GGR462 GIS Research Project

Professor Kristian Larsen

Demographic Change and Culturally Specific Restaurant Presence in Toronto Neighbourhoods

Chinatown & Danforth

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Contributors

M. Ma (Project Leader) led the ANOVA analysis and statistical model fitting, performed high-level exploratory analysis on restaurant data, acquired rent data from CHASS, integrated restaurant and census data for analysis, identified limitations of statistical models, and co-wrote methods, results, and limitations sections of the document. T. Scott (Database Manager) acquired census datasets (Language at Home, Ethnic Origin, and Income), created the project's custom study areas, digitized DMTI restaurant data, managed map creation, and assisted with manually coding the restaurants of Chinatown. B. Snow (Research Manager) led the literature review, cluster analysis, discussion, and conclusion components of the project, and the planning and organizing of group meetings and communications. He co-wrote the methods and results sections of the document. R. Spencer (GIS Analyst) coded restaurant data for the Danforth and provided spatial join to dissemination areas. He created the methods flowchart and wrote about the changes in methods, limitations, and manual coding procedures.

All contributors were involved in creating presentation slides and co-writing the final report.

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1. Literature Review and Statement of Problem

1.1 Introduction

Toronto has long been known as a gateway city for immigration, and currently has the highest proportion of foreign-born population of any city in Canada (Fong, 2014; Ontario Ministry of Finance, 2016). According to Fong (2014), immigration patterns into the city were traditionally thought to follow Burgess' (1925) succession model, where immigrants would move directly into the zone in transition before gaining the economic and social capital to move towards the outer edges. However, some newer ethnic enclaves are emerging in Toronto's suburbs, while many older enclaves in downtown Toronto have demonstrated retention of their cultural character in varying ways (including via Business Improvement Areas and continued presence of culturally specific restaurants), complicating Burgess' model (Hernandez & Jones, 2005; Luk & Phan, 2005; Hackworth & Rekers, 2005; Qadeer et al. 2010; Zhuang, 2019). These neighbourhoods can provide services that may be helpful to newcomers (such as language learning support), but also culturally relevant food, a sense of community, and a physical space for community organizing, which can be useful for newcomers and long-time residents alike (Collins, 2018; Wang, 2004). We used geographic information systems (GIS) and other statistical analyses to determine whether changes in independent, culturally specific restaurant presence in Toronto's Chinatown and Greektown align with demographic changes in these ethnic enclaves. While this was true for average rent price and language spoken at home in Chinatown, there was no significant correlation between neighbourhood demographics and culturally specific restaurants in Greektown. Given that these two neighbourhoods have distinct histories and

cultures, it is not unsurprising that there are different processes potentially occurring in Chinatown and Greektown.

1.2 Chinatown

While there has been significant Chinese immigration to Canada since the 1850s (with the construction of the Canadian Pacific Railway), the scale and other characteristics have changed over time (Lo & Wang, 1997). Chinese immigration grew exponentially in the 1960s and 1970s with the loosening of immigration laws (Lo & Wang, 1997). Re-development shifted the location of Toronto's initial Chinatown westward from the area centred around Bay and Dundas to that centred around Spadina and Dundas in the 1950s (Lo & Wang, 1997). The location continued to extend even farther west in the 1970s (Luk & Phan, 2005). Beginning in the 1980s, more and more Sino-Vietnamese immigrants settled in Toronto's Chinatown, with this diversification reflected through the 1990s and early 2000s, with more Vietnamese owned businesses and restaurants appearing towards the outskirts of Chinatown (Luk & Phan, 2005; Luk & Phan, 2008; Hyung, 2012).

1.3 Greektown

While both Chinatown and Greektown can be considered ethnic enclaves with clear cultural identities, they also both have distinct histories and distinct continuing processes. Greektown was established as a major place of settlement for Greek immigrants starting in the 1960s (Murdie & Teixeira, 2003). Murdie and Teixeira (2003) also noted that while by the 1990s much of the Greek settlement had shifted towards the suburbs, many Greek businesses remained. Hackworth and Rekers (2005) note that this incongruity is present not only in Greektown, but in

some of Toronto's other ethnic enclaves as well, attributing much of the remaining culturally-specific neighbourhood character to an attempt to market the space by Business Improvement Areas (BIAs).

1.4 Using the Literature to Inform Methods

Business composition analysis has been used to explore processes in various ethnic enclaves (Luk & Phan, 2005; Hackworth & Rekers, 2005), and Jeng (2010) specifically acknowledges the importance of food to cultural identity by analyzing restaurant locations and demographic change over time. Perez et al. (2019) used spatial analysis with immigration data to look at clustering in Montreal, while Lo and Wang (1997) have applied more straightforward census data analysis to studying Chinese ethnic enclaves. We applied similar methods in a Toronto context to answer our research question, by performing analysis of census data (similarly to Lo & Wang, 1997) and neighbourhood business/restaurant change analysis (much like Luk and Phan, 2005; Hackworth & Rekers, 2005) but with a more explicitly GIS based element such as that taken on by Perez et al. (2019).

2. Study Areas

2.1 Modifying Boundaries

Due to their general popularity and the existence of relevant literature, we have chosen Chinatown (excluding Kensington Market) and the Danforth, otherwise known as "Greektown" along Danforth Avenue, as our neighbourhoods of interest.

In working with these two neighbourhoods, we initially used Toronto's default neighbourhood shapefiles, which were found on the City of Toronto's Open Data portal. The resulting datasets were too general, exhibiting limited variability throughout our selected dataset years. Furthermore, both "Kensington-Chinatown" and the two neighbourhoods representing the Danforth, "Danforth Village East York" and "Danforth Village Toronto", lacked sufficient consideration of their important retail corridors. Finding Toronto's default neighbourhood borders inadequate for our project, we chose to create our own study areas with reference to Toronto's dissemination areas for the years of 2001, 2006, and 2016, which match our chosen census years (to be elaborated upon later). The mapping API Google MyMaps was used for creating the new study areas. The resulting custom borders were joined to dissemination areas using a Spatial Join in ArcMap.

As seen in Figure 2.1, "Kensington-Chinatown" is the Torontonian neighbourhood that includes the Chinatown intersection at Spadina Avenue and Dundas Street West. However, the neighbourhood also includes Kensington Market, which based on site visits, is an area with an identity that differs greatly from the Chinese-influenced Chinatown.

Chinatown Custom Borders, Toronto, Canada. 2001.

Figure 2.1. Toronto's Kensington-Chinatown neighbourhood. The neighbourhood's retail centre is located at the intersection of Spadina Avenue and Dundas Street West

In creating our own study area, we looked to focus in and around the neighbourhood's main intersection at Spadina Avenue and Dundas Street West, while also including nearby residential areas off of the intersection in order to extract needed census data. As seen in figure 2.2, we were able to successfully eliminate most of Kensington Market. In order to capture commercial spots, we aimed to have our borders cover both sides of Dundas and Spadina.

Chinatown Custom Borders, Toronto, Canada. 2001.

