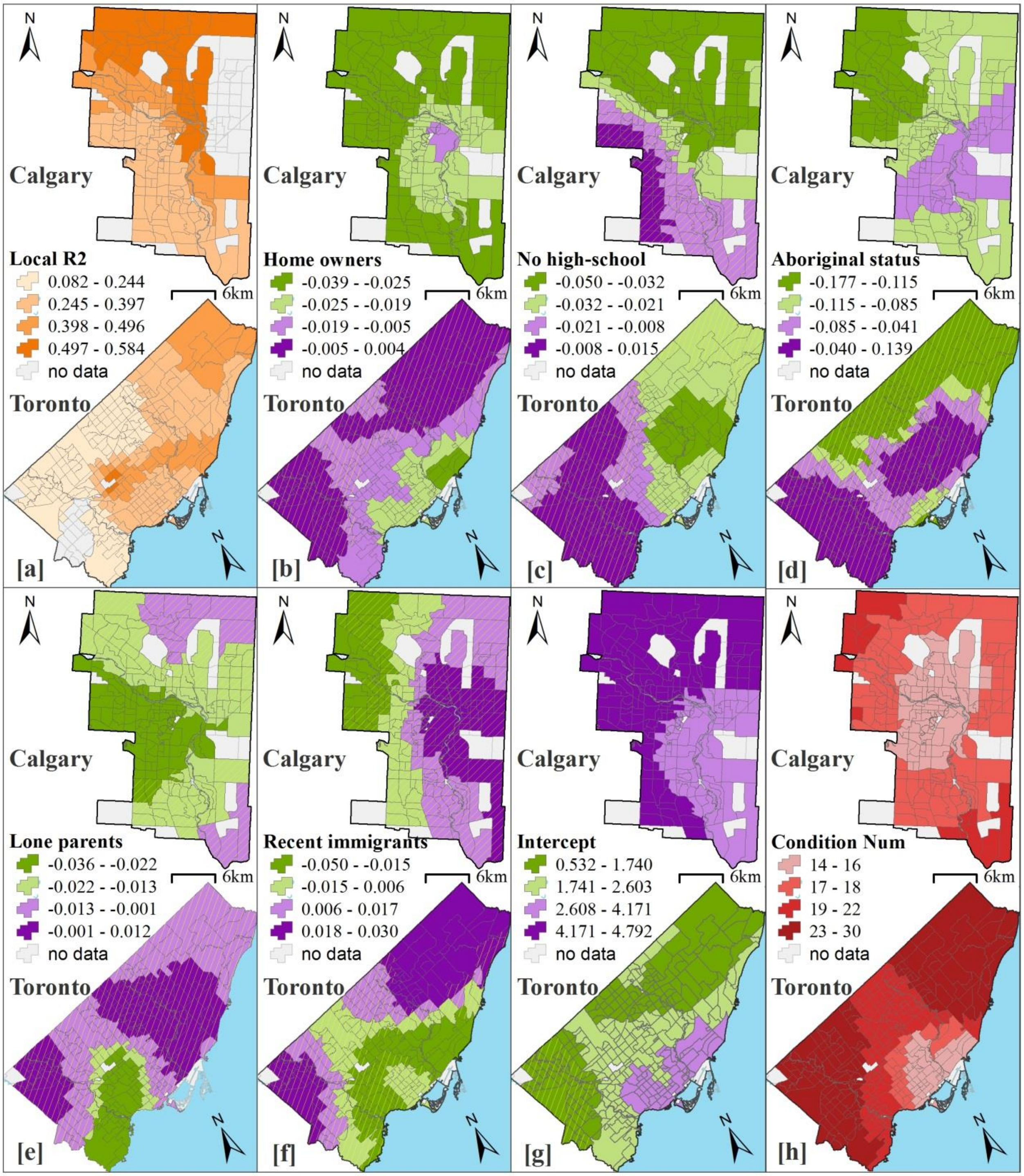

Figure 2. Multi-city model - the distribution of the GWR results: local R-square (a), coefficient estimates (b-g), and condition number (h). All maps are prepared using quantile classification scheme with four classes and hatch patterns are used to show the pseudo t-values range from -1.96 to 1.96

