PEER-REVIEWED ARTICLE

Food Protection Trends, Vol 40, No. 4, p. 232–240

2900 100th Street, Suite 309, Des Moines, IA 50322-3855

Deborah Li Ting Ng,[1] M. Anne Harris,[1,2] Tor H. Oiamo[3] and Ian Young[1*]

[1*]School of Occupational and Public Health, Ryerson University, 350 Victoria St., Toronto, ON M5B 2K3, Canada
[2]Dalla Lana School of Public Health, University of Toronto, 155 College St., Toronto, ON M5T 3M7, Canada
[3]Dept. of Geography and Environmental Studies, Ryerson University, 350 Victoria St., Toronto, ON M5B 2K3, Canada

Spatial Distribution and Characteristics of Restaurant Inspection Results in Toronto, Ontario, 2017–2018

ABSTRACT

Food safety inspection data have been analyzed for relationships between violations and sociodemographic neighborhood factors, but spatial trends of inspection results have rarely been investigated. This study included a descriptive analysis, mapping, and identification of geo-spatial clustering patterns and hot spots of 2017/2018 restaurant inspection results (pass, conditional pass/closed) obtained from Toronto's public disclosure system. Negative binomial regression modeling was conducted to identify associations between census demographic information and the rate of conditional pass/closed outcomes. Of 5,950 first annual restaurant inspections performed in 2017, 5,510 (92.6%) restaurants passed, 438 (7.4%) attained a conditional pass, and 2 (0.03%) were closed. Of 6,457 first annual restaurant inspections in 2018, 5,907 (91.5%) restaurants passed, 540 (8.4%) attained a conditional pass, and 10 (0.15%) were closed. The Global Moran's I statistic showed positive and significant spatial autocorrelation ($P < 0.01$) of conditional pass/closed counts and percentages in both years. Additional hot spot analyses identified four and three census tract clusters in 2017 and 2018, respectively. Census-tract information on low-income households, immigration status, and non-official languages spoken at home were associated with rates of conditional pass/closed inspection outcomes. The findings provide insights into spatial characteristics of results of food premise inspections, which can inform food safety policy and practice.

INTRODUCTION

Geographic Information Systems (GIS) are tools that allow for the visualization, transformation, and analysis of data containing spatial and non-spatial attributes *(39)*. Applications of GIS in public health efforts have increased significantly over the past three decades, for example, as a surveillance tool for vector-borne diseases, a planning tool for analyzing the cost effectiveness of interventions, and an analytic tool for determining risk levels in sensitive populations *(12)*. In public health research, GIS has been

*Author for correspondence: Phone: +1 416.979.5000, ext. 557614; Fax: +1 416.979.5377; Email: iyoung@ryerson.ca

used to identify various correlations between environmental factors and health outcomes, such as foodborne illnesses and socioeconomic status *(1, 38)*, geographic factors affecting utilization of health services *(2)*, and built the environment and chronic disease *(25)*.

Routine food premise inspections are an important public health activity for providing snapshots of, as well as for improving the performance and safety of, food premises. Inspection reporting methods are standardized across local government jurisdictions but may vary slightly among countries, provinces, and states. The Toronto, Ontario, food safety inspection program, called DineSafe, has had its inspection results publicly available since its inception in 2001 *(37)*. Inspections identify minor, significant, or crucial infractions observed at the time of inspection. The type of infractions observed affect the premises' risk categorization (low, moderate, high) and establishment status (pass, conditional pass, closed) *(7)*. Risk categorization determines how often the restaurant should be inspected per year (1–3 times), and establishment statuses are issued as a green (pass), yellow (conditional pass), or red (closed) sign that must be publicly displayed near the restaurant's front entrance *(7)*. Restaurants are permitted to continue business operations if they pass inspection (zero infractions or only minor infractions observed), but if they receive a conditional pass (at least one significant infraction observed), they must correct the infractions within 24–48 hours in order to receive a pass upon re-inspection *(7)*. However, if they receive a closed result (one or more crucial infractions observed), they must cease all operations and correct all crucial infractions for re-inspection before being allowed to resume operation *(7)*.

Many restaurant characteristics affect food inspection results. For example, previous studies have investigated the impact of operator and restaurant ethnicity on the number of critical health violations *(15)*, the chain status of restaurants on violation type *(22)*, and food-handler certification of kitchen managers on the presence and type of violation *(3)*. Other studies have investigated whether inspections are influenced by the characteristics of the inspectors themselves, such as the gender of the inspector *(19)* or potential inspector biases that are knowingly or unknowingly present *(20, 26)*. However, few researchers have investigated whether spatial characteristics such as location or neighborhood attributes are associated with inspection outcomes in restaurants.

Lee et al. investigated locational factors in Miami hotel restaurants and reported that high proximity to beaches and downtown cores was associated with increased rates of critical food safety violations, whereas high proximity to airports was associated with decreased rates *(21)*. Darcey and Quinlan investigated neighborhood socioeconomic factors in Philadelphia restaurants and reported that a higher frequency of inspections was associated with high poverty rates and high concentrations of minority populations *(9)*. They also found increased rates of critical health violations in specific groups of ethnic restaurants located in census tracts with higher proportions of minority populations, a trend observed in food stores (grocery stores) as well *(9)*.