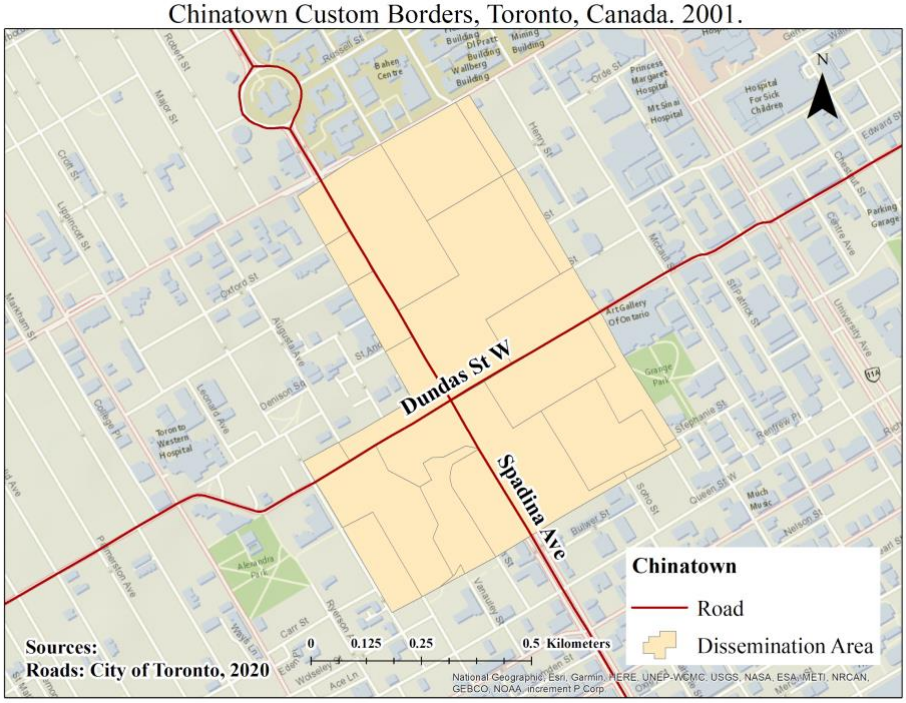

Figure 2.2. Our custom Chinatown borders

Our second study area is The Danforth, which Toronto divides in half between two neighbourhoods, as seen in figure 2.3. Although the "Danforth Village Toronto" captures stores on the northern side of Danforth Avenue, the southern side is left unaccounted for. Furthermore, neither neighbourhood captures the length of the Greektown retail strip, which stretches roughly from Broadview Avenue in the west through to the suburb of Scarborough in the east.

Danforth Custom Borders, Toronto, Canada. 2001.

Figure 2.3. Toronto's Danforth Village East York and Danforth Village Toronto neighbourhoods

In creating our custom study area for The Danforth, we chose to extend our borders to the west and east, attempting to capture as much of the retail strip along Danforth Avenue as possible. Similarly to Chinatown, we had our border overlap the area's arterial roads for restaurant gathering purposes. Finally, we extended our borders far to the north past O'Connor Drive in order to extract census data and to capture any outlying restaurants. Figure 2.4 shows off the significant number of changes made for our Danforth study area.

Danforth Custom Borders, Toronto, Canada. 2001.

Figure 2.4. Our custom study area for The Danforth-Greektown

As seen in Figure 2.5, our derived Danforth-Greektown border touches quite a few neighbourhoods, far beyond Toronto's two neighbourhoods representing the area. As we were looking to capture as much of the lengthy Greektown retail corridor as possible, running into nearby neighbourhoods was inevitable.

Danforth Derived Borders, Toronto, Canada. 2001.

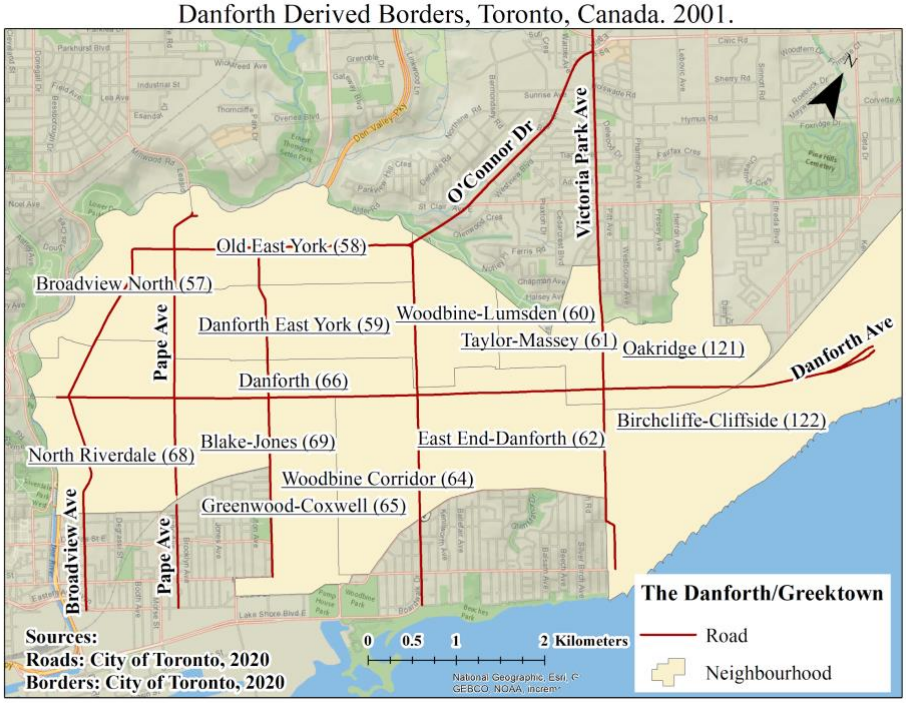

Figure 2.5. Neighbourhoods with portions found inside our custom Danforth study area (see Figure 2.4)

Due to their retail layouts, both study areas are vastly different in appearance and scale. As seen in Figure 2.6, The Danforth-Greektown custom study area is far larger than the Chinatown study area due to its long retail corridor. In comparison, the restaurants of Chinatown are much densely packed around the Spadina Avenue and Dundas Street West intersection. Despite their differences in size, we believe our chosen study areas are reflective of the retail and residential realities of both neighbourhoods.

Figure 2.6. The locations of our study areas in Toronto. Note the size differences between the two study areas

3. Data

3.1 Census Data Querying

Census data was gathered using the Computing in the Humanities and Social Sciences (CHASS) portal. Census data for the years of 2001, 2006, and 2016 included Median Household Income, Average Monthly Shelter Costs for Rented Dwellings, Chinese and Greek Ethnic Origin (20% data for 2001 and 2006, 25% for 2016), and finally, Language at Home data (20% for 2001 and 2006, 25% for 2016).

Initial tests for income used Average Household Income, which resulted in problematic and illogical income jumps between our census years. Median Household Income was eventually chosen, resulting in a smoother dataset.

Querying for Language at Home was more of an involved process, as there are a multitude of Chinese languages. Chinese languages chosen included:

- Mandarin
- Cantonese
- Hakka (2001)
- Taiwanese (2006 and 2016)
- Chinese, not otherwise specified (2001 and 2006).

It must be mentioned that these languages were not necessarily available across our chosen years, further complicating our census gathering process.

Languages were queried for dissemination areas. The previously-mentioned languages would have been selected and combined into a number via field modification and table additions in ArcMap. As the 2016 census included a combined “Chinese languages” option within its

Language at Home category, modifications for the year were minimal. Finally, each resulting table was joined to our custom Chinatown study area for the years of 2001, 2006, and 2016.

Greek was chosen for our Danforth-Greektown analysis. None of our census years included any Greek dialects, simplifying the process. Much like with Chinatown, Greek data for Language at Home was joined to our Danforth-Greektown study area for the years of 2001, 2006, and 2016.

Census datasets allow us to anticipate categories that may be significant in predicting any specific percentage of restaurants in Chinatown or Danforth-Greektown. As an example, figure 3.1 depicts a strong percentage of Chinese languages spoken at home within our Chinatown study area for the year of 2001.

