

**Spatial and spatio-temporal analyses of neighborhood retail
food environments: evidence for food planning and
interventions**

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

I hereby clarify authors' contributions to the three articles that comprise this dissertation.

The first article, entitled “Identifying food deserts and swamps based on relative healthy food access: a spatio-temporal Bayesian approach” and presented in Chapter 2, is coauthored with Dr. Jane Law and Mr. Matthew Quick. Dr. Law provided constructive suggestions for Bayesian analysis. Mr. Quick and I compiled the dataset. All authors revised and proofread the article. This paper has been published in *International Journal of Health Geographics*.

The second article, entitled “Do marginalized neighborhoods have less healthy retail food environments? An analysis using spatial latent factor and hurdle models” and presented in Chapter 3, is coauthored with Dr. Leia Minaker and Dr. Jane Law, who critically commented on the draft, suggested for additional references, and participated in editing and proofreading the article. This paper has been published in *International Journal of Health Geographics*.

The third article, entitled “Diving into the consumer nutrition environment: a Bayesian spatial factor analysis approach for assessing neighborhood restaurant environment” and presented in Chapter 4, is coauthored with Dr. Jane Law and Dr. Martin Lysy, who provided constructive comments on Bayesian spatial analysis. All authors edited and proofread the article. This paper is under review at *Spatial and Spatio-temporal Epidemiology*.

As the first author of these three articles, I initiated and conceptualized the studies, conducted the literature review, performed statistical analyses of the datasets, prepared the figures, and drafted and revised the articles.

Abstract

The food system has been increasingly recognized as an indispensable component in professional planning in Canada. As its retailing part, the Retail Food Environment (RFE) has recently gained considerable attention, since it plays an important role in shaping residents' eating behaviors and diet-related health outcomes, especially obesity. Identifying the strengths and weaknesses of the RFE in a neighborhood is essential for successful food planning and interventions. Yet current neighborhood RFE assessment mainly uses secondary food outlet datasets to evaluate absolute food access, largely overlooks the dynamic nature of the RFE and the variations of in-store features between food outlets, and predominantly applies descriptive RFE measures.

Comprised of three articles that focus on a common theme, neighborhood RFE assessment, this dissertation uses novel spatial and spatio-temporal statistical modeling approaches to explore neighborhood RFE in the Regional Municipality of Waterloo with food outlet datasets that include the information of both the community and consumer nutrition environments. Firstly, this research explores spatio-temporal variations of relative healthy food access (RHFA) with a multiple-year RFE dataset. The results suggest that food swamps are more prevalent than food deserts in the study region and that food swamps have become more prevalent during the study period. Spatio-temporal food swamps, neighborhoods where RHFA is decreasing faster than the regional trend, are highlighted for interventions.

Secondly, this research investigates the association between marginalization and neighborhood RFE at various geographical scales. 'Healthy' and 'less healthy' food outlets are differentiated based on in-store features from a primary food outlet dataset. RFE 'healthfulness' is a relative measure of healthy food access, which is modeled via probability distributions. The results indicate that neighborhoods with higher residential instability, material deprivation, and population density are more likely to have access to healthy food outlets within a walkable distance from a binary 'have' or 'not have' access perspective. At the walkable distance scale however, materially deprived neighborhoods are found to have less healthy RFE (i.e., lower RHFA).

Finally, this research applies a spatial factor analysis model to assess neighborhood restaurant environment (NRE) for the city of Kitchener with multiple restaurant assessment indicators. Neighborhoods with least healthy NRE (simultaneously suffer from lower relative availability of healthy eating options, higher prices of healthy eating, and lower/higher healthy eating facilitator/barrier) are identified. Facilitator/barrier is found to be most relevant with NRE healthfulness.

This research significantly advances our understanding of neighborhood RFE. Conceptually, it extends the definition of food swamps by incorporating a temporal dimension and provides empirical evidence that the deprivation amplification hypothesis in the RFE context holds only at specific geographical scales when neighborhood RFE is assessed with specific strategies. It also challenges the uncertainties associated with descriptive RFE measures that purport to represent the underlying concept – the ‘healthfulness’ of neighborhood RFE. Methodologically, this research facilitates the application of spatial and spatio-temporal statistical approaches in RFE studies. Findings from this research could assist planners and policy makers in developing food intervention programs to improve neighborhood RFE and promote population-wide healthy eating in the Region of Waterloo.

Acknowledgements

Completing a Ph.D. degree in Planning in the past five years has been the most challenging but worth journey in my life so far. This journey, mixed with anxiety, confusion, pain, but mostly joys, is a rewarding experience, which I will cherish forever.

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I also would like to thank my committee members for assisting my research in various aspects: Dr. Leia Minaker for providing the dataset and sharing expertise in retail food environment assessment; Dr. Jennifer Dean for providing constructive and detailed comments on planning policy implications; Dr. Martin Lysy for advising me on Bayesian analysis; and Dr. Su-Yin Tan for serving as my comprehensive exam committee member. I am grateful for my external examiner, Dr. Jason Gilliland, who raised critical and thoughtful questions during my defense.

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Dedication

To my parents,

Yaqin Xu and Jishan Luan.

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List of Abbreviations

ANGELO: Analysis Grid for Environments Linked to Obesity

APA: American Planning Association

CDC: Centers for Disease Control and Prevention

CrI: Credible Interval

DA: Dissemination Area

DIC: Deviance Information Criterion

FRESH: Food Retail Expansion to Support Health program

GIS: Geographic Information System

ICAR: intrinsic Conditional Autoregressive

INLA: Integrated Nested Laplace Approximation

mRFEI: modified Retail Food Environment Index

MCMC: Markov chain Monte Carlo

NEMS: Nutrition Environment Measure Survey

NEWPATH: Nutrition, Environment in Waterloo Region, Physical Activity,
Transportation and Health

NRE: Neighborhood Restaurant Environment

OPPI: Ontario Professional Planners Institute

RFE: Retail Food Environment

RHFA: Relative Healthy Food Access

USDA: The U.S. Department of Agriculture

WHO: World Health Organization

Chapter 1: Introduction

1.1. Context and motivation

1.1.1. Obesity and retail food environments

The World Health Organization (WHO) has announced that obesity would be an epidemic in the 21st century as early as 2003 on the basis of drastic increases of obesity rates in numerous developed and developing countries (WHO, 2003). In Canada specifically, the obesity rate has tripled in the past three decades with one in four adult Canadians and one in ten Canadian children being obese or overweight (Canadian Obesity Network, 2016). As a major risk factor for chronic diseases including high blood pressure, type 2 diabetes, stroke, and heart diseases, obesity is increasingly burdening Canada's healthcare system, accounting for 4.1% of the total healthcare costs (Canadian Obesity Network, 2016).

With the increasing prevalence of obesity being insufficiently explained by individuals' social and psychological factors, recent studies have been directed to explore neighborhood-scale and environmental risk factors, including retail food environments (RFE) (Pearce & Witten, 2010). As the retailing part of a food system¹, RFE is composed of food stores where people can buy food to cook at home and restaurants where people can eat away from home². RFE merit attention since obesity is ultimately a consequence of imbalance between energy expenditure and energy consumption (Cummins & Macintyre, 2006; Papas et al., 2007; Raychaudhuri & Sanyal, 2012). In this context, numerous ecological models have been proposed, incorporating neighborhood RFE as a vital contributor to eating behaviors and diet-related health outcomes including obesity. Proposed by Swinburn and colleagues (1999), the ANGELO (Analysis Grid for Environments Linked to Obesity) model is one of the earliest ecological frameworks that dissected obesogenic factors (i.e., food and physical activity) into various environmental

¹ A food system is "...a complex set of activities and relationships including production, processing, distribution, marketing, retail, consumption and waste" (Toronto Public Health, 2015, p.2).