The purpose of this study was to investigate the spatial distribution of restaurant inspection results in Toronto, Ontario, and to investigate possible associations between census tract demographic information and the rate of conditional pass/closed (CP/C) inspection results. To achieve these objectives, we performed a simple descriptive analysis of inspection outcomes in 2017 and 2018; a spatial autocorrelation test to determine whether substandard inspection outcomes were clustered or randomly distributed across Toronto; a hot spot analysis to identify the locations of substandard outcome clusters; and negative binomial regression modeling to identify associations with CP/C inspection rates. This study demonstrates the potential for GIS to be used as a tool to inform public health and food safety efforts and planning.

METHODS

Data acquisition and organization

The DineSafe database, obtained from the City of Toronto's Open Data Catalogue *(8)* on January 3, 2019, contained 89,757 entries from November 28, 2016 to January 3, 2019. The database is updated in real time, but contains results dating back only approximately 2 years, depending on the date of access. It contains inspection details of any food premises within the boundaries of the City of Toronto and includes the address, GIS coordinates, infraction details, infraction severity, risk categorization, and inspection outcomes.

The DineSafe database records at least one entry for each inspection. If one inspection has multiple violations, each unique violation is recorded as a separate entry with the same inspection details (i.e., date, location, outcome). For the purposes of this study, we were only interested only in the inspection outcome. Therefore, duplicate entries containing extra infraction details (n = 37,186) were dropped by retaining only the first entry for each inspection. Next, any food premises that were not labeled as "restaurant" were removed (n = 26,619), as were any inspections performed in 2016 (n = 4,022). Finally, if a restaurant had more than one inspection performed within each year, entries on all of the subsequent inspections for that year were removed (2017: n = 7,108; 2018: n = 6,437) to ensure inclusion of results of only one inspection per restaurant per year. This left an analytic dataset consisting of 5,950 inspection results for 2017 and 6,457 results for 2018.

Data mapping

Census tracts were selected as the geographic unit of analysis. One census tract typically contains between 2,500 and 8,000 residents, and the boundaries are rarely changed *(34)*. Boundaries are based on road networks and natural features, and in large urban centers with high population densities such as Toronto, they are relatively compact and socioeconomically homogenous *(34)*. This makes collected census data representative and comparable among tracts. Each tract has a unique identifier, allowing for other tabular data to be joined by corresponding identifiers. The GIS program ArcMap 10.6.1, from the Environmental Systems Research Institute (ESRI, Redlands, CA, United States), was used to consolidate and map data.

Census tract and public health unit digital boundary files were obtained from Statistics Canada *(35, 36)*. Any census tracts falling outside the boundaries of Toronto Public Health Unit (which follows the same boundaries of the City of Toronto) were removed. The locations and outcome types of each inspection were shown visually by importing each year's outcomes as separate tables to ArcMap and then geocoding the coordinates as separate map layers. The number of first annual inspection outcomes per census tract was then counted by spatially joining the restaurant coordinates of each inspection outcome to its respective tract. Since the number of inspections with closed results was very low (2017: n = 2; 2018: n = 10), the results of these were combined with the conditional pass results for all further analysis. The percentage of CP/C results per census tract was calculated for each year using the total count of first inspections for each census tract as the denominator.

To visually display the rates of CP/C per census tract across Toronto, two maps were created for each study year (2017 and 2018). The first set of maps was created by using equal interval classification and the second set by using the Jenks natural breaks algorithm. Equal interval classification was used to create five equally defined classes to facilitate relative comparisons across years and to other maps, and the Jenks natural breaks algorithm was used to calculate five classes that best visually represent the data within each map. The Jenks natural breaks calculation divides continuous data into groupings that are most similar within groups, while maximizing differences across groups. This allows for a more meaningful representation of data values that are not evenly distributed *(10, 11)*.

Spatial analysis

The Global Moran's I statistic was used to measure the overall spatial pattern of how higher and lower rates of CP/C results were distributed by census tract. This statistic uses the set of features and the associated attribute to calculate whether the distribution pattern is clustered, dispersed (high and low values evenly spread), or random *(13)*. Moran's index value is calculated, along with a z-score and *P*-value, to identify the significance of the index. A significant and positive index value suggests that adjacent observations are highly likely to be similar.

To test for and identify local clustering, Getis-Ord Gi*, also known as hot spot analysis, was used. This statistic indicates whether a feature is a significant hot spot by proportionally comparing the local sum of the target feature and its surrounding features to the sum of all features *(28)*. If the difference between the observed local sum and the expected local sum is too large to be due to chance alone, a statistically significant z-score is obtained.

Regression modeling

Negative binomial regression analysis was conducted to detect associations between selected census-tract demographic variables and the rate of CP/C results per census tract *(24)*. The outcome for these models was the number of CP/C instances per number of first restaurant inspections across the two study years. Prior to this analysis, census tracts with zero restaurants in either study year were excluded, resulting in a sample size of 469. Negative binomial models were calculated instead of Poisson, as preliminary modeling indicated significant over-dispersion.