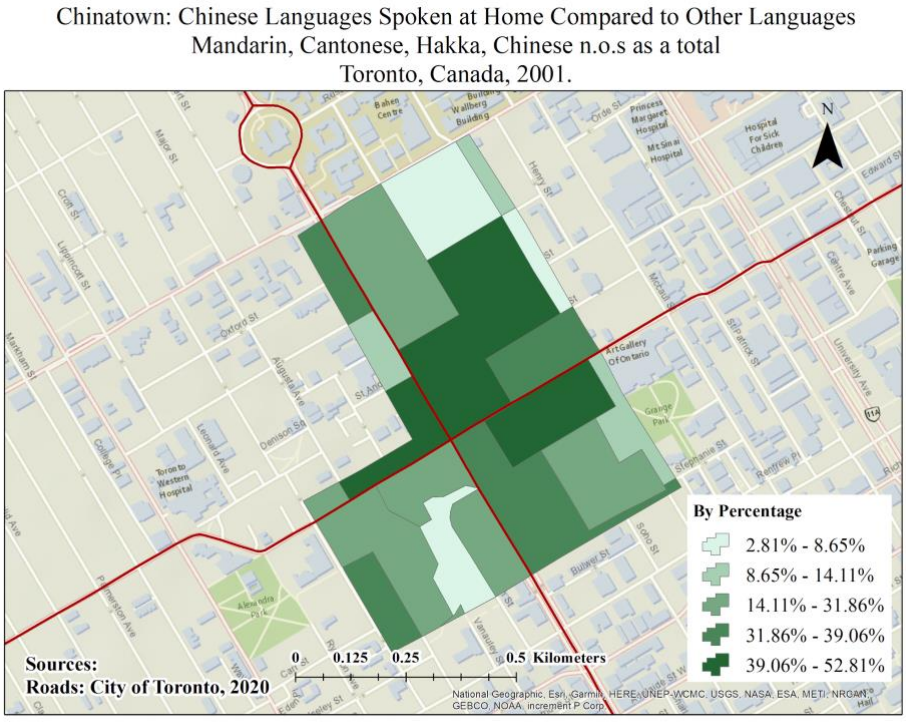

Figure 3.1. Chinese Languages spoken at home as a percentage for 2001 in Chinatown

We continue to see a strong percentage of Chinese languages spoken at home in Figures 3.2 and 3.3, which represent 2006 and 2016 respectively. As such, it becomes clear that Language at Home is an ideal candidate for evaluation for our final analysis.

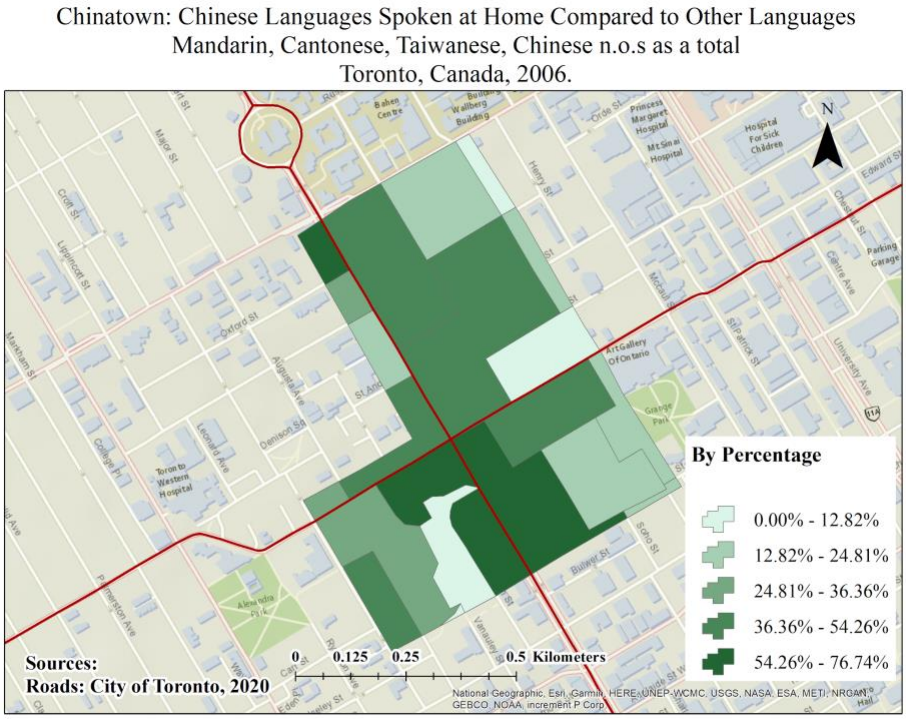

Figure 3.2. Chinese Languages spoken at home as a percentage for 2006 in Chinatown

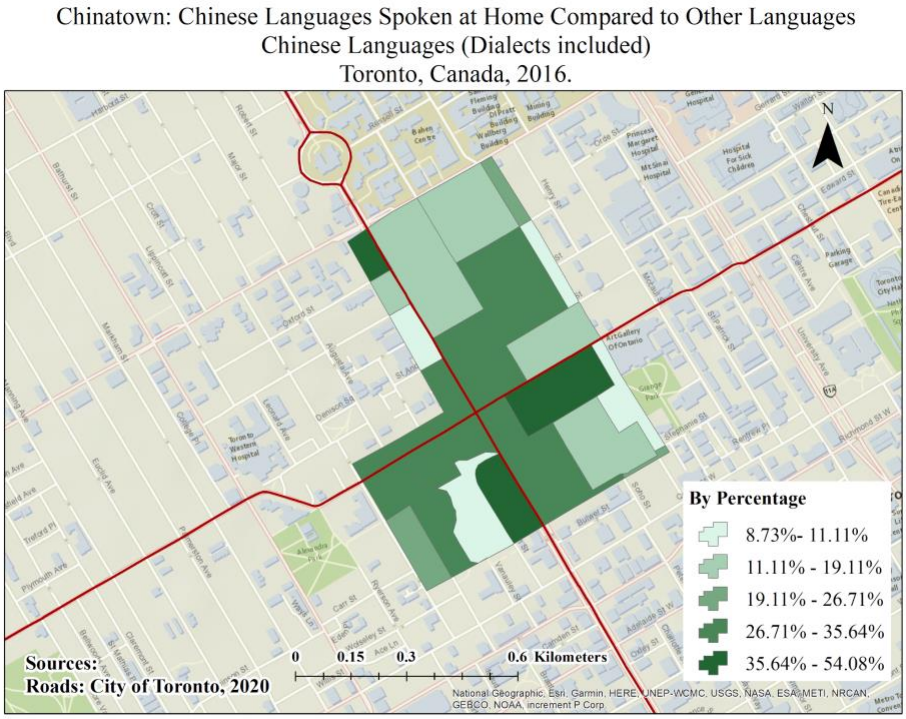

Figure 3.3. Chinese Languages spoken at home as a percentage for 2016 in Chinatown

3.2 Restaurant Data Gathering

DineSafe data for years prior to 2018 was unavailable, forcing us to rely upon DMTI Spatial's Enhanced Points of Interest (EPOI) for the years of 2002, 2006, and 2018. These chosen years were the closest to our selected census years of 2001, 2006, and 2016. The DMTI EPOI year of 2001 was ignored due to its lack of address points. Finally, we chose to use DMTI's 2018 dataset instead of 2016 due to wanting a newer and more substantive restaurant dataset.

3.2.1 Standard Industrial Classification Codes (SIC)

Standard Industrial Classification codes make up DMTI various EPOI categories, defining the type of industry existing in any specific location. For our project, we chose 5812 and 5813.

5812 codes include fast-food restaurants, sit-in restaurants, carry-out (takeout) restaurants, diners, and cafes (DMTI Spatial, 2002). 5813 codes include bars, night clubs, and taverns (DMTI Spatial, 2002). Although 5813 points were few, some of the existing points were indeed culturally specific to our observed ethnicity groups, justifying the code's inclusion.

We first converted our downloaded files to excel and ArcGIS compatible formats, such .csv and .dbf. Using Python, we then iterated through our "location" field, deleting points for municipalities and provinces outside of Toronto (Appendix 1). Afterward, the points were geocoded in ArcMap using the City of Toronto's Address Points dataset. Finally, we selected our 5812 and 5813 SIC categories and excluded the rest using ArcMap's "Select by Attribute" tool.