² Food retailers in organizations such as schools and workplaces are excluded for analyses in this dissertation.

types (i.e., physical, economic, political, and socio-cultural) at different environmental levels (i.e., micro settings such as homes, schools, and workplaces, and macro sectors such as the transportation system, health system, and food manufacturing) (Table 1-1). The ANGELO framework emphasizes the significance of assessing obesogenic environments from a holistic perspective. In the context of food for example, there is a necessity to include physical food environment such as availability of grocery stores in neighborhoods (i.e., micro-environmental setting), economic food environment such as costs of healthy foods, political food environment including food product labeling (i.e., macro-environmental sector), and socio-cultural food environment including social norms on healthy eating. Other ecological models in the literature that link the food environment and eating behaviors and diet-related health outcomes have been summarized elsewhere (Minaker, 2013).

Table 1-1: The ANGELO conceptual framework (Swinburn et al., 1999)

Type \ Size	Micro-environment (settings)		Macro-environment (sectors)	
	Food	Physical activity	Food	Physical activity
Physical	What is available?			
Economic	What are the financial factors?			
Political	What are the rules?			
Socio-cultural	What are the attitudes, beliefs, perceptions, and values?			

These multi-facet and multi-scale food environmental variables have been incorporated into the behavioral pathways (Figure 1-1) through which the food environment³ influences diet and diet-related health outcomes (Morland, 2015a).

³ *Food environment* is a relevant but different concept compared with *food system*. Broadly, it refers to “virtually all potential determinants of what people eat that are not clearly individual factors” (Glanz, 2009, p.93), ranging from policy variables such as national regulations on food advertising to environmental variables including density of food retailers in a community. *Food environment* can also be narrowly defined as “features of the local physical environment that facilitate the consumption of certain types of food and detract from the consumption of others” (Diez Roux, 2009, p.27). In the literature, RFE is synonymous to *food environment* in some cases.

Corresponding variables from the ANGELO framework are highlighted in red. This diagram clearly demonstrates how various aspects of the food environment impact the final dietary decisions.

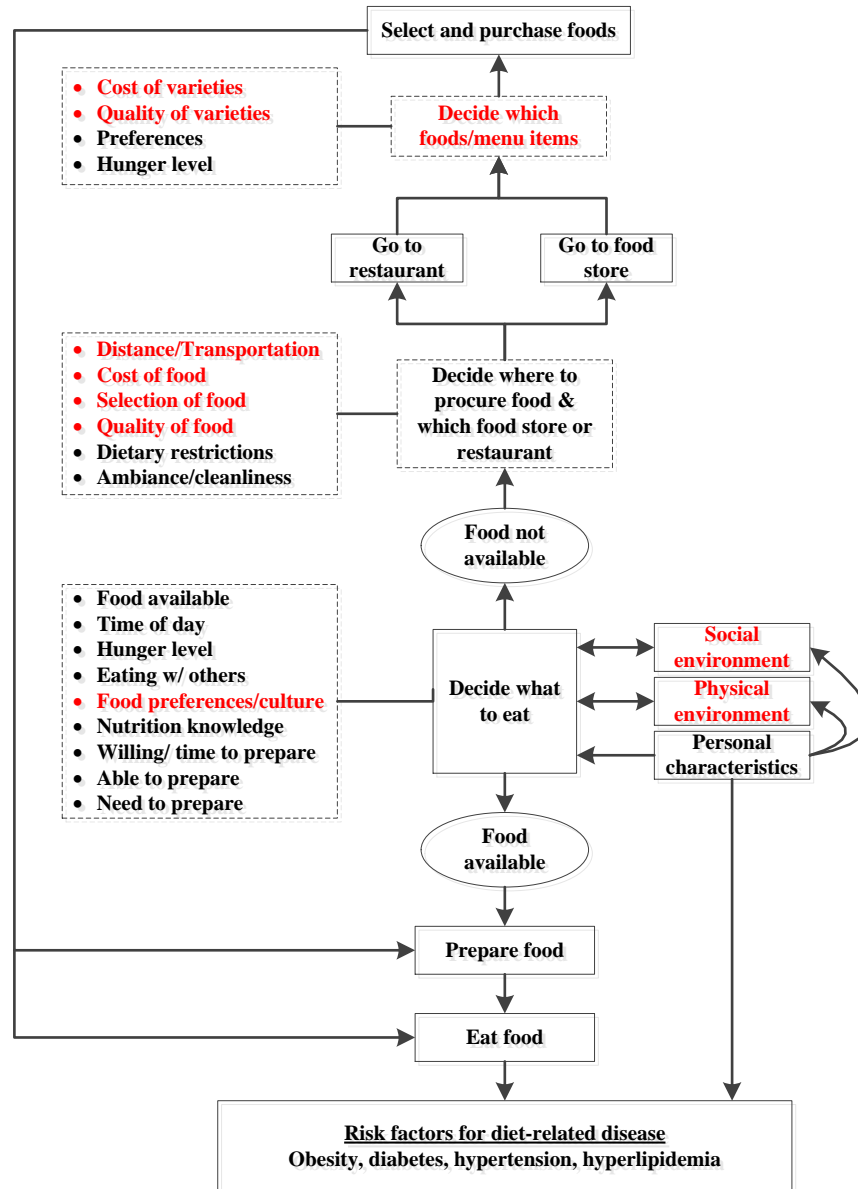


Figure 1-1: Decision making processes based on the food environment’s impact on eating behaviors and diet-related disease risk (Morland, 2015a)

On the basis of these conceptual models, a growing body of public health studies explored the role of neighborhood RFE in shaping residents’ dietary behaviors and diet-related health outcomes, in particular obesity. Although findings are mixed, studies increasingly show that residents living in a neighborhood with healthier RFE are more

likely to have healthier diets and lower body weight, and less likely to be burdened by diet-related diseases (C. Black, Moon, & Baird, 2014; Caspi, Sorensen, Subramanian, & Kawachi, 2012; Engler-Stringer, Le, Gerrard, & Muhajarine, 2014; Kirkpatrick et al., 2014; Laraia, Hendrickson, & Zhang, 2015; Williams et al., 2014; Zenk, Thatcher, Reina, & Odoms-Young, 2015).

1.1.2. Food planning and interventions

1.1.2.1. Food system planning

Compared with other areas of planning such as transportation and housing, food planning is relatively new (Raja, Born, & Russell, 2008). The food system was largely a “stranger to the planning field” (Pothukuchi & Kaufman, 2000, p.113) until late 1990s. Although food related issues such as the establishment of food stores is an indispensable component of urban design, historically, constructions and operations of food stores have been largely left to private industrial sectors (Donofrio, 2007).

A seminal paper by Pothukuchi and Kaufman (1999) suggested putting the food system in the planning agenda; however, planners, at least those in North America, perceive food issues to be beyond their purview and assume that food system responds well to market forces (Pothukuchi & Kaufman, 2000). Consequently, few municipalities adopted plans that exclusively focus on or include an element of community food systems. Nevertheless, planners have recently changed their attitudes towards food planning and gained renewed interests in incorporating food issues into professional planning, probably recognizing that the food system is important to residents’ eating behaviors (and ultimately health status) and community vitalities. Such positive changes have been initiated in the U.S. In 2004 and for the first time, special issues were devoted entirely to food system planning in journals (i.e., *Journal of Planning Education and Research*, Vol.23, No.4, 2004; and *Progressive Planning*, Winter 2004) for academics and practitioners of professional planning (APA, 2007; Kaufman, 2009). Special track of sessions on food system planning were held at the American Planning Association (APA) National Planning Conference in 2005, again, for the first time. Due to unexpected overwhelming responses, a follow-up session was also offered in the 2006 conference (APA, 2007), where a group of planners presented a white paper on food planning to the APA Delegate Assembly. Approved by

the APA Legislative and Policy Committee (APA, 2007), the white paper promoted the development and adoption of the *APA Policy on Community and Regional Food Planning* (APA, 2007), which was recognized as the “most significant indication” (Kaufman, 2009, p.13) of accepting food issues in professional planning. More recently, Raja et al. (2008) developed the Planning Advisory Service report entitled “*a planners’ guide to community and regional food planning*”, which provides strategies for planners to build healthier food systems. As well, their report comprehensively reviewed successful examples of food system planning initiatives in North America as of 2008. What was also revealed was the increasing recognition and support from APA members regarding more planning involvement in food-related issues, including the modification of zoning codes in comprehensive plans (“official plan” in Canada) to regulate food retails (advocated by 73% surveyed APA member).