Census 2016 demographic data collected at the census tract level was obtained from the City of Toronto *(6)*. The following demographic variables were selected for evaluation in a series of bivariate models: population density per square kilometer; median age; prevalence of low income households. based on the low-income measure, after tax (LIM-AT); prevalence of immigration status households; prevalence of households using a nonofficial Canadian language (i.e., other than English or French) most often at home; and prevalence of labor households working in the accommodation and food service sectors (North American Industry Classification System, NAICS, 72). The LIM-AT variable, calculated by Statistics Canada, considers households to be low-income status if they fall significantly below the median income of all households in Canada. A combination of continuous *P*-values and 95% confidence intervals were used to assess the statistical and practical significance of each relationship. Regression coefficients were expressed as incidence rate ratios (IRR). Given that this was an exploratory analysis, we did not construct a multivariable model. Pearson correlation coefficients were also calculated between each pair of demographic variables. Regression modeling was conducted using Stata IC (Version 14.2).

RESULTS

Descriptive analysis of inspection results

Of the first annual inspections performed in 2017 (n = 5,950), 92.6% resulted in a 'Pass,' 7.4% resulted in a 'Conditional Pass,' and 0.03% resulted in a 'Closed' result. Of the first annual inspections performed in 2018 (n = 6,457), 91.5% resulted in a 'Pass,' 8.4% resulted in a 'Conditional Pass,' and 0.15% resulted in a 'Closed' result.

Of the 572 census tracts located in the Toronto Public Health Unit, 93 (16.3%) did not contain any inspected restaurants in 2017, and 97 (17.0%) did not contain any inspected restaurants in 2018. Among the 469 census tracts with at least one inspected restaurant in both study years, the median number of restaurants was 8 in each year (range 1 – 225 in 2017 and 1 – 253 in 2018). The average CP/C rate per number of inspections in these 469 tracts was 0.07 (SD = 0.14) in 2017 and 0.09 (SD = 0.15) in 2018.

Spatial analysis

The geographic distribution of CP/C results as a percentage of the number of inspections in each census tract in 2017 and 2018 is shown in *Figure 1.* (Equal interval classification) and *Figure 2.* (Jenks natural breaks). The distribution and number of census tracts within each class varies greatly between the classification methods — the maps are less nuanced when represented as five equal intervals *(Fig. 1)*. In contrast, the results of the Jenks natural breaks method showed that the lowest natural grouping was 0.0–4.2% CP/C in 2017 and 0.0–4.4% in 2018, and that the highest natural grouping was 44.5–100.0% in 2017 and 66.8–100.0% in 2018 *(Fig. 2)*.

The Global Moran's I results showed that high rates of CP/C counts and percentages were significantly clustered in both years, as all calculated index values were positive, with positive z-scores and significant *P*-values *(Table 1)*. The hot spot analysis of CP/C percentage revealed significant local clusters of high values in both years *(Fig. 3 and 4)*. Red gradients denote high value features surrounded by other high values, and blue gradients denote low value features surrounded by other low values. The more intensely high or low values cluster together, the higher the significance and darker the color of the census tracts. In 2017, four distinct hot spot clusters with 99% significance were identified. Each cluster spanned 2 to 8 census tracts toward the north part of Toronto and 3 to 16 census tracts toward the east side of the city. In 2018, three distinct hot spot clusters with 99% significance were identified, only one of which overlapped with a previous year's cluster. One cluster spanned 29 census tracts, the majority of which were toward the north end of the city.

Regression modeling

The correlation matrix between each pair of demographic variables examined by negative binomial regression is shown in *Table 2*. Immigration status and non-official language spoken at home were very highly correlated ($r = 0.916$), while the LIM-AT variable was also strongly correlated with these two variables and with the percent of the labor force working in the accommodation and food service industries *(Table 2)*.

The results of the negative binomial regression analyses are shown in *Table 3*. Census tracts with a higher percentage of

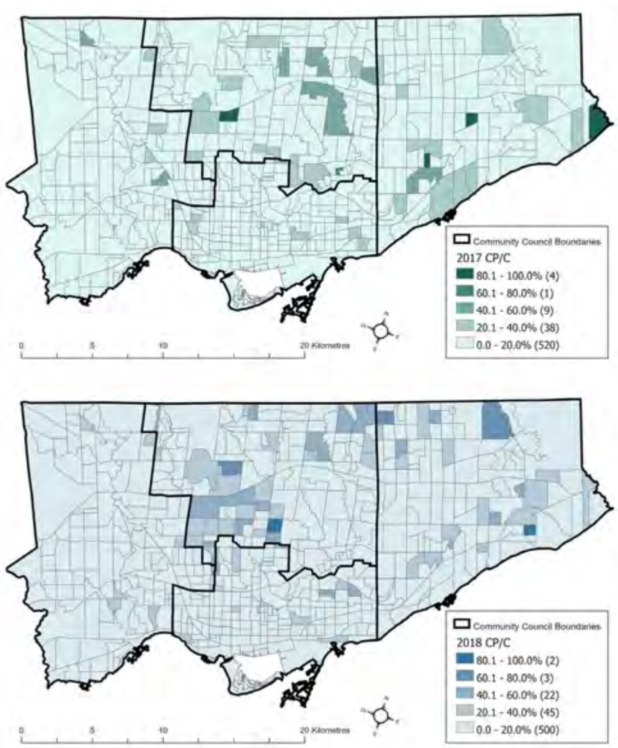

FIGURE 1. Percent of CP/C inspection results per number of inspected restaurants by census tract in Toronto, Ontario, 2017/2018; classified with equal intervals. Numbers in brackets represent the number of census tracts within that classification.