3.2.2 Manually Coding DMTI Data

DMTI is a private digital map production company, which is the "Canadian market leader in location based information and data quality" (Our Story, n.d.). DMTI data for Toronto includes restaurant names, addresses, and the aforementioned SIC codes. The DMTI data was manually coded as shown in Table 3.1, as the cultural specificity of the restaurants are not included in the dataset. In Chinatown, 35, 106, and 122 restaurants were coded in 2002, 2006, and 2018 respectively. Additionally, in Danforth (Greektown), 32, 276, and 447 restaurants were coded in 2002, 2006, and 2018 respectively. The three areas of interest which were manually coded for were as follows: Culturally specific to the neighbourhood of interest (Y/N), whether it

is a Chain (Y/N), and if neither Chinese nor Greek for each respective neighbourhood, what cultural cuisine does it represent if applicable. The first resource used for finding culturally specific restaurants using the name and address of the restaurants was websites such as Yelp, Zomato, Google Maps, and Yellow Pages. In most cases these websites would identify what type of cuisine the restaurant was serving. If that information was unavailable as shown in Figure 3.4, we would use personal knowledge from human experience of the restaurant to justify it's cultural specificity. Lastly, if no data was available, the name of the restaurant could be analyzed to determine cultural specificity by location names (Table 3.2), specific dishes (Table 3.3), and language/etymology (Table 3.4).

NAME	Greek	Chain	Culture
SIR GREEK & SIR SUB	2	1	
BLUE NILE RESTAURANT	1	1	ethiopian
UNITY CAFE CORP	1	1	indian

Table 3.1. Example of coding restaurants on Excel

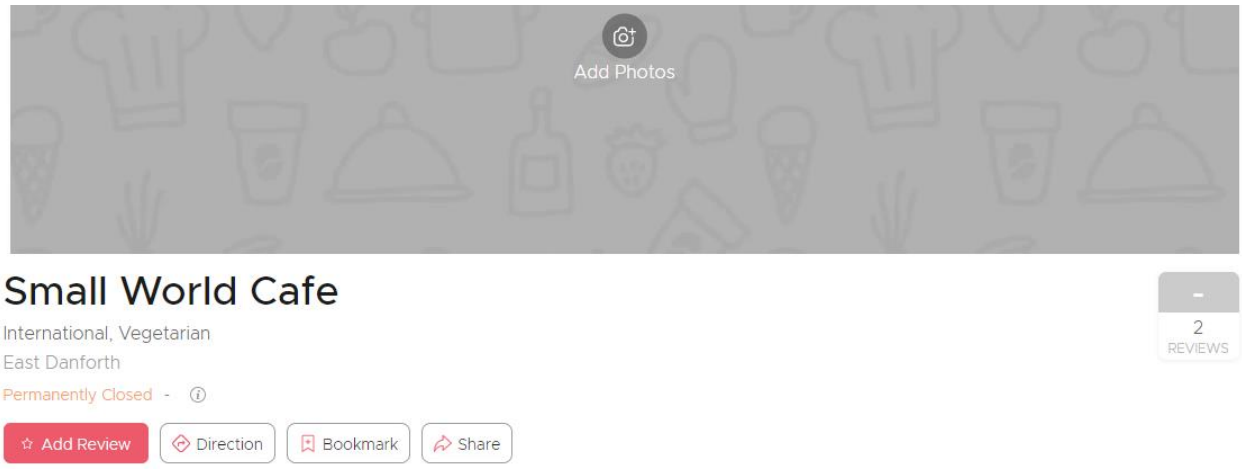

Figure 3.4. Example of Zomato page which does not have cuisine specificity available. Most restaurant pages on zomato included a specific culture in place of the word "international"

DJERBA LADOUCE CAFE	1	1	tunisian

Table 3.2. Djerba is an island in Tunisia, and Djerba Ladouce seems to be related to tourist locations such as resorts and hotels on the island

DANFORTH ROTI SHOP	1	1	indian

Table 3.3. Roti is a flatbread which is native to India

SPIROS KANELLOPOULOS	2	1	greek

Table 3.4. Kanellopoulos (Κανελλόπουλος) is a Greek surname meaning “son of Kanellos” and is the 169th most frequently identified with in Greece (Kanellopoulos, n.d.)

4. Methods

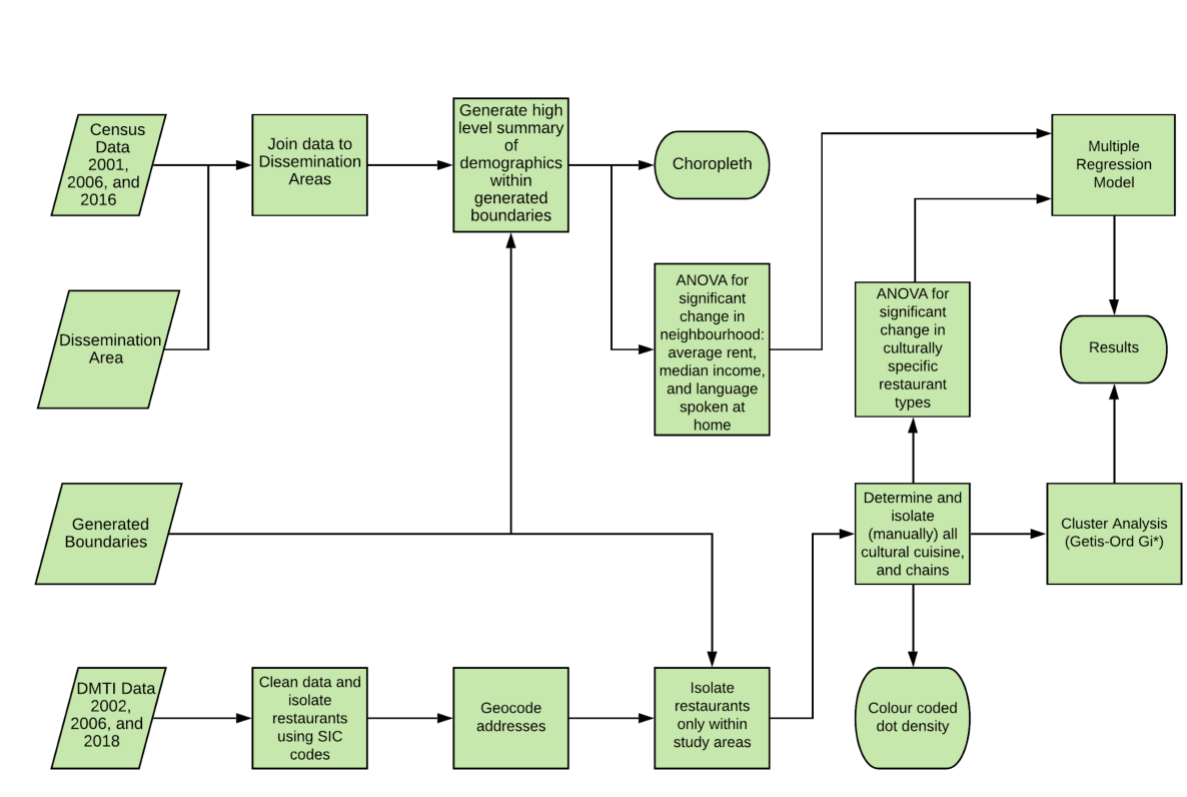

Figure 4.1. Flowchart illustrating the methodological approach

Our methods focus heavily on manipulation of Census data (years 2001, 2006, and 2016) and DMTI data (years 2002, 2006, 2018) separately before analyzing how they affect one another (see Figure 4.1). The census data was joined to the dissemination areas touching our newly generated boundaries. We then created a high level summary of the demographics within the generated boundaries and average rent, median income, and language spoken at home, which we visualized using choropleth maps and analyzed using ANOVA to determine significant change.