Although lagging behind its American counterpart, Canadian planning is getting more involved in community food systems in recent years, reflected by the continuing efforts and increasing supports from professional planning practitioners and academics. The inclusion of a special track on food planning at the Canadian Institute of Planners conference in 2008 (Kaufman, 2009), as well as a special issue completely devoted to food security as a growing concern in professional planning in the journal *Plan Canada* (Vol 49, No.2, 2009), exemplifies initial signs of this positive trend. Later, the Ontario Professional Planner Institution (OPPI) held a symposium entitled “*Healthy Communities and Planning for Food – a Harvest of Ideas*” in Guelph, Ontario in October 2010. The meeting convened professional urban and rural planners for discussing how professional planning can address food issues. Following these efforts, OPPI has recently called for action on planning for a healthy food system for Ontario by engaging planners with food relevant issue (OPPI, 2011).

Two models for food system planning have been identified from the literature. First, stand-alone plans can be implemented to exclusively deal with the food system. Such plans provide a comprehensive guide for communities who intend to improve their food systems and facilitate healthy eating. The Region of Waterloo exemplifies the first Canadian municipality that published a stand-alone plan for creating a healthy food system, in which

“all residents have access to, and can afford to buy safe, nutritious, and culturally-acceptable food that has been produced in an environmentally sustainable way and that sustains our rural communities” (Region of Waterloo Public Health, 2007, p.4). The overall goal, specific objectives, and corresponding strategies were outlined in Figure 1-2. Waterloo’s plan covers a wide range of topics relevant to the food system: from food production (e.g., preserve and protect agriculture lands), processing (e.g., support on-farm food processing facilities), to retailing (e.g., strengthen local farmer’s market), from the economic dimension (e.g., boost local food processing industry) to the physical dimension (e.g., limit the establishment of unhealthy food outlets), and from the supply side (e.g., increase the availability of healthy foods) to the demand side (e.g., enhance consumers’ awareness of healthy eating). Improving the availability of healthy foods in every neighborhood and limiting unhealthy foods in specific neighborhoods are identified as two pivotal recommendations. Raja et al. (2008) outlined seven general steps that a community can follow for implementing stand-alone food system plans (Figure 1-3). Notably, gathering and analyzing relevant (food environment) datasets (phase IV) guides the implementation of plans, which are devised from phases I to III, during phases V to VII, making it a critical task in the process of planning for the food system.

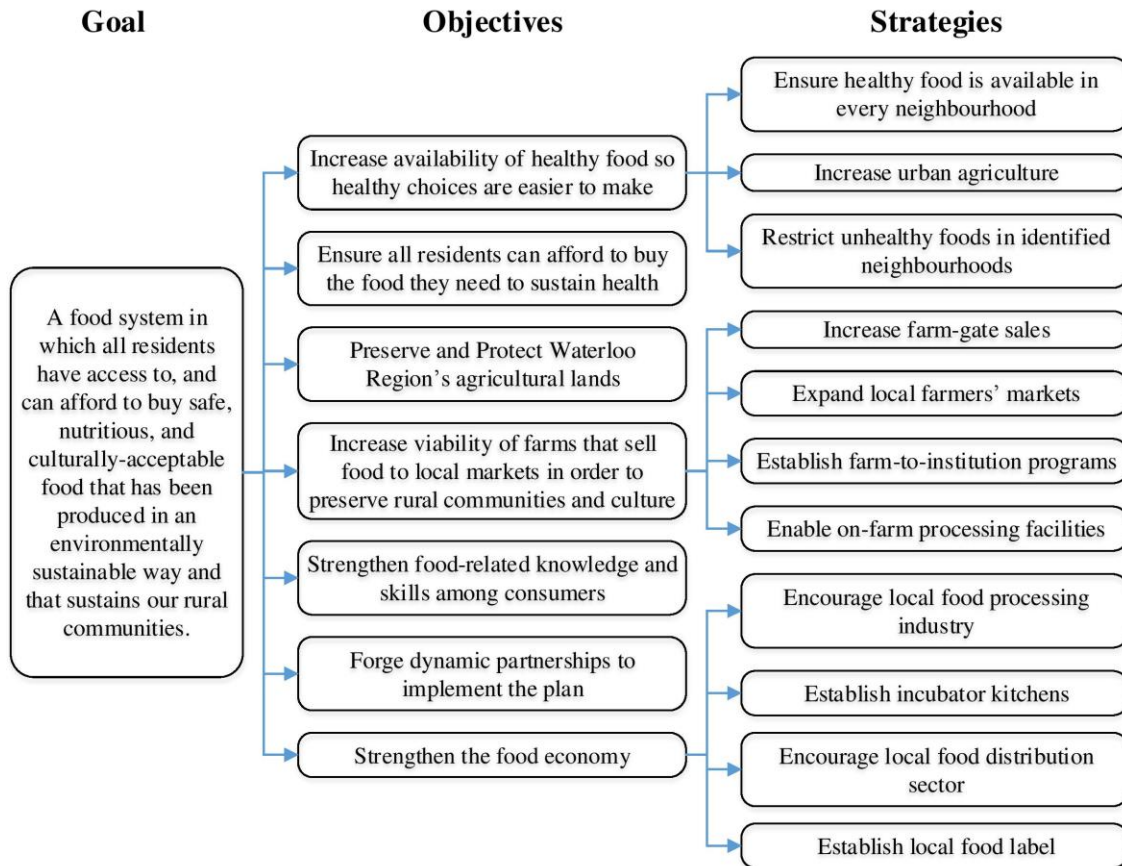


Figure 1-2: Stand-alone food system plan for the Region of Waterloo (Region of Waterloo Public Health, 2007, p.5)

Phase I	Identify partners in the planning process
Phase II	Devise a planning approach that fits the community's need
Phase III	Visioning process
Phase IV	Gather and analyze relevant data
Phase V	Prepare preliminary recommendations and establish benchmarks for measuring process
Phase VI	Review findings and recommendations with interested stakeholders
Phase VII	Implement the recommendations and measure progress

Figure 1-3: Planning process for stand-alone food system plans (Raja et al., 2008)

Second, the food system can be incorporated as a component in the comprehensive or official plan that establishes a long-term blueprint for future community growth (Ministry of Municipal Affairs and Ministry Of Housing, 2015). The inclusion of food issues in a comprehensive/official plan ensures a well-operated community food system that enables all residents to access to healthy and affordable foods in the near future, along with ensuring sufficient housing, jobs, and transportation. In June 2009, Region of Waterloo included a brief section of food system planning in its regional official plan for the first time, paralleling with plans for housing, (active) transportation, energy, air quality, cultural heritage, and human services for improving the livability in the region. Policies and actions targeting food and agriculture related activities were profiled (Region of Waterloo, 2009). For example, the region would provide mixed land uses (including food destinations) that are located together to promote residents' access to locally grown healthy foods. This official plan was officially approved in January 2010. Likewise, Toronto included food system planning in its official (and also subsequently updated) plans (City of Toronto, 2015). Programmatic (e.g., farmer's market and community and rooftop gardens), policy (e.g., Toronto's Food Charter), and planning/zoning guidelines were developed to facilitate food system planning in Toronto. Very recently, the city of London, Ontario has also explicitly incorporated the food system into its official plan, which has been submitted to Council for final approval (City of London, 2016). Similar efforts as those proposed by Toronto's official plan were emphasized for creating a healthy and sustainable food system in London. Of note, the planning process for comprehensive/official plans that incorporate food as an element is similar to that of stand-alone plans that exclusively deals with food systems as shown above, but with a narrower scope (Raja et al., 2008). Examples of stand-alone food system plans and comprehensive plans that incorporate food issues implemented in the U.S. can be found in Raja et al. (2008) and Kaufman (2009).