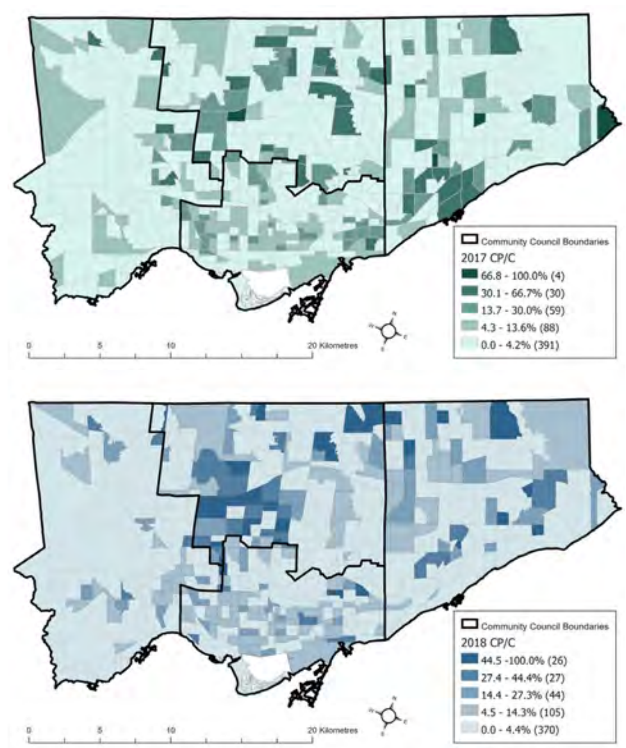

FIGURE 2. Percent of CP/C inspection results per number of inspected restaurants by census tract in Toronto, Ontario, 2017/2018; classified with Jenks natural breaks algorithm. Numbers in brackets represent the number of census tracts within that classification.

TABLE 1. Spatial distribution of CP/C restaurant inspection results in Toronto in 2017 and 2018, as measured by Global Moran's I

Year	Outcome	Moran's index	z-score	*P*-value
2017	CP/C count	0.195	12.233	< 0.001
	CP/C %	0.038	2.461	0.014
2018	CP/C count	0.170	10.990	< 0.001
	CP/C %	0.078	4.910	< 0.001

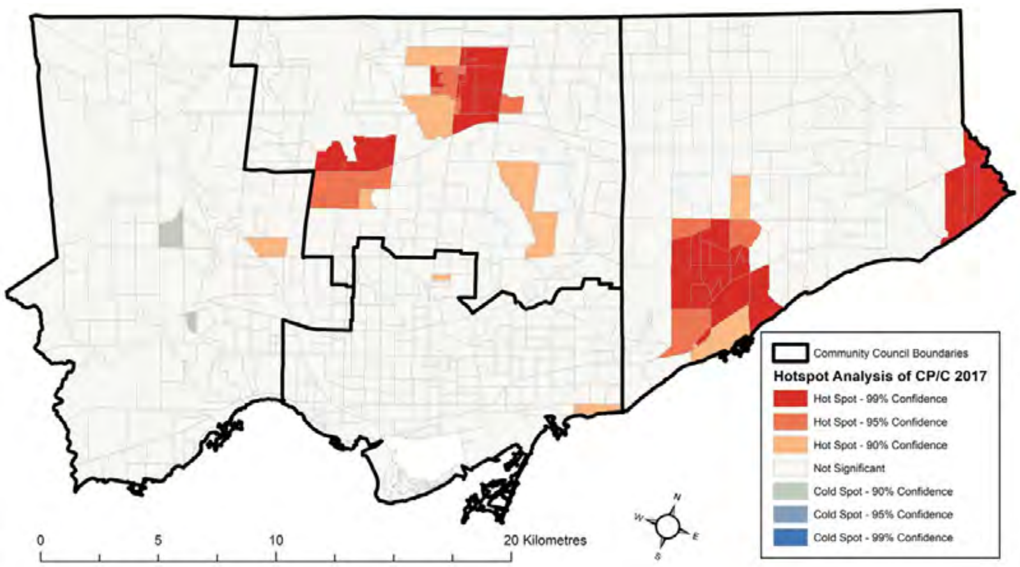

FIGURE 3. CP/C spatial hot spots in Toronto, Ontario, 2017.