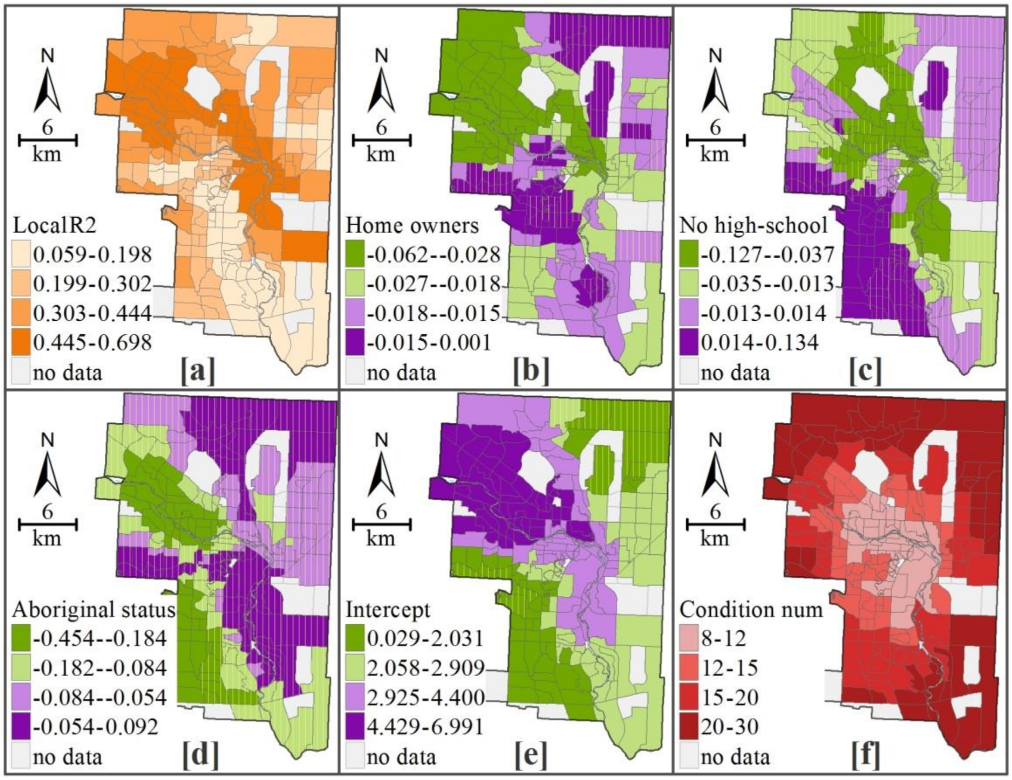

Figure 3. Calgary model - the distribution of the GWR results: local R-square (a), coefficient estimates (b-e), and condition number (f). All maps are prepared using quantile classification scheme with four classes and hatch patterns are used to show the t-values range from -1.96 to 1.96

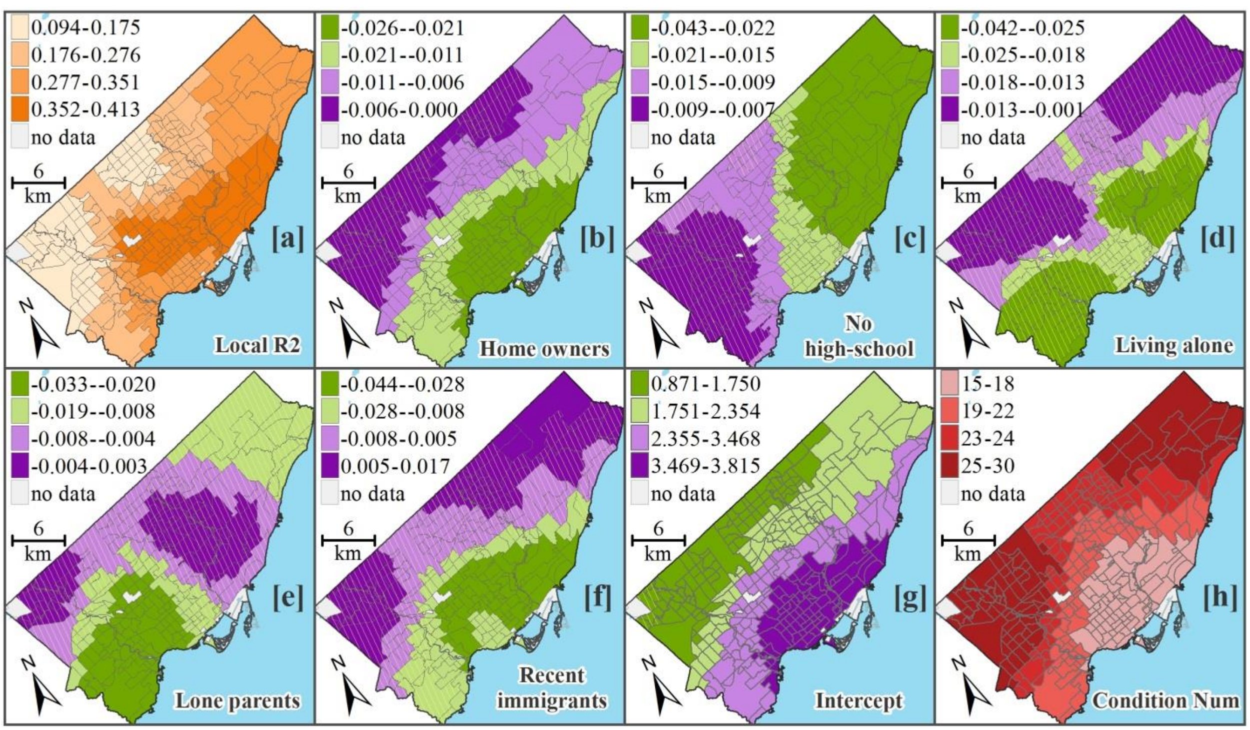

Figure 4. Toronto model - the distribution of the GWR results: local R-square (a), coefficient estimates (b-g), and condition number (h). All maps are prepared using quantile classification scheme with four classes and hatch patterns are used to show the t-values range from -1.96 to 1.96

4. DISCUSSIONS AND CONCLUSION

This study was designed to explore the intra-urban variations of geographical accessibility to PHC services in relation to various socio-demographic factors. To this end, geographically weighted regression was used to estimate coefficients for each neighbourhood in two urban Canadian settings. The results of the regression analyses that were performed in the two different settings are quite revealing on several fronts.