The DMTI data was isolated to establishments that serve food and drinks using SIC codes 5812 and 5813. The data was then further reduced by geocoding the addresses and removing all restaurants which fall outside of our generated boundaries. The data was then manually coded to find whether or not they are culturally specific to the neighbourhood of interest. We are also investigating the number of chains within the neighbourhoods, and what other cultural cuisines are most represented. We then visualized this using a colour coded dot density, and performed a cluster analysis (Getis-Ord Gi*) to explore where in our neighbourhoods these culturally specific restaurants were clustered. An ANOVA is used to justify significant change over the different time periods for the coded DMTI restaurant data. We then provide a Multiple Regression Model in order to analyze the relationship between the Census Data and DMTI Restaurant Data and justify our results.

4.1 Cluster Analysis

The hot spot analysis tool in ArcGIS online uses the Getis-Ord Gi* statistic to determine statistically significant hot and cold spots (clusters of high values and clusters of low values) (ESRI, n.d.). The software optimizes the distance at which nearby points are considered neighbours for each dataset, uses this weights matrix to run the Gi* statistic, and then applies a false discovery rate correction (ESRI, n.d.).

We performed cluster analysis on the restaurant data for each year (2002, 2006, and 2018) in both of our neighbourhoods to determine where the culturally specific restaurants were concentrated within the study areas. We did this by first joining the coded restaurant table with the DMTI spatial data and creating a new field, assigning culturally specific restaurants a value of 1 and all others a value of zero. We then ran the hot spot analysis on this field with the default

optimization settings. The output of this analysis is a point layer describing points where their neighbours have a significantly higher or significantly lower value than the overall dataset. We repeated this process to obtain results for each study area and each year of study.

4.2 Analysis of Variance (ANOVA)

Analysis of variance, also known as ANOVA, is a statistical method used to test differences between two or more group means with respect to a single variable. Inferences about means are made by analyzing variances. ANOVA asks the question whether the means vary so greatly between groups that they exceed individual differences within groups, or are the between-group variances big enough relative to the within-group variances to detect a difference.

We performed ANOVA on both the response variables- the percentage of Chinese restaurants in Chinatown and the percentage of Greek restaurants in Danforth, and the independent variables- language spoken at home, average rent, and median income, for both neighbourhoods. ANOVA allows us to answer the first research question: how have demographics and restaurant composition changed in Chinatown and Danforth over time?

4.3 Generalized Linear Mixed Model

Generalized linear mixed model enables the measure of individual and combined effects of various independent variables on a single dependent variable. This allows us to bridge the gap between restaurants and census data and generate predictions. We are able to predict the

proportion of cultural-specific restaurants based on demographic data over census years, including language at home, average rent, and median income, as well as quantitatively measure the causal intensity of each demographic variable on the outcome.

We fit two identical regression models for Chinatown and Danforth, using Chinatown and Danforth datasets, respectively. The generalized linear mixed regression models are as follows:

$$Y_{ij}|U_i \sim N(\mu_{ij}, \tau^2)$$

$$\mu_{ij} = X_{ij}\beta + U_i$$

$$[U_1, \ldots, U_M]^\tau \sim MVN(0, \Sigma)$$

$Y_{ij}$is the response variable, in our case, the percentage of Chinese/Greek restaurants for the $i$the dissemination area in jth year. X_{ij}has an intercept and an effect for median income, average rent, and language spoken at home. All dependent variables range on the scale from 0 to 100 since all covariates have been transformed to percentage format. $U_i$is the year jth baseline percentage and $\tau^2$is random chance and potentially other unmeasured confounders. We chose to account for variations in data across census years by assigning years random effects because some of the covariates change on statistically significant levels over time.

The above models allow us to answer the second research question: how has the number of culturally specific restaurants changed with census variables (language spoken at home, average rent, median income)?

5. Results

5.1 Restaurant Data

5. 1. 1 Overview

There are 35, 106, and 122 restaurants coded in 2002, 2006, and 2018 respectively in Chinatown and 32, 276, and 447 restaurants coded in Danforth in total, as figure 5.1 shows. The percentage of Chinese restaurants in Chinatown is 40%, 56%, and 51% in 2002, 2006, and 2018. The percentage of Greek restaurants in Danforth is 12%, 19%, and 15% in 2002, 2006, and 2018, respectively.

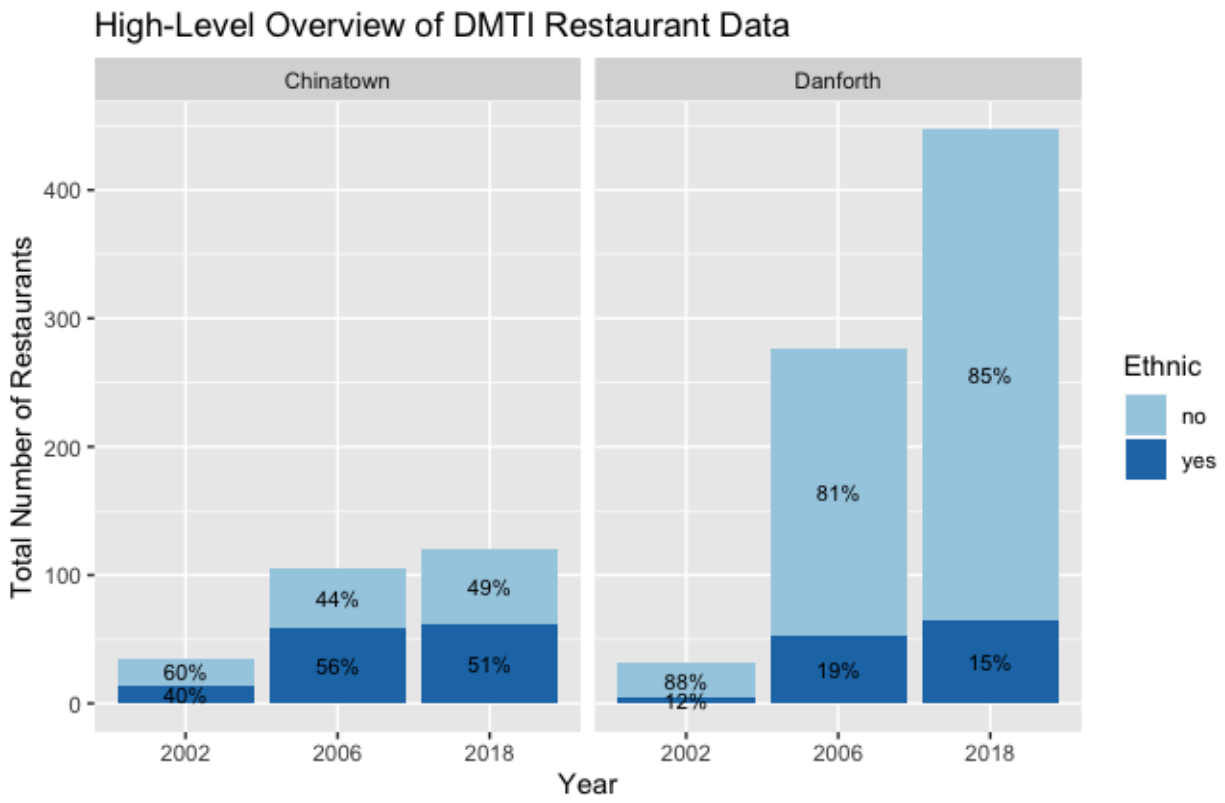

Figure 5.1. Stacked bar graph of DMTI restaurant data

5. 1. 2 Cluster Analysis

The output of our hot spot analysis using Gi* reveals differing results for Chinatown throughout the three study years. In 2002 there was significant clustering of Chinese restaurants (C.I. = 99%) on the stretch of Dundas between Spadina Ave and Beverly St, and a cluster of non-Chinese restaurants (C.I. = 95%) in the northeast portion of our study area (see figure 5.2). The hot spot analysis of the restaurant data from 2006 found no significant clustering in the neighbourhood (see figure 5.3). In 2018 there was some clustering of Chinese restaurants along the same stretch of Dundas between Spadina Ave and Beverly St as in 2002 (C.I. = 90%) (see figure 5.4).