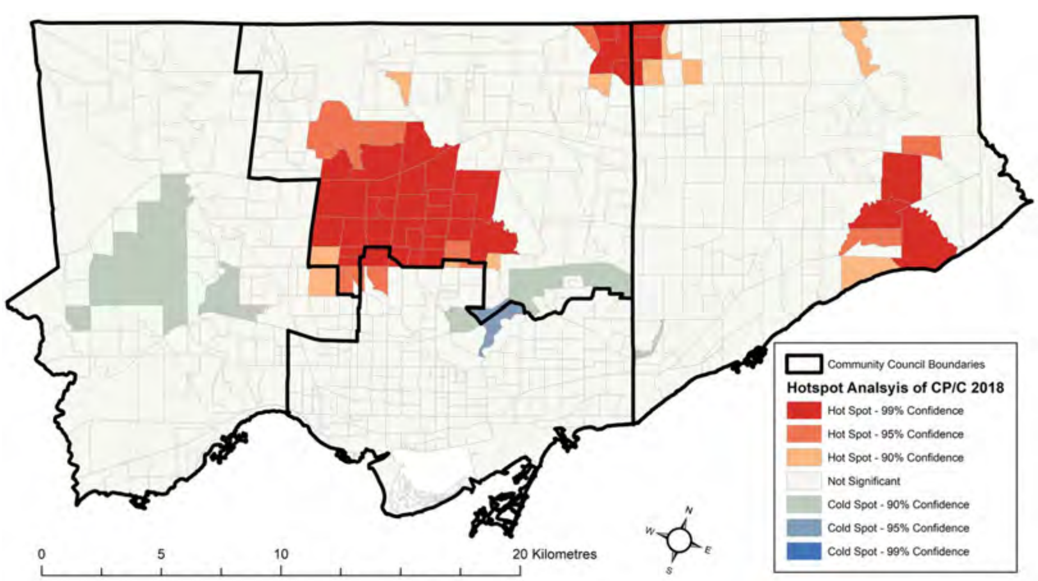

FIGURE 4. CP/C spatial hot spots in Toronto, Ontario, 2018.

TABLE 2. Pearson correlation matrix for 2016 census-level demographic variables in Toronto

Variable	POP	AGE	LIM	IMM	LAN	LAB
Population density per km^2 (POP)	-					
Median age (AGE)	-0.377	-				
Low-income measure (LIM)	0.378	-0.359	-			
Immigration status (IMM)	0.012	-0.018	0.511	-		
Non-official language spoken at home (LAN)	0.074	-0.019	0.519	0.916	-	
Labor population working in accommodation and food service (LAB)	0.172	-0.155	0.502	0.309	0.415	-

TABLE 3. Bivariate negative binomial regression modeling results of the association between census-level demographic variables and the rate of CP/C instances per census tract (n = 469)

Variable	IRR	95% CI	*P*-value	Alpha[a]
Population density (per km^2)	1.000	1.000, 1.000	0.485	0.445
Median age	1.011	0.996, 1.027	0.146	0.434
Low-income measure (LIM-AT)	1.013	1.002, 1.023	0.013	0.426
Immigration status	1.014	1.008, 1.021	< 0.001	0.389
Non-official language spoken at home	1.015	1.008, 1.022	< 0.001	0.388
Labor population working in accommodation and food service	1.012	0.983, 1.041	0.430	0.445

CI = confidence interval; IRR = incidence rate ratio

[a]This value is the over-dispersion parameter, which would equal zero if over-dispersion were not present (i.e., a Poisson model). In all models, the parameter was significantly different from zero ($P < 0.001$) with use of a likelihood ratio test.

households that are classified as immigrants (IRR = 1.014, 95% CI = 1.008, 1.021) and that speak non-official languages at home (IRR = 1.015, 95% CI = 1.008, 1.022) were associated with higher rates of CP/C outcomes across both study years *(Table 3)*. A similar association was found with regard to the percentage of low-income households (LIM-AT) *(Table 3)*. For a 10% increase in these variables in a census tract, the rate of CP/C outcomes increased by a factor of 1.15 (immigration status, 95% CI = 1.08, 1.23), by a factor of 1.16 (non-official language, 95% CI = 1.09, 1.25), and by a factor of 1.14 (LIM-AT, 95% CI = 1.03, 1.26). Population density was not related to the CP/C rate in a census tract, while median age and the percentage of working households employed in accommodation and food service were not consistently associated, with 95% CIs crossing the null *(Table 3)*.

DISCUSSION

Our results contrast with Lee et. al's spatial analysis of Miami restaurants *(21)*; we did not identify Toronto's waterfront and downtown core areas as significant hot spots, or the areas near the island airport as a significant cold spot. In 2017, we found, with 99% confidence, that two of four hot spot clusters were located along the eastern shoreline. They overlapped with two of 11 public beaches in the city. However, in 2018, the only hot spot identified with 99% confidence along Toronto's waterfront did not overlap with any public beaches. Additionally, no hot spots of any significance were identified within the core downtown of Toronto in either year, although a few hot spots were identified around the edges in both years. These findings suggest that the distribution of restaurant inspection infractions may be highly localized.