In practice, planners could greatly contribute to improving the food system via planning tools such as zoning and regulation. For reference, zoning refers to "...the control by authority of the use of land, and of the buildings and improvements thereon" (Historica Canada, 2016). For instance, the city of Vancouver, British Columbia, adopted a planning guideline that used rezoning to incorporate urban agriculture into their landscape

development plans (City of Vancouver, 2008). Two components of urban agriculture on private development sites, shared garden plots and edible landscape, were addressed. Another example in Canada is the implementation of a neighborhood produce market program in underserved areas in the city of Kitchener (Maan Miedema, 2008), responding to the stand-alone food system plans published in the Region of Waterloo as noted above. This program encountered regulatory barriers since no bylaws or license existed for vendors that sell fruits and vegetables. Kitchener eventually removed this barrier (i.e., do not require a varied license for these markets under the extant zoning bylaws), and permitted the establishment of these markets in that they benefit the community.

1.1.2.2. Zoning and regulating the RFE

Recently, planners' roles in shaping RFE (a subset of the entire food system) with zoning and regulation have been increasingly acknowledged. Although food retailing, especially food outlet establishment, is driven by the private market, it does not happen automatically or evenly (Raja et al., 2008), making it possible for the planners to engage with food retailer prioritizations. A theoretical support comes from the retail location theory, which indicates that land use planners do play a role in shaping (food) retailers' distributions among other actors including developers, managers, and owners (S. Brown, 1993). Interestingly, despite the newly acceptance of food issues into professional planning, urban planning, in particular zoning, is one of the two major determinants of (food) retailer distributions, apart from the commercial siting process, which involves a comprehensive assessment of both risks and rewards of establishing a new retailer (Black, Carpiano, Fleming, & Lauster, 2011). For instance, past research has revealed that planning practices tend to zone out commercial venues from residential neighborhoods where (semi-) detached houses dominate, in order to maintain house values (Shlay & Rossi, 1981).

Driven by public health concerns especially the emerging obesity epidemic, zoning has been extensively proposed as a proactive tool for promoting health in North America, not surprisingly, by public health researchers. As early as 2003, Ashe and colleagues (2003) have suggested using zoning bylaws to restrict fast-food restaurant establishments in the academic journal *American Journal of Public Health*. Following Ashe et al.'s recommendations, several scholars who specialized in both law and public health (Mair,

Pierece, & Teret, 2005) prepared a monograph, wherein a number of zoning techniques, namely, conditional zoning, incentive zoning, and performance zoning, were proposed to limit fast-food restaurants while encouraging healthier alternatives. In particular, conditional zoning allows municipalities to rezone land parcels for designated land uses but prohibits certain uses such as establishments of fast-food restaurants at specific sites. This approach is exemplified by the Los Angeles case (Stephens, 2007), where zoning bylaws were passed by the government for regulating fast foods because of public health concerns. Incentive zoning encourages the construction of amenities that benefit a public interest, such as a supermarket in the RFE context, while exempting charges of contract zoning. This approach is usually coupled with financial incentives. For instance, New York City initiated the Food Retail Expansion to Support Health (FRESH) program to incentivize chain supermarkets to relocate in underserved neighborhoods (City of New York, 2009). Incentives such as waiving mortgage recording tax and abating real estate tax are included in FRESH. Lastly, performance zoning acts as a supplement to actual land use zoning in that it does not regulate how the land is used but instead sets specific standards that land users must meet. Although performance zoning is primarily applied in industrial land uses, for instance, limiting pollution levels, it can be adapted for regulating RFE. As an example, the municipality could request fast-food restaurants to offer a minimum of healthy eating options on their menus (Mair et al., 2005). Another example is that restaurants could be required to provide a “healthy offerings check” (Raja et al., 2008, p.99) in the licensing process when they are applying for a land use permit, certifying that they will offer healthy foods that meet the minimum nutritional quality suggested by the public health agency.

As for zoning fast-food restaurants in particular, it manifests in a variety of regulation forms (Mair et al., 2005), which can be summarized as (i) prohibiting fast-food outlets and/or driving services; (ii) forbidding “formula” restaurants; (iii) banning fast foods in specific areas; (iv) regulating the number of fast-food restaurants via quota; (v) regulating densities of fast-food restaurants; and (vi) regulating fast-food restaurants from other uses including schools and day care. These regulations are recently resonated by Canadian reports that guide the development of healthy communities (Canadian Institute of Planners, 2013) and the intervention for regulating fast-food outlets around schools in

Quebec (Quebec Public Health Association, 2011). In addition to restricting less healthy foods, zoning has also been proposed for improving healthy food access. Raja et al. (2008) suggested examining and slightly modifying existing zoning ordinances to allow fruit and vegetable markets in all zoning districts. Supplementary to this zoning code modification, accelerating the licensing process for fruit and vegetable vendors to start up a business and waiving licensing fees were also recommended.

1.1.2.3. Other RFE intervention approaches

Apart from urban planning such as zoning, two other intervention approaches have been proposed to improve neighborhood RFE and facilitate healthy eating: (i) *transforming consumer environments* and (ii) *a culture of transparency and participation* (Mah, Cook, Rideout, & Minaker, 2016, p.eS64) ⁴.

Compared with planning tools such as zoning that focus on built environment factors, *transforming consumer environments* enhances shopping experiences via improving in-store characteristics of food retailers. The Healthy Corner Store program exemplifies this type of effort. Defined as “businesses that stock and offer healthy food retail options” (Seeton, 2012, p.24), healthy corner stores aim to improve the availability and affordability of healthier foods including dairy, fresh produce, and high quality protein, replacing unhealthy and energy-dense options that commonly available in convenience stores. In contrast to attracting new healthy retailers via zoning and financial incentives as mentioned above, this initiative is less challenging for improving healthy food access by gradually increasing the stock of healthy and fresh foods in existing retailers (Seeton, 2012). Originated in the U.S., the Healthy Corner Store program has been implemented in a number of Canadian municipalities, including Ottawa (Just Food, 2016), Vancouver (Seeton, 2012), Toronto (Toronto Food Policy Council, 2014), Branch (in Newfoundland and Labrador) (Food First NL, 2015), and Winnipeg (in Manitoba) (Winnipeg Regional Health Authority, 2014). In addition to modifying in-store features of existing food retailers, *transforming consumer environments* can also be implemented via the mobile vending model (Mah et al., 2016), which brings fresh fruits and vegetables to neighborhoods

⁴ Mah et al. (2016) also included an intervention, *economic and fiscal instruments*, for improving RFE. These approaches are primarily applied in organizational food environments, but some can be adapted for improving RFE for the public, for example, taxing sugar-sweetened beverages.

without adequate fresh produce by truck or bus. Examples include the Market Mobile project in Ottawa (Ottawa Public Health, 2016) and the Mobile Good Food Markets project in Toronto (FoodShare, 2016).