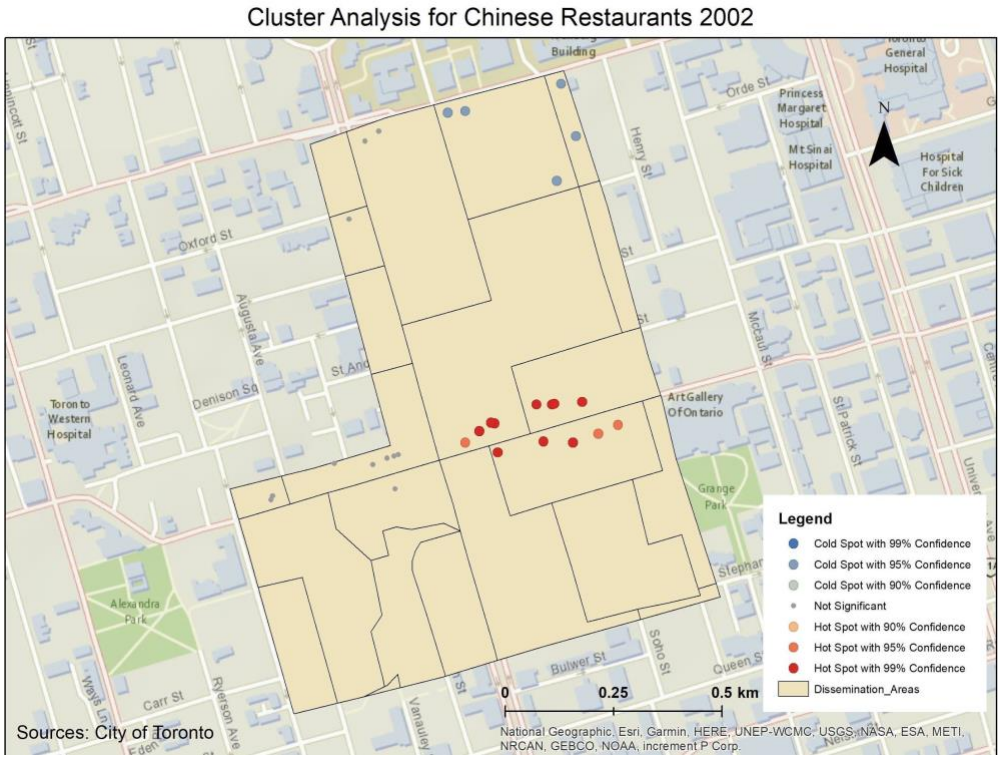

Figure 5.2. Significance of Clustering (Gi*) in Chinese Restaurants in 2002

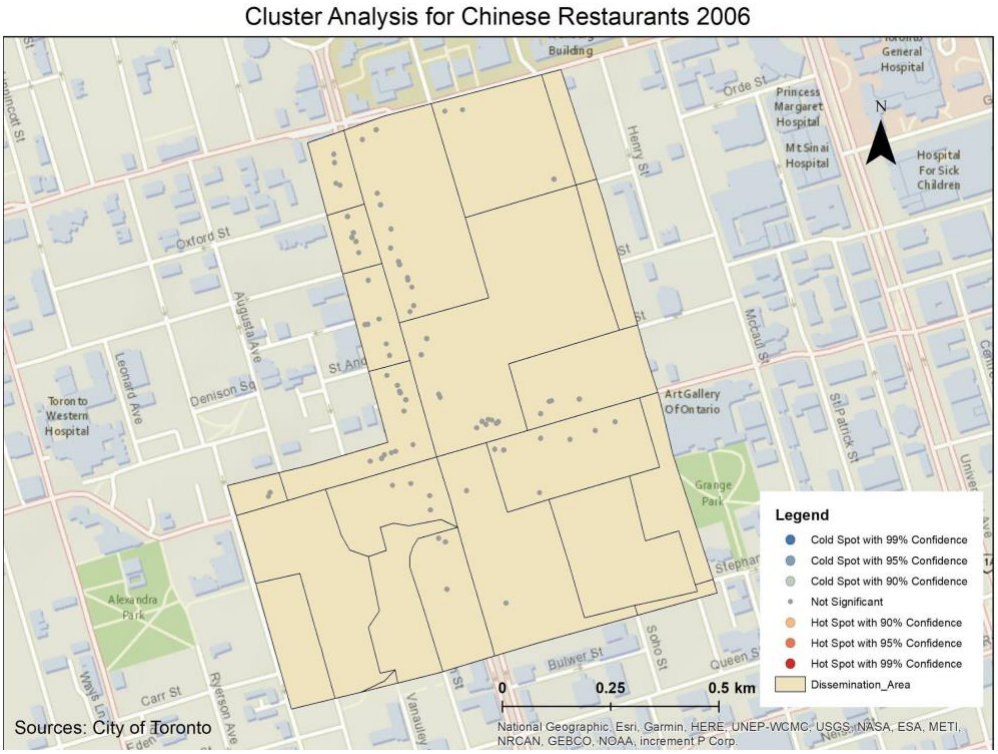

Figure 5.3. Significance of Clustering (Gi*) in Chinese Restaurants in 2006

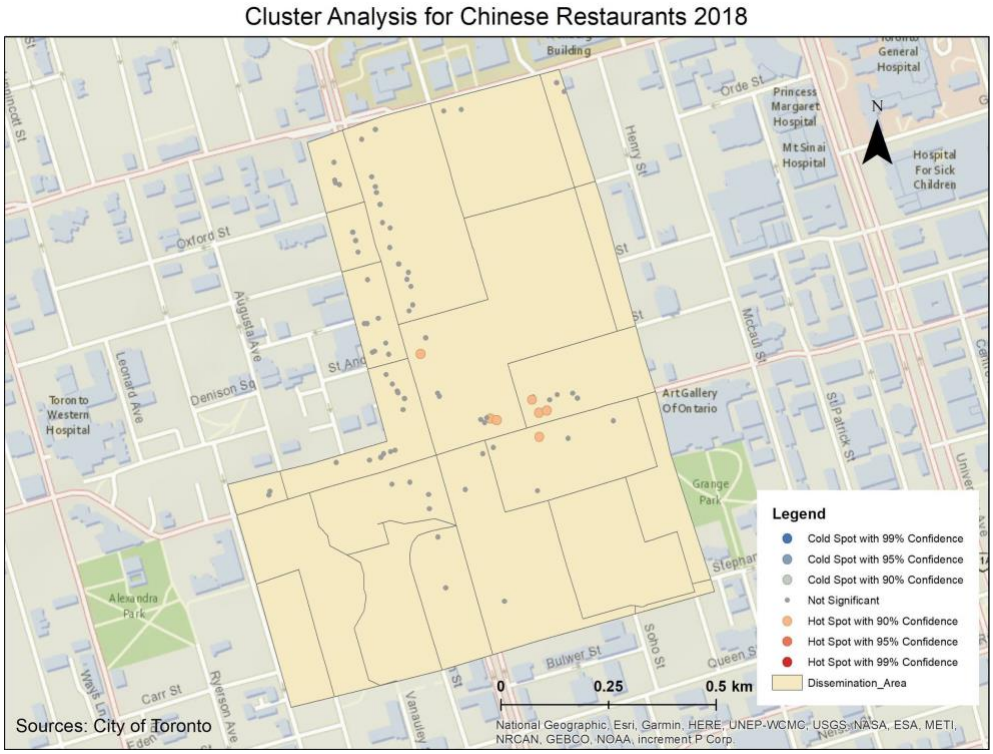

Figure 5.4. Significance of Clustering (Gi*) in Chinese Restaurants in 2018

The Gi* hot spot analysis output remains relatively consistent for the Danforth study area throughout the three study years. In 2002 there was some clustering of Greek restaurants right at the intersection of Danforth Ave and Pape Ave (C.I. = 95%) (see figure 5.5). In 2006 we saw slightly more intense clustering concentrated slightly further west along Danforth (C.I. = 95%) (see figure 5.6). Similarly in 2018, Greek restaurants were heavily clustered along Danforth from Hampton Ave. to Pape Ave (C.I. = 99%) (see figure 5.7). There are no significant cold spots in the Danforth analyses, indicating that other than the hot spots we previously identified, Greek restaurants were relatively dispersed throughout our study area.