Although the downtown region had the highest number of CP/C outcomes, our results showed that this area did not differ significantly from other areas when the total percentage of restaurants inspected was considered, because of the high concentration of restaurants in the downtown area. Downtown Toronto is a major tourism destination in Ontario, and restaurants are particularly attracted to neighborhoods with high levels of tourist activity *(41)*. However, because high real estate prices may deter smaller businesses from settling in the core downtown area, it may contain a higher ratio of high-end or chain restaurants compared with other parts of Toronto. Chain restaurants have been found to have lower rates of violations than independently owned restaurants, because of their own quality control and food safety monitoring programs *(14)*. Thus, further research regarding the distribution of chain vs. non-chain restaurants should be conducted in Toronto to investigate whether an association exists between chain status and food safety violations.

Our hot spot analysis also showed that although some clusters were quite large and occurred in similar areas across 2017 and 2018, only one hot spot in 2018 directly overlapped with a hot spot in 2017. Inspector biases may influence the clustering locations of high violation counts *(26)*. Medeiros and Wilcock performed a qualitative survey of public health inspectors to determine possible factors that may influence their judgment during inspections and found that confirmation bias, length of relationship with operators, intimidation effect, and availability bias played more definitive roles than other types of biases *(26)*. Pothukuchi et al. found that for critical violations, the gender of the inspector was significant; females found more critical violations than males *(30)*. Kramer also found that male inspectors found fewer non-critical, critical, and total violations than female inspectors did *(19)*. Future research could investigate whether inspector bias is associated with inspection outcomes or number and type of violations in the study region.

Our regression analysis showed that CP/C violations were correlated with the percentage of immigrants and percentage of individuals who did not use English or French as their home language. Both factors were very highly correlated ($r = 0.92$), making it difficult to determine the primary association. Increased adverse inspection outcomes or critical violations have shown some association with increased risk of foodborne illnesses *(16, 17, 29, 31)*, which may put the surrounding neighborhood populations at risk. Immigrants with poor command of the official language already face considerable challenges in accessing the healthcare system, while also facing higher rates of poverty and unemployment *(33, 42)*. Additionally, in Toronto, seniors (age 65 and over) make up a disproportionate part of the non-official-language speaking immigrants (44.6%), since seniors account for only 15.6% of the city's overall population *(33)*.

We also found that census tracts with higher rates of household poverty scores (measured by LIM-AT) were associated with more CP/C results, immigration, and non-English home language. Neighborhoods experiencing higher rates of poverty may struggle to maintain costly buildings and equipment. An analysis of restaurant inspections in Las Vegas found that 37.2% of violations were attributable to non-human factors (e.g., equipment failure, missing equipment, inaccessible sinks) in restaurants *(5)*. Neighborhoods with lower socioeconomic status and more minority groups have also been found to have differential access to safe food in some settings, with increased rates of microbiological contamination in certain foods sold at food retailers in these neighborhoods *(18, 32)*. However, it is uncertain if those living in lower socioeconomic status neighborhoods actually experience more foodborne illness from all food sources, because of potential reporting biases *(27)*. Future research should investigate the microbiological quality and food safety practices in restaurants in different socioeconomic status neighborhoods to identify which populations are at highest risk for consuming unsafe foods and experiencing foodborne illness.

This study has several limitations. For example, the analysis was restricted to the first annual inspection results in restaurants, so that only 12,407 (24.6%) inspections out of 52,571 unique inspections across 2017 and 2018 were included. This was done to reduce the dataset to one inspection per premise per year and to reduce bias from the follow-up inspections designed to require restaurants to achieve a pass. Further research could also investigate clustering of inspections within premises over time. In addition, we focused only on restaurants, and future work could examine differences in CP/C rates between other food premise types.

In addition, the published DineSafe data does not include the identities of the inspectors; therefore, when the inspection results were analyzed, it was assumed that the data was completely objective and not subject to inspector bias. However, as previously mentioned, existing research suggests that inspectors are not completely free from subjective and gender biases during inspections *(19, 26)*. Finally, drawing associations between census tract characteristics and CP/C outcomes assumes that only the respective populations within each census tract are at risk of poor food safety practices of those restaurants. Liu et al. *(23)* found that only 25% of sit-down restaurants to which participants traveled were located within their respective census tracts, and that on average, individuals traveled 3.3 miles to visit them. This may suggest that a wider scope of population demographics should be observed in future studies.

There are also potential challenges to comparing this study to similar research. Local inspection outcome type was analyzed, making comparison to other food safety inspection systems difficult, as the type of scores or outcomes assigned may vary across different jurisdictions *(4, 37, 40)*. Additionally, many of the studies referenced in this article compared neighborhood characteristics to number and type of violations, as opposed to overall inspection outcomes, making comparisons between findings more difficult. Furthermore, although the use of equal interval classification and Jenks natural breaks have their own merits, the defined classes do not represent a threshold of acceptability or significance, as they were arbitrarily selected to best represent the data for visualization and comparison. Finally, although the use of Jenks natural breaks is useful for visualizing natural groupings inherent in the data, it is not suitable for comparison across different datasets, since they are data-specific classifications *(11)*. Future research should be done to determine which CP/C thresholds may point toward significant food safety issues that require more attention from public health officials.