Disclosing nutritional information to the consumers and getting a wide variety of stakeholders involved with food system planning have also been proposed as proactive approaches for improving neighborhood RFE, which correspond to *a culture of transparency and participation* as mentioned above. As an example of the former approach, the menu labeling legislation will take effect in Ontario as of January 1, 2017 (Ontario's Regulatory Registry, 2016). Specifically, food premises with more than 20 or more outlets in Ontario and serve prepared ready-to-eat foods are required to label calorie information on their menus. This regulation is adopted based on the assumption that the visibility of nutritional information encourages consumers to make healthier consumption decisions. Some experimental studies have demonstrated the effectiveness of this intervention in the Canadian context (Girz, Polivy, Herman, & Lee, 2012; Hammond, Goodman, Hanning, & Daniel, 2013; Scourboutakos, Corey, Mendoza, Henson, & L'Abbé, 2014; Vanderlee & Hammond, 2014). The latter approach solicits opinions from various research fields and/or organizations, for instance, public health professionals and Food Policy Council, for identifying and prioritizing policy issues (Mah et al., 2016), thus making it more likely to establish effective policies for promoting healthy RFE.

1.1.3. Assessing neighborhood RFE⁵

The first step for planning a healthy food system is to identify strengths and weaknesses of the food system via community or neighborhood food assessment (Pothukuchi, 2004), among which neighborhood RFE assessment is an indispensable component. Although RFE can be assessed at various geographical levels, at least including regional, municipal, and neighborhood (Raja et al., 2008), neighborhood RFE assessment merits special attention mainly for two reasons: one, assessing neighborhood

⁵ This dissertation focuses exclusively on objective RFE assessment. Comparisons between objective and subjective (based on residents' perception) RFE assessment can be found in a couple of studies in the literature (Barnes et al., 2015; Giskes, Van Lenthe, Brug, Mackenbach, & Turrell, 2007; Health Canada, 2012; Moore et al., 2008; Sohi, Bell, Liu, Battersby, & Liese, 2014). Individuals' exposure to RFE has also been quantified in several recent studies (Christian, 2012; Crawford et al., 2014; Kestens et al., 2012, 2010; Sadler et al., 2016; Zenk et al., 2011); but again, it is not the focus of this dissertation.

RFE reveals heterogeneity of food access that might be masked by regional or municipal assessment. For example, people in a city with abundant grocery stores might still reside in neighborhoods lacking access to healthy foods; and two, neighborhood is a suitable and feasible intervention unit for planners to promote population-wide healthy eating. Of note, neighborhood in this dissertation is exclusively area-based (e.g., a dissemination area) rather than individual- or household-based, given that evaluating areal RFE is more relevant and practical for food planning and interventions. Neighborhood RFE assessment also corresponds to Phase IV, *gather and analyze relevant data*, in the planning process for the food system (Figure 1-3).

As of 2012, over 500 food environment measures exist in the extant literature (National Cancer Institute, 2016). These measures have been summarized in recent review papers (Gustafson, Hankins, & Jilcott, 2012; Kelly, Flood, & Yeatman, 2011; Ohri-Vachaspati & Leviton, 2010). In light of the evidence from these reviews, a framework, which involves various aspects of neighborhood RFE assessment, can be summarized in Figure 1-4. Essentially, five elements should be considered: the strategy, dimension, data, scale, and methodology. Any neighborhood RFE assessment is a combination of these five elements, which interconnect with each other.

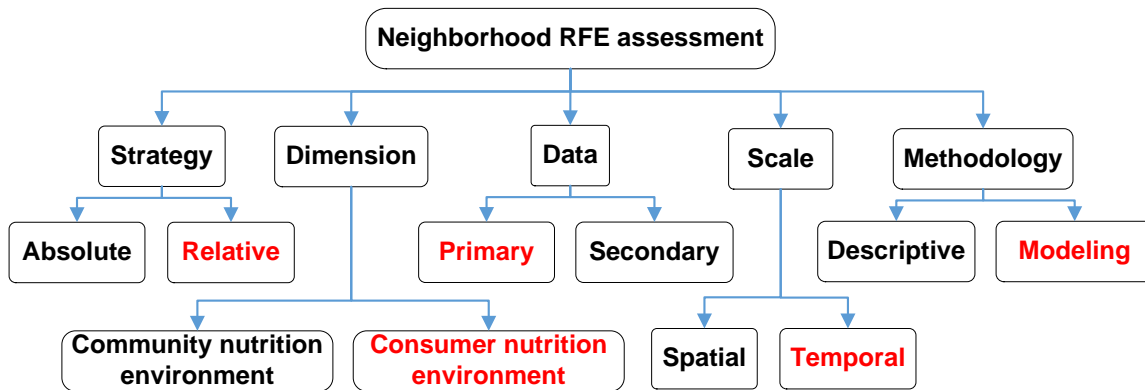


Figure 1-4: Essential elements of neighborhood RFE assessment (Areas under-researched are highlighted in red)

1.1.3.1. Dimensions of neighborhood RFE assessment

A conceptual framework that has been widely adopted for guiding RFE assessment is Glanz and colleagues' ecological model of the food environment (2005) (Figure 1-5). In particular, RFE assessment usually involves the community and consumer nutrition environments. These two dimensions of the complex and multi-facet food environment have a higher priority as they are less explored in the literature but could have broad impacts (Glanz et al., 2005). For reference, the community nutrition environment focuses on aspects such as the type, number, and location of food outlets. It is commonly evaluated by geographic access measures including proximity (e.g., the distance from the neighborhood centroid to the nearest supermarket), density (e.g., concentration of fast-food restaurants within a neighborhood), and variety (i.e., the extent to which different types of food retailers exist in a neighborhood). These measures are usually implemented in a Geographic Information System (GIS) (Charreire et al., 2010; Thornton, Pearce, & Kavanagh, 2011).

On the other hand, the consumer nutrition environment represents in-store characteristics that consumers encounter when they reach a food retailer (Glanz et al., 2005). This dimension of the food environment manifests in a variety of variables including food availability, affordability, quality, and healthy eating facilitator/barrier. In particular, *food availability* directly measures the availability of food (e.g., shelf-space devoted to vegetables and fruits in a food store, or healthy eating options in a restaurant). This measure

overcomes the limitation of the assumption that food retailer type is a sufficient proxy for food availability, and food availability is invariant within food outlet types (Health Canada, 2012; Minaker et al., 2011). *Food affordability* is conventionally used to depict “the cost of food relative to an individual’s or household’s income or purchasing power” (Health Canada, 2012, p.14). Nevertheless, this measure has been adapted to understand food costs within a neighborhood, and it can be absolute (e.g., the cost of a healthy food basket) or relative (e.g., the cost of healthy foods in relation to their unhealthy counterparts). *Food quality* measures the quality characteristics of foods in food retailers. This measure is more subjective compared with food availability and affordability in that even trained raters dispute over the degree to which fruits and vegetables have bruised or wilted (Health Canada, 2012). Lastly, *facilitator/barrier* evaluates whether healthy eating is encouraged in a restaurant by measures such as whether reduced-size portion and nutritional information are provided (Saelens, Glanz, Sallis, & Frank, 2007). Numerous tools have been developed for measuring these in-store or in-restaurant features, including the widely adopted Nutrition Environment Measure Survey (NEMS) developed for food stores (NEMS-S; Glanz, Sallis, Saelens, & Frank, 2007) and restaurants (NEMS-R; Saelens, Glanz, Sallis, & Frank, 2007).