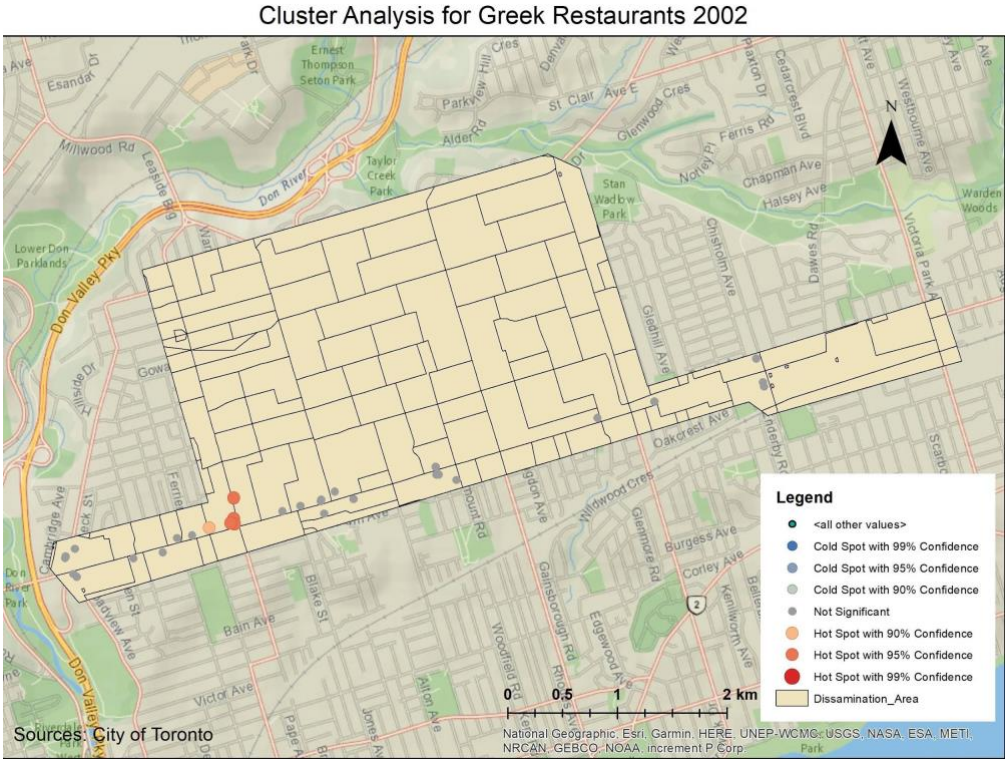

Figure 5.5. Significance of Clustering (Gi*) in Greek Restaurants in 2002

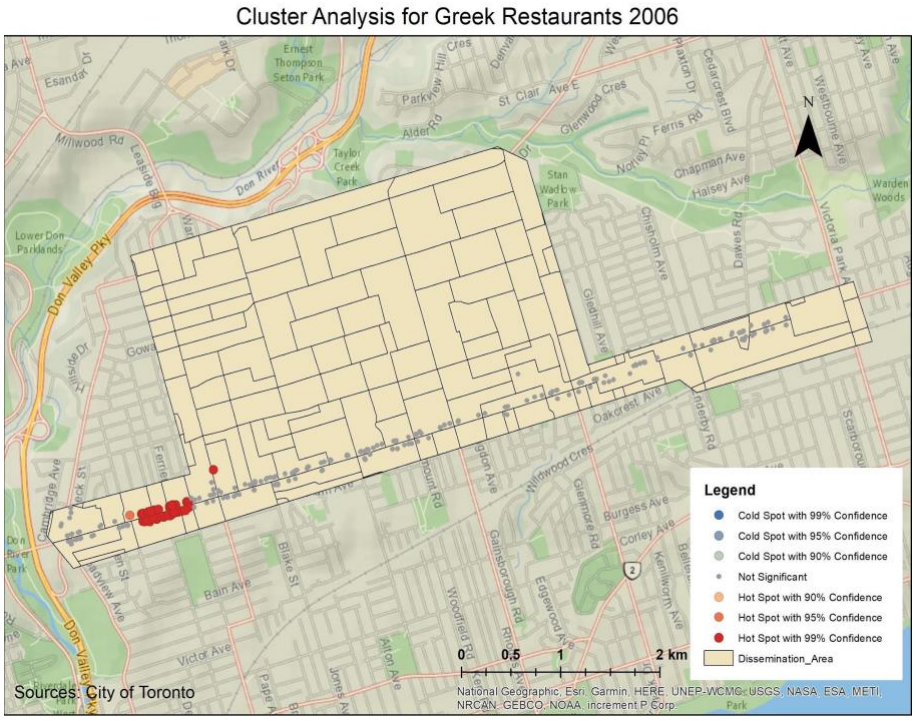

Figure 5.6. Significance of Clustering (Gi*) in Greek Restaurants in 2006

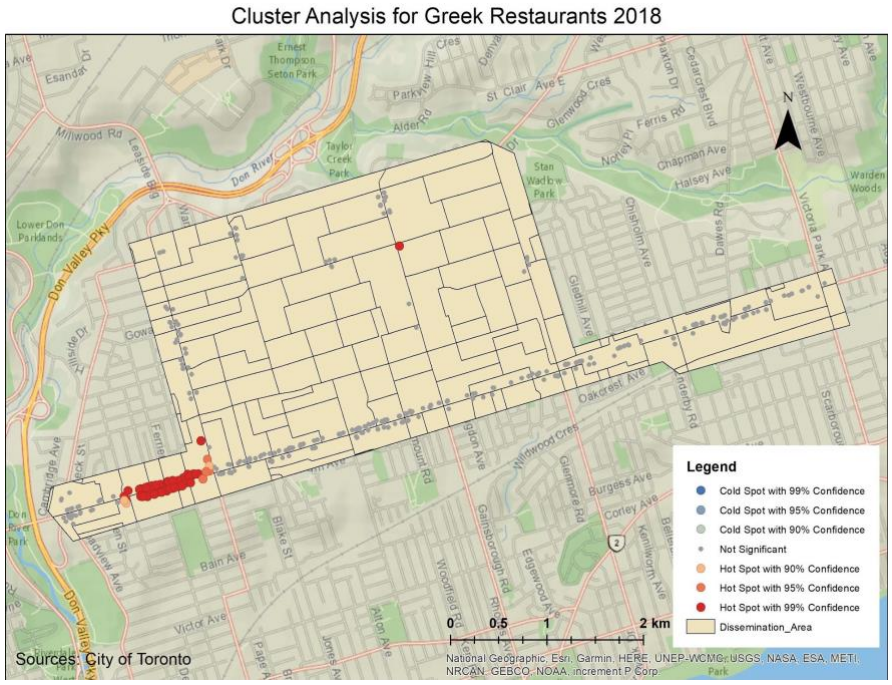

Figure 5.7. Significance of Clustering (Gi*) in Greek Restaurants in 2018

5. 1. 3 Analysis of Variance (ANOVA)

We performed two separate ANOVA tests on two response variables: percentage of Chinese restaurants within Chinatown and percentage of Greek restaurants within Danforth.