Based on the multi-city OLS model, a higher proportion of all five significant explanatory variables (as given in Table 2) are found associated with smaller accessibility scores (i.e., indicating poor geographic accessibility to PHC services). In this model, Toronto has a significantly negative influence (-45% on average) for accessibility scores compared to Calgary. Interestingly, a 10 percentage point change in any one of the significant predictors (except for aboriginal status) would result in an approximately 0.2 point change (i.e., 0.2 physicians per 1000 people). In the case of aboriginal status, the same 10 percentage point change would result in an approximately 0.9 point change in accessibility score. GWR estimates local coefficients for the same significant explanatory variables to examine variability across space. The coefficient estimates for the proportion of home owners in comparison to OLS (i.e., -0.023), range from -0.039 to 0.004 with a median of -0.019 (see Table 2). This indicates that the relationship between home owners and accessibility is not constant within study areas. What is interesting in the distributions of the local coefficients for this variable is that a stronger magnitude (first quarter, -0.039 to -.025) is observed in the neighbourhoods just outside the downtown area in Calgary whereas in Toronto, such patterns are found within downtown areas (see Figure 2b). The coefficient estimates for the proportion of the population aged 15 and over without their high-school certificate in comparison to OLS (i.e., -0.018), range from -0.05 to 0.015 with a median of -0.021 (see Table 2); this suggests variation of coefficients across the study area. A stronger magnitude in relation to accessibility score (-0.039 to -0.025 (first quarter)) can be seen in the northeastern and some parts of northwestern Calgary neighbourhoods; and in the case of Toronto, is clustered east of the downtown area (see Figure 2c). For the relationship between the proportion of aboriginal population and accessibility score, local coefficients range from -0.177 to -0.115, with interesting patterns observed in Calgary's northeastern neighbourhoods (Figure 2d). This indicates a stronger magnitude as compared to the OLS outcome (i.e., 0.089). The distribution of local coefficients for the proportion of lone parent families in relation to accessibility score are shown in Figure 2e, and display interesting patterns in southwestern neighborhoods along with a few downtown neighbourhoods in Calgary; whereas in Toronto, downtown and some southeastern neighbourhoods present stronger values (-0.036 to -0.022). The local coefficient estimates for the proportion of recent immigrants (2001 - 2006) in comparison to OLS estimates (i.e., -0.019), range from -0.050 to 0.030 with a median of -0.006 (see Table 2), indicating that the relationship of this variable with accessibility score is not constant across space. A stronger magnitude (0.018 to 0.03) is observed in the Toronto eastern neighbourhoods – specifically in the Scarborough district (see Figure 2f).

Based on individual models, three out of five significant variables (home owners, no high-school education, and aboriginal status) in the Calgary model and four out of the five significant predictors (all except for proportion of population aged 65 and over living alone) in the Toronto model are the same significant predictors as found in the multi-city regression model (see, Tables 3 and 4; Figure 3b-3c and 4b-f). In both city models, similar to the multi-city model, a negative association was recognized for all predictors in relation to accessibility score, however these involved different strength and ranges of the local regression coefficients. In the Calgary model, a large range of local coefficients is found in all three predictors that indicate stronger intra-urban variations in relation to accessibility score (see, Table 2 and 3). The Toronto GWR model presents smaller ranges in local coefficients (see, Table 2 and 4).

In all three cases, the GWR model that estimates model coefficients for each neighbourhood shows a significant improvement in model fitting over the OLS model. These findings enhance our understanding of geographic accessibility to PHC services (i.e., accessibility score). Associations with socio-demographic factors along with the intra-urban variations found highlight the significance of local spatial regression methods in disaggregating relationships at a local scale. These findings also suggest that a more careful modeling approach is required when analysing data with spatial effects. The findings of this study have a number of policy implications for improving geographic accessibility to PHC services with a focus on urban areas. The 3SFCA accessibility score should be measured on a regular basis to observe changes in the distributions of PHC services in association with socio-demographic characteristics. This study maps the local regression parameters and identifies hot-spots where more PHC resources are required in relation to population health care needs; enabling better data to be available to policy makers and city planners while designing programs to support, facilitate, and guide physicians in practice site identification. Future research should focus on how different units of analysis predict distribution of health care services in the context of modifiable social factors at a local scale.

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