Overall, spatial analysis using Moran's I shows that first annual inspections of restaurants receiving CP/C results are significantly clustered together, indicating that inspection results are not independent from each other. The spatial distribution of high CP/C rates is more prominent outside the downtown core of Toronto, and hot spot analysis confirms that these clusters are significant. The descriptive findings show that spatial autocorrelation may have some utility in food safety inspection analysis, despite its limitations and assumptions. The regression analysis shows where some neighborhood characteristics, such as immigration, poverty, and English-speaking proficiency, may point toward specific populations and locations where more public health and food safety resources and outreach could be provided to enhance food safety. Annual spatial analysis of inspection results could inform public health and food safety authorities about where to focus future education and training efforts or interventions and could aid in identifying unknown geographical biases influencing inspections.

ACKNOWLEDGMENTS

The authors thank Noel Damba from Ryerson University's Geospatial Map & Data Centre for assistance with map projections and formatting, and Cornelius Ng for assistance with GIS troubleshooting. We acknowledge the City of Toronto's Open Data initiative as the source of data for these analyses.

REFERENCES

1. Akil, L., and H. A. Ahmad. 2016. *Salmonella* infections modelling in Mississippi using neural network and geographical information system (GIS). *BMJ Open* 6:1–9.
2. Arcury, T. A., W. M. Gesler, J. S. Preisser, J. Sherman, J. Spencer, and J. Perin. 2005. The effects of geography and spatial behavior on health care utilization among the residents of a rural region. *Hlth. Serv. Res.* 40:135–155.
3. Cates, S. C., M. K. Muth, S. A. Karns, M. A. Penne, C. N. Stone, J. E. Harrison, and V. J. Radke. 2009. Certified kitchen managers: do they improve restaurant inspection outcomes? *J. Food Prot.* 72:384–391.
4. Choi, J., and R. L. Scharff. 2017. Effect of a publicly accessible disclosure system on food safety inspection scores in retail and food service establishments. *J. Food Prot.* 80:1188–1192.
5. Choung, J. 2010. An analysis of restaurant food safety violations: human factors, non-human factors, and foodborne illness. Master's thesis. University of Nevada, Las Vegas, NV.
6. City of Toronto. 2018. 2016 Census basic profile. Available at: https://www.toronto.ca/wp-content/uploads/2017/12/9521-edc-census-basic-profile-by-census-tract-roll-up-2016.xlsx. Accessed 13 December 2019.
7. City of Toronto. 2019. About DineSafe. Available at: https://www.toronto.ca/community-people/health-wellness-care/health-programs-advice/food-safety/dinesafe/about-dinesafe/. Accessed 13 December 2019.
8. City of Toronto. 2019. Open data catalogue: DineSafe. Available at: https://open.toronto.ca/dataset/dinesafe/. Accessed 13 December 2019.
9. Darcey, V. L., and J. J. Quinlan. 2011. Use of Geographic Information systems technology to track critical health code violations in retail facilities available to populations of different socioeconomic status and demographics. *J. Food Prot.* 74:1524–1530.
10. Environmental Systems Research Institute. 2019. Change style reference. Available at: https://doc.arcgis.com/en/arcgis-online/create-maps/styling-reference.htm. Accessed 13 December 2019.
11. Environmental Systems Research Institute. 2019. Data classification. Available at: https://desktop.arcgis.com/en/arcmap/latest/extensions/geostatistical-analyst/data-classification.htm. Accessed 13 December 2019.
12. Fletcher-Lartey, S. M., and G. Caprarelli. 2016. Application of GIS technology in public health: successes and challenges. *Parasitology* 143:401–415.
13. Getis, A., and J. K. Ord. 2010. The analysis of spatial association by use of distance statistics. *Geogr. Anal.* 24:189–206.
14. Harris, K. J., R. B. DiPietro, K. S. Murphy, and G. Rivera. 2014. Critical food safety violations in Florida: relationship to location and chain vs. non-chain restaurants. *Int. J. Hosp. Manag.* 38:57–64.
15. Harris, K. J., K. S. Murphy, R. B. DiPietro, and G. L. Rivera. 2015. Food safety inspections results: a comparison of ethnic-operated restaurants to non-ethnic-operated restaurants. *Int. J. Hosp. Manag.* 46:190–199.
16. Irwin, K., J. Ballard, J. Grendon, and J. Kobayashi. 1989. Results of routine restaurant inspections can predict outbreaks of foodborne illness: the Seattle-King County experience. *Am. J. Publ. Hlth.* 79:586–590.
17. Jemaneh, T. A., M. Minelli, A. Farinde, and E. Paluch. 2018. Relationship between priority violations, foodborne Illness, and patron complaints in Washington, D.C., restaurants (2013–2015). *J. Environ. Hlth.* 80:14–19.
18. Koro, M. E., S. Anandan, and J. J. Quinlan. 2010. Microbial quality of food available to populations of differing socioeconomic status. *Am. J. Prev. Med.* 38:478–481.
19. Kramer, A. J. 2016. Neighborhood effects on restaurant food safety performance. Sc.D. thesis. Tulane University, New Orleans, LA.
20. Lee, J. E., D. C. Nelson, and B. A. Almanza. 2010. The impact of individual health inspectors on the results of restaurant sanitation inspections: empirical evidence. *J. Hosp. Mark. Manag.* 19:326–339.
21. Lee, Y., L. Pennington-Gray, and J. Kim. 2019. Does location matter? Exploring the spatial patterns of food safety in a tourism destination. *Tour. Manag.* 71:18–33.
22. Leinwand, S. E., K. Glanz, B. T. Keenan, and C. C. Branas. 2017. Inspection frequency, sociodemographic factors, and food safety violations in chain and nonchain restaurants, Philadelphia, Pennsylvania, 2013-2014. *Publ. Hlth. Rep.* 132:180–187.
23. Liu, J. L., B. Han, and D. A. Cohen. 2015. Beyond neighborhood food environments: distance traveled to food establishments in 5 U.S. cities, 2009–2011. *Prev. Chronic Dis.* 12:1–9.
24. Long, J. S., and J. Freese. 2014. Regression models for categorical dependent variables using Stata, 3rd ed. Stata Press, College Station, TX.
25. Malambo, P., A. P. Kengne, A. De Villiers, E. V. Lambert, and T. Puoane. 2016. Built environment, selected risk factors and major cardiovascular disease outcomes: a systematic review. *PLoS One* 11:e0166846.
26. Medeiros, P., and A. Wilcock. 2006. Public health inspector bias and judgment. *Food Prot. Trends* 26:930–940.