The null hypothesis is the percentage of Chinese restaurants within Chinatown is the same in 2001, 2006, and 2016 for Chinatown and the percentage of Greek restaurants within Greektown is the same in 2001, 2006, and 2016 for Greektown. The alternative hypothesis is that at least one year's restaurant composition is different from the others in either neighbourhood. Table 5.1 summarizes the result of ANOVA tests for Chinatown and Danforth.

Since both p-values are greater than the significance value 0.05, we fail to reject the null hypothesis. The percentages of Chinese and Greek restaurants in Chinatown and Danforth, respectively, do not fluctuate over census years on statistically significant levels.

	Chinese Restaurants in Chinatown	Greek Restaurants in Danforth
P-value	0.269	0.853

Table 5.1 Analysis of variance p-value results, percentage of Chinese restaurants in Chinatown and percentage of Greek restaurants in Greektown

5.2 Census Data

5.2.1 ANOVA

We performed six independent ANOVA tests on three covariates for Chinatown and Danforth datasets: language spoken at home (proportion of population speaking Chinese at home

within each dissemination area in Chinatown, proportion of population speaking Greek at home within each dissemination area in Greektown), average rent, and median income.

The null hypothesis is that the proportion of population speaking Chinese/Greek in Chinatown/Greektown, average rent, or median income is the same in 2001, 2006, and 2016. The alternative hypothesis is that at least one year's data is different from the others in either neighbourhood. Table 5.2 summarizes the result of ANOVA tests for Chinatown and Danforth.

Since both p-values are greater than the significance value 0.05 for language spoken at home, we fail to reject the null hypothesis. The proportion of the population speaking Chinese and Greek at home in Chinatown and Danforth, respectively, do not fluctuate over census years on statistically significant levels. Since all p-values are smaller than 0.05 for average rent and median income, we reject the null hypothesis. Average rent and median income in both Chinatown and Danforth increase significantly over at least two of three census years.

	Chinatown	Danforth
Language Spoken at Home	0.066	0.181
Average Rent	1.49e-06 ***	<2e-16 ***
Median Income	0.018 *	<2e-16 ***

Table 5.2. Analysis of variance p-value results, 2001, 2006, 2016 Canadian census data

5.3 Generalized Linear Mixed Model

We ran our models described above separately on both Chinatown and Danforth datasets. The response variables are the percentage of Chinese and Greek restaurants in Chinatown and

Greektown, respectively. The predictors are the proportion of population speaking Chinese or Greek at home, average rent, and median income. Year is our random effect accounting for potential variations over time.

The results for the Chinatown model (Table 5.3) show that average rent and language at home are statistically significant in predicting the percentage of Chinese restaurants in Chinatown. Given all other variables remain constant, for every 1% increase in rent, we anticipate a 0.63% increase in percentage of Chinese restaurants; for every 1% increase in the proportion of population speaking Chinese at home, we anticipate a 1.03% increase in the percentage of Chinese restaurants in the same dissemination area. Income does not have a significant effect on Chinese restaurants. Lastly, census year explains close to 0% of the variation we see in the model.

Random effects:		
Groups	**Name**	**Variance**
Year	(Intercept)	2.434e-07
Residual		535.800
Fixed effects:		
	Estimate	**Pr (> |z|)**
(Intercept)	-14.535	0.555
Income	-0.445	0.157
Rent	0.637	0.032 *
Language at Home	1.029	0.001 ***

Table 5.3. Generalized linear mixed model results, Chinatown

The results for the Danforth model (Table 5.4) show that none of the covariates, average rent, median income, and proportion of people speaking Greek at home are statistically significant in predicting the percentage of Greek restaurants in each dissemination area in the Danforth neighbourhood.

Random effects:		
Groups	**Name**	**Variance**
Year	(Intercept)	3.742e-03
Residual		701.100
Fixed effects:		
	Estimate	**Pr (> |z|)**
(Intercept)	22.412	0.054
Income	-0.064	0.760
Rent	-0.039	0.899
Language at Home	-0.182	0.817

Table 5.4. Generalized linear mixed model results, Danforth

6. Discussion

The more dynamic changes to Chinese restaurant distribution in Chinatown in contrast to the relatively static distribution of Greek restaurants in Greektown may be indicative of Chinatown as still a neighbourhood in flux regarding its status as a true ethinc enclave. The positive correlation between Chinese as language(s) spoken at home and proportion of Chinese restaurants may make intuitive sense. Speaking Chinese as a language at home may indicate more recent waves of immigration or a stronger identification with the culture and food, perhaps making someone more likely to open a Chinese restaurant. The positive correlation between average rent and proportion of Chinese restaurants was an unexpected finding. However, this could be indicative of the growing mainstream popularity of restaurants that are considered to serve "authentic" ethnic food (Tsai & Lu, 2012). This could lead to increased desirability of the neighbourhood and therefore increased average rent

A lack of significant change in demographic factors over time indicates that the Danforth neighbourhood has remained relatively stable since 2002. This may explain why the location of the clustering of Greek restaurants has also remained static. Although Hackworth and Reker (2005) noted both significant restaurant and demographic change from 1971 and 2001, it could be that this change has been in the process of levelling out over the following 16 years that we studied. The clustering of Greek restaurants is heavily concentrated within the Greektown BIA boundaries, which runs along Danforth, centred on Pape and extending east. These restaurants are likely established and stable, perhaps because of the marketing of the neighbourhood as ethnically Greek by the BIA.

7. Limitations

Our most significant limitations surround data availability as well as manual coding. The quantity of restaurants changed drastically over the three years being analyzed. This can be assumed to be an error in the DMTI data, as such a significant change seems unrealistic, although, we use proportions to make the data comparable and effective in our analysis. Dinesafe data would have been a more reliable data source to fix the issue of drastic changes in restaurant quantity, however this was inaccessible as Open Data Toronto is in the process of uploading historical Dinesafe data presently. The manual coding may incur unfactual descriptions on non peer reviewed websites like Yelp. Human error can also occur while coding as well as incorrect deduction of the cultural specificity of restaurants.

Our second limitation is due to small sample size. The assumption of a generalized linear mixed model requires our response variable, the percentage of Chinese/Greek restaurants in Chinatown/Danforth, to be normally distributed. Since we only have a limited amount of data, we decided to not run normality tests and preserve all data for analysis, resulting in the violation of model assumption. Furthermore, the clustering of restaurants result in zero restaurant counts in certain dissemination areas. This creates problematic results because by default the model omits all rows in the dataset with NA in any column, and some census data is omitted because NAs in restaurant data.

8. Conclusion

While our research certainly has its limitations, we have worked with available data to explore some of the potential trends occuring in perhaps two of Toronto's most well known neighbourhoods. Our results may be useful in informing further, in-depth quantitative or qualitative research in one or both of these neighbourhoods to explore the trends and processes that are happening on the ground. One particular example of an area for further research may be to explore the positive correlation between average rent and Chinese restaurant proportion in Chinatown.

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Appendix A

Example of the EPOI editing process for the year 2002. Cursors were used for all our chosen years.

```
# environment workspace
arcpy.env.workspace = "C:/Yr III/GIS Research Project/Dmti_data"
# Cursor Process
CAN_2002 = "C:/Yr III/GIS Research Project/DMTI 2002/CAN.dbf"
cursor = arcpy.da.UpdateCursor(CAN_2002, ["City"])
for row in cursor:
   if row[0] != "TORONTO":
      cursor.deleteRow()
del row
del cursor
```

Example of the EPOI editing process for the year 2002. Cursors were used for all our chosen years.