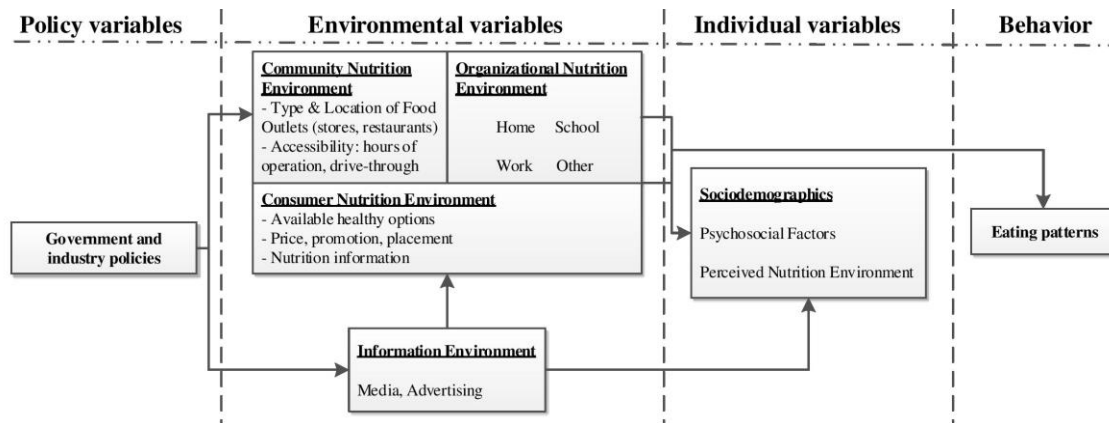


Figure 1-5: Ecological Model of Community Nutrition Environments (Glanz et al., 2005)

1.1.3.2. Strategies of neighborhood RFE assessment

Two main strategies exist in the literature for neighborhood RFE assessment: absolute and relative. Absolute RFE assessment focuses on a specific type of food outlet (e.g., supermarkets) or a specific item (e.g., healthy foods). It manifests in a variety of

forms including the presence/absence, density, and proximity of a food outlet as well as the absolute price of a food item. In contrast, relative RFE assessment involves multiple types of food outlets and food items. For example, the modified Retail Food Environment Index (mRFEI) (CDC, 2011) is a measure of relative healthy food access, which is calculated by dividing the number of accessible healthy food outlets by the total number of accessible healthy and less healthy food outlets. NEMS scores of in-store features are also relative measures of healthy and less healthy food items.

1.1.3.3. Food outlet data for neighborhood RFE assessment

Food outlet datasets for neighborhood RFE assessment can be classified as either primary or secondary. Such datasets include essential information including addresses or coordinates and store types, and optional information such as opening hours and time stamp if temporal investigation is conducted. Primary food outlet datasets are obtained via field observation, which is resource-intensive but offers the most accurate information. For example, in the Cardiovascular Health of Seniors and the Built Environment study, food outlets within participants' 300m radius buffer zone were repeatedly recorded (Morland, 2015a).

Secondary food outlet datasets from private commercial companies could also be utilized for neighborhood RFE assessment, with InfoUSA (Ma et al., 2013) and DMTI Spatial (Clary & Kestens, 2013) as two examples from the U.S. and Canadian contexts, respectively. For researchers, these commercial data are usually cost free in university geospatial libraries, but have been extensively criticized for their information errors in terms of food outlet count, type, and geospatial coordinates (Liese et al., 2013; Lucan et al., 2013). A recent investigation (Ma et al., 2013) found that these inaccuracies could lead to variations in identifying low food access areas with different commercial data sources. Innovative approaches (Clary & Kestens, 2013; Lyseen & Hansen, 2014; Ma et al., 2013), for example, the remote sensing technology (Rossen et al., 2012), have been applied to validate these secondary data. Unfortunately, results indicated that field census is the most reliable validation method. Within this context, the literature suggests using government registry data, which contains higher levels of accuracy, rather than commercial data, if secondary data is the only option for cost-effective reasons (Fleischhacker et al., 2013). In

Canada for example, the food premise inspection data can be requested from the public health department.

1.1.3.4. Spatial and temporal scales of neighborhood RFE assessment

Neighborhood RFE assessment is inherently a spatial and temporal issue. First, the operationalization of ‘neighborhood’ requires spatial boundary information. For areal RFE assessment, neighborhoods are usually defined with administrative boundaries, an approach that benefits policy implementations and planning as local governments have jurisdiction over these administrative areas (Health Canada, 2012). Simply assessing RFE falling within the administratively bounded areas however, could be problematic since food retailers are often located in close proximity to small-area (e.g., Census Tract) borders (Black et al., 2011). To alleviate this problem, buffering zones, which are created around the geometric or population centroid⁶ of an administrative area, are used instead. While these buffering zones can be circular- or network-based, the latter better captures realistic neighborhood RFE (Oliver, Schuurman, & Hall, 2007; Seliske, Pickett, Rosu, & Janssen, 2013). Nevertheless, the buffering size remains debatable in the literature, with various distance thresholds set as the cut-off. Relatively shorter distances such as 500m, 800m, and 1km (Apparicio, Cloutier, & Shearmur, 2007; J. L. Black et al., 2011; Gilliland et al., 2012; He, Tucker, Gilliland, et al., 2012; He, Tucker, Irwin, et al., 2012; Larsen & Gilliland, 2008; Smoyer-Tomic, Spence, & Amrhein, 2006) and longer distances such as 3km, 5km, and 8km (Barnes, Bell, Freedman, Colabianchi, & Liese, 2015; Larsen & Gilliland, 2008) have both been applied in Canadian RFE studies. A reasonable justification for the choice of distance cut-offs could be based on transportation modes (e.g., walking, public transit, and driving) and research contexts (e.g., urban vs. rural). For example, Larsen et al. (2008) calculate supermarket accessibility for London, Ontario, based on 1km and 3km, which represent reasonable distances for walking and public transit, respectively. The U.S. Department of Agriculture (USDA) defines urban and rural food deserts as neighborhoods without or with few healthy food options within 1 mile and 10 miles, respectively (USDA, 2014).

⁶ These centroids have also been used for operationalizing ‘proximity’ (i.e., the distance from the neighborhood centroid to the closest food outlet, see for example Black et al. (2011), Daniel et al., (2009), and Wang et al. (2016).

Second, neighborhood RFE varies at different temporal scales (Chen & Clark, 2015; Widener & Shannon, 2014): daily owing to opening hours of food retailers (as shown in Glanz et al.'s model, Figure 1-5) (Chen & Clark, 2013, 2015), seasonally due to the opening of temporary food retailers such as farmers' markets (Widener, Metcalf, & Bar-Yam, 2011), and annually attributable to the opening and closing of food outlets (Chen & Wang, 2014; Filomena, Scanlin, & Morland, 2013). Variations of public transit availability due to transit schedule and frequency also contribute to the temporal variations of neighborhood RFE (Farber, Morang, & Widener, 2014; Widener, Farber, Neutens, & Horner, 2015). Although beyond the scope of this dissertation, it should be noted that temporal food access relies on individual consumers' time availability as well (Horner & Wood, 2014). More details of the temporality of neighborhood RFE are provided in Chapter 2.

1.1.3.5. Methodology of neighborhood RFE assessment

To date, the methodology used for assessing neighborhood RFE is predominantly descriptive. For instance, the number of fast-food restaurants (e.g., Polsky, Moineddin, Dunn, Glazier, & Booth, 2016) and proportions of healthy food outlets (e.g., CDC, 2011) have been used for assessing the community nutrition environment. The cost of healthy food basket (e.g., Dawson et al., 2008) and mean NEMS scores (e.g., Duran, Diez Roux, Latorre, & Jaime, 2013) exemplify two descriptive approaches for evaluating the consumer nutrition environment of a neighborhood.