27. Newman, K. L., J. S. Leon, P. A. Rebolledo, and E. Scallan. 2015. The impact of socioeconomic status on foodborne illness in high-income countries: a systematic review. *Epidemiol. Infect.* 143:2473–2485.

28. Ord, J. K., and A. Getis. 2010. Local spatial autocorrelation statistics: distributional issues and an application. *Geogr. Anal.* 27:286–306.

29. Petran, R. L., B. W. White, and C. W. Hedberg. 2012. Health department inspection criteria more likely to be associated with outbreak restaurants in Minnesota. *J. Food Prot.* 75:2007–2015.

30. Pothukuchi, K., R. Mohamed, and D. A. Gebben. 2008. Explaining disparities in food safety compliance by food stores: does community matter? *Agric. Human Values* 25:319–332.

31. Serapiglia, T., E. Kennedy, S. Thompson, and R. de Burger. 2007. Association of food premises inspection and disclosure program with retail-acquired foodborne illness and operator noncompliance in Toronto. *J. Environ. Hlth.* 70:54–59.

32. Signs, R. J., V. L. Darcey, T. A. Carney, A. A. Evans, and J. J. Quinlan. 2011. Retail food safety risks for populations of different races, ethnicities, and income levels. *J. Food Prot.* 74:1717–1723.

33. Social Planning Toronto. 2018. Talking access and equity: a profile of City of Toronto residents who speak neither official language. Available at: https://d3n8a8pro7vhmx.cloudfront.net/socialplanningtoronto/pages/ 2015/attachments original/1531846236/Language_Report_J5-v5-web.pdf?1531846236. Accessed 13 December 2019.

34. Statistics Canada. 2018. Census tract: detailed definition. Available at: https://www150.statcan.gc.ca/n1/pub/92-195-x/2011001/geo/ct-sr/def-eng.htm. Accessed 13 December 2019.

35. Statistics Canada. 2018. Health region boundary files. Available at: https://www150.statcan.gc.ca/n1/pub/82-402-x/2018001/hrbf-flrs-eng.htm. Accessed 13 December 2019.

36. Statistics Canada. 2019. 2016 Census – boundary files. Available at: https://www12.statcan.gc.ca/census-recensement/2011/geo/bound-limit/bound-limit-2016-eng.cfm. Accessed 13 December 2019.

37. Thompson, S., R. De Burger, and O. Kadri. 2005. The Toronto food inspection and disclosure system. *Br. Food J.* 107:140–149.

38. Weisent, J., B. Rohrbach, J. R. Dunn, and A. Odoi. 2012. Socioeconomic determinants of geographic disparities in campylobacteriosis risk: a comparison of global and local modeling approaches. *Int. J. Hlth. Geogr.* 11:45.

39. Wieczorek, W. F., and A. M. Delmerico. 2009. Geographic Information Systems. *Comput. Stat.* 1:167–186.

40. Wong, M. R., W. McKelvey, K. Ito, C. Schiff, J. B. Jacobson, and D. Kass. 2015. Impact of a letter-grade program on restaurant sanitary conditions and diner behavior in New York City. *Am. J. Publ. Hlth.* 105:e81–87.

41. Yang, Y., W. S. Roehl, and J.-H. Huang. 2017. Understanding and projecting the restaurantscape: the influence of neighborhood sociodemographic characteristics on restaurant location. *Int. J. Hosp. Manag.* 67:33–45.

42. Zanchetta, M. S., and I. M. Poureslami. 2006. Health literacy within the reality of immigrants' culture and language. *Can. J. Publ. Hlth.* 97(Supp 2):S26–30.