In contrast, modeling approaches, which are usually applied by geographers and transportation researchers, take into account realistic constraints or uncertainties for assessing neighborhood RFE. Studies from Dai and Wang (2011) and Lee and Lim (2009) provide examples of accounting for distance decay effects, which assume that people would more likely to procure foods in their immediate vicinity. Thus, food outlets closer to the centroid of a neighborhood should be more weighted. In reality however, this assumption has been challenged by recent findings that residents do not necessarily shop at the closest food outlet to their homes (LeDoux & Vojnovic, 2013; Shannon, 2014; Zenk et al., 2011). Variations in transportation availability, in particular public transit, have also been considered in neighborhood RFE assessment. For example, incorporating nuanced details such as boarding and alighting time, Farber et al. (2014) and Widener et al. (2015)

modeled supermarket accessibility for public transit-dependent residents. Results revealed that factoring transit schedules into food accessibility measurement enables to depict “a more complete and realistic picture” (Farber et al., 2014, p.149) of the food environment. Additionally, residents’ available time for food procurement has been taken into account for modeling neighborhood RFE. Adapting the space-time prism that accounts for individuals’ space-time constraints, Widener et al. (2013, 2015) assessed supermarket accessibility at the neighborhood level. Compared with traditional assessments focusing on residential neighborhoods only, their approach accounted for supermarkets that are accessible to residents on the way back home from work, provided that residents have a fixed amount of free time for activities including food shopping after work.

Table 1-2 provides examples of descriptive and modeling methods for assessing community and consumer nutrition environments using absolute and relative measures.

Table 1-2: Examples of descriptive and modeling approaches for neighborhood RFE assessment

		Community nutrition environment	Consumer nutrition environment
Descriptive	Absolute	Number of accessible fast-food restaurants (e.g., Polsky, Moineddin, Dunn, Glazier, & Booth, 2016)	Cost of healthy food basket (e.g., Dawson et al., 2008)
	Relative	Crude proportions of healthy food outlets such as mRFEI (CDC, 2011)	Mean NEMS score in a neighborhood (e.g., Duran, Diez Roux, Latorre, & Jaime, 2013)
Modeling	Absolute	Models accounting for (1) distance decay effects (Dai & Wang, 2011; Lee & Lim, 2009) and (2) supermarkets accessible on the way back home (Widener et al., 2015, 2013)	Not available
	Relative	Not available	

1.1.3.6. Marginalization and neighborhood RFE

Extending neighborhood RFE assessment studies from a social justice and food equity perspective, researchers have investigated whether certain groups, based on socio-economic status, have reduced healthy food access. Theoretical bases for such

investigations include the deprivation amplification hypothesis (Macintyre, 2007) and Lytle's ecological model of individuals' eating behaviors (Lytle, 2009).

The concept of deprivation amplification posits that compared to their more-affluent counterparts, deprived neighborhoods have less health-promoting resources including recreational amenities, physical activity facilities, and healthy food outlets. These disadvantageous environments magnify individual vulnerability, resulting in (built-) environmental characteristics more detrimental to health in deprived areas (Macintyre, 2007). Likewise, Lytle's model of eating behaviors demonstrates how individual, social, and environmental factors interact to influence eating behaviors (Figure 1-6). As individual and social factors become more restricted, the environmental characteristics explain more variance of eating behaviors. In contrast, eating patterns of residents with less restricted individual and social factors are less constrained by environmental factors. In this sense, it is necessary to understand whether marginalized neighborhoods have less healthy RFE given that the diet quality of residents restricted by individual and social factors largely depend on environmental factors.

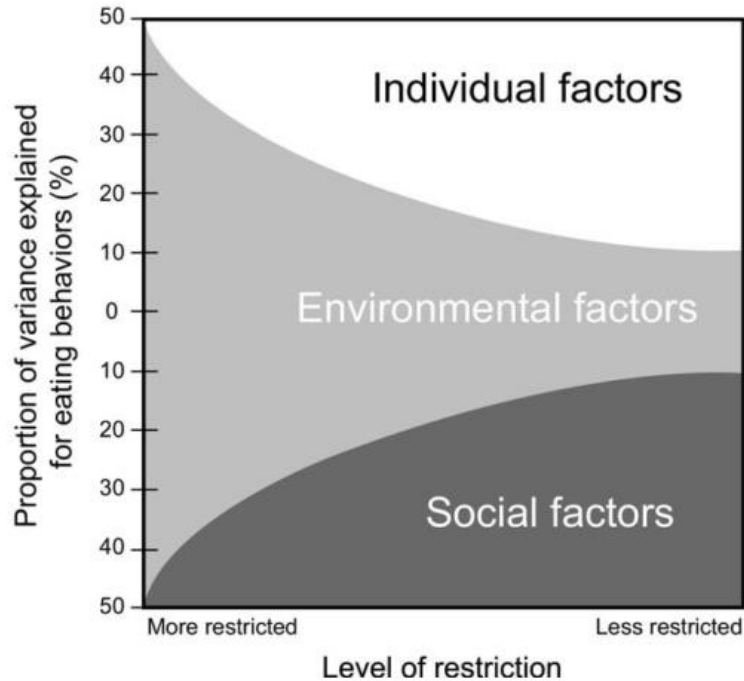


Figure 1-6: Lytle's model of individuals' eating behaviors (Excerpt from Lytle, 2009, p.S142)

Findings regarding the association between marginalization and neighborhood RFE are quite consistent in the U.S., suggesting that marginalized neighborhoods (i.e., lower income and higher proportion of minority residents) have lower access to food retailers that sell nutritious and affordable foods. The evidence is weak in other developed countries including Canada, the UK, Australia, and New Zealand (Beaulac, Kristjansson, & Cummins, 2009; Larson, Story, & Nelson, 2009).

1.1.3.7. Limitations in neighborhood RFE research

Past neighborhood RFE assessment studies suffer from a couple of limitations, which are highlighted in red in Figure 1-4. First, the temporality of neighborhood RFE is under researched. RFE measures are predominantly spatial, overlooking the dynamic nature of neighborhood RFE, although changes in the numbers and types of food retailers may lead to changes in food purchasing and consumption behaviors (Filomena et al., 2013). As it may take a long time for neighborhood RFE to manifest its health effects, ignoring RFE changes, especially at a small temporal scale (e.g., annually), might result in inconsistent findings regarding the impact of RFE on health (Health Canada, 2012; Zenk et al., 2015).

Second, a majority of studies use secondary and commercial RFE datasets that exclusively contain information of the community nutrition environment such as outlet addresses and types. Using secondary dataset is understandable from a cost-effective perspective, but it could result in biased findings that may adversely contribute to food interventions and planning, given that these datasets are subject to food outlet misclassification and data incompleteness as mentioned above.

Third, neighborhood RFE assessment mainly focuses on the community nutrition environment dimension, ignoring the consumer nutrition environment (i.e., in-store characteristics). This overlook could be problematic since the literature has suggested variations of in-store food availability, quality, and prices within the same outlet type across neighborhoods (Franco, Diez Roux, Glass, Caballero, & Brancati, 2008; Zenk et al., 2006). In this context, a multi-dimensional approach for assessing neighborhood RFE, which integrates both community and consumer nutrition environments, has been proposed (Rose, Bodor, Hutchinson, & Swalm, 2009) but rarely applied in the extant RFE literature. For reference, a multi-dimensional approach refers to the case in which RFE are assessed based on “information provided on the location dimension as well as dimensions regarding food product availability, pricing, and other in-store characteristics” (Rose et al., 2009, p.1171).

Fourth, absolute rather than relative measures have been extensively utilized for evaluating neighborhood RFE. Emphasizing on a specific type of food outlet or food item rather than evaluating the full spectrum of the complex RFE is limited in representing the underlying ‘healthfulness’ of neighborhood RFE, then subsequently limited in guiding food planning and interventions. The literature has suggested that a neighborhood could simultaneously have good access to both healthy and less healthy food outlets (Mason, Bentley, & Kavanagh, 2013; Polsky, Moineddin, Glazier, Dunn, & Booth, 2014). Furthermore, growing evidence has shown that relative measures of RFE better represent food shopping and consumption behaviors (Clary, Ramos, Shareck, & Kestens, 2015; Mason et al., 2013; Mercille et al., 2012; Thornton, Bentley, & Kavanagh, 2009) as well as health outcomes such as weight status (Kestens et al., 2012; Mehta & Chang, 2008;

Polsky et al., 2016; Spence, Cutumisu, Edwards, Raine, & Smoyer-Tomic, 2009), making it necessary to assess neighborhood RFE using relative rather than absolute strategies.

Finally, methodological limitations exist in extant studies that use descriptive approaches for assessing neighborhood RFE. Such descriptive measures are associated with uncertainties for evaluating the ‘healthfulness’ of neighborhood RFE, arising mainly from two sources. On the one hand, descriptive RFE measures fail to account for RFE in adjacent neighborhoods. While the choice of buffering sizes based on transportation modes makes sense to a certain extent, residents could still travel beyond the pre-defined zones. Incorporating neighboring RFE information strengthens RFE ‘healthfulness’ estimation and enables the differentiation between areas with the same descriptive RFE measure but varying RFE in adjacent neighborhoods. Such information could help prioritize neighborhoods for interventions. On the other hand, the number of total accessible food outlets is masked when relative measures are applied for neighborhood RFE assessment. For example, two areas with the same value of mRFEI or mean NEMS scores are regarded as equally healthy, although one might locate at central urban areas with numerous accessible food outlets, while the other locates at peripheral areas that can access much fewer outlets.

Apart from the limitations as aforementioned, studies exploring the association between marginalization and neighborhood RFE are subject to additional limitations including inadequate characterization of marginalization as well as applying non-spatial statistical approaches to respond to this ultimately spatial issue. These limitations are described with more details in Chapters 2 to 4.

1.1.4. RFE datasets in the Region of Waterloo

As noted above, the Region of Waterloo is one of the leading municipalities that incorporate food issues into professional planning, using both stand-alone and official plans. Annually it inspects every food premise within the three cities, Waterloo, Kitchener, and Cambridge, as well as four townships, Wellesley, Woolwich, Wilmot, and North Dumfries. This inspection results in a food outlet database with spatial information such as outlet type and location. Temporal information including outlet opening and closing dates can be derived from this spatio-temporal dataset. In response to the open data movement

in Canada, Region of Waterloo has recently released its food inspection datasets for public use (Region of Waterloo Public Health, 2014).

In addition, the Region of Waterloo conducted the interdisciplinary NEWPATH (Nutrition, Environment in Waterloo Region, Physical Activity, Transportation and Health) project that evaluates how different built environments impact health-related behaviors and outcomes, such as physical activity levels, walking rates, diet, and health in the urban areas of the three cities. A component that evaluates the quality of the RFE was included in this project. Specifically, the RFE-assessment component identifies food stores and restaurants based on the food outlet inspection database as mentioned above, followed by direct observations to identify additional food outlets, remove non-existent food outlets, and rectify outlet misclassification (Minaker et al., 2013). In-store characteristics of food stores and restaurants were assessed by the adapted NEMS-S (Glanz et al., 2007) and NEMS-R (Saelens et al., 2007) for Canadian studies, respectively. These two measures are inventory-based, which record every food item available in a food outlet (National Cancer Institute, 2016). Shelf-space devoted to fruits and vegetables as well as energy-dense foods including salty snack food, cookies & crackers, doughnuts & pastries, candy, and carbonated beverages in a food store was also measured. More details of these RFE datasets can be found in Chapters 2 to 4.

Nevertheless, these rich food outlet datasets in the Region of Waterloo have not yet been fully exploited for RFE assessment, especially at areal-neighborhood level, but could advance the understanding of neighborhood RFE and benefit food planning and interventions for promoting population-wide healthy eating.

1.2. Study purposes and research questions

Motivated by addressing the limitations of neighborhood RFE assessment in current literature as noted above, this article-based dissertation analyzes RFE datasets at both community and consumer nutrition environment levels using novel spatial and spatio-temporal statistical approaches. The connections between the guiding frameworks, the common theme, limitations in existing studies, and the three articles are presented in Figure 1-7.

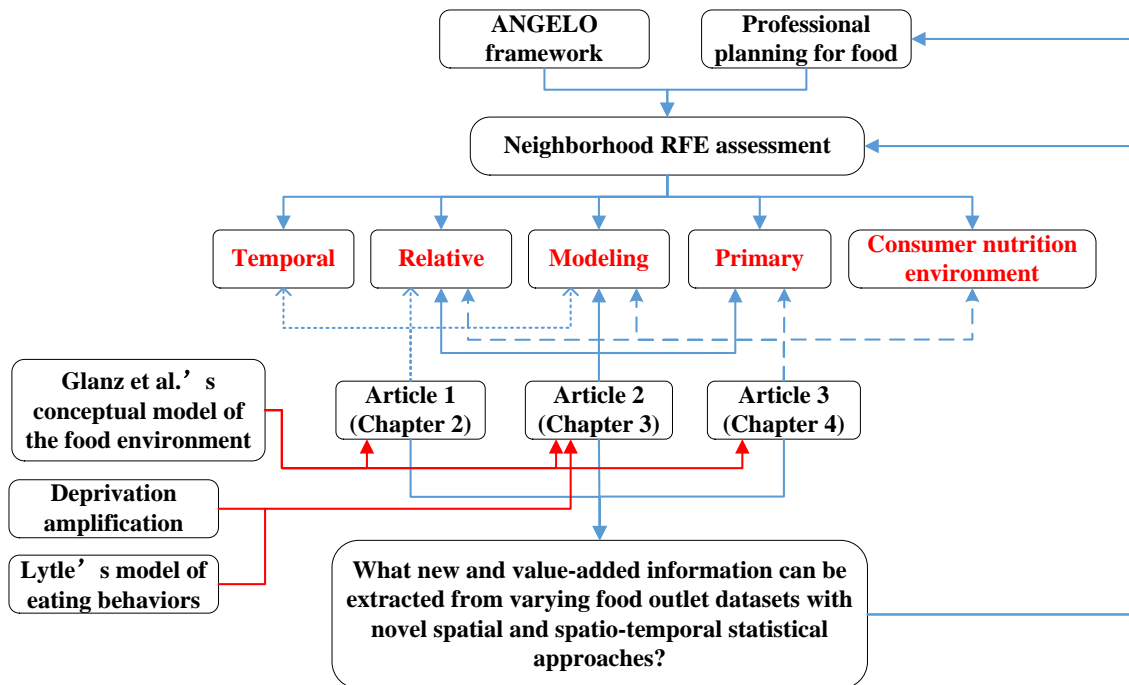


Figure 1-7: Connections between the guiding frameworks, the common theme, limitations in existing studies, and the three articles

Generally, the ANGELO framework and professional planning for food emphasize the necessity of neighborhood RFE assessment, which is the common theme of this dissertation and has the aforementioned limitations. Glanz et al.’s conceptual model of the food environment guides all three articles in terms of what food environment features to assess. Article 2 is also guided by the deprivation amplification hypothesis as well as Lytle’s model of eating behaviors. All three articles analyze relative RFE measures with modeling approaches, but each has its own objective, intending to fill in specific gaps as demonstrated in Figure 1-4 and Table 1-2. Specifically, Article 1 aims to analyze spatio-temporal variations of relative healthy food access (RHFA) using spatio-temporal modeling approaches; Article 2 intends to explore how different marginalization dimensions associate with neighborhood RFE ‘healthfulness’ with hierarchical spatial models; and Article 3 aims to assess neighborhood restaurant environment (NRE) with a multi-dimensional approach that combines both community and consumer nutrition environments. Corresponding research questions are formulated in Table 1-3. Together, these three articles explore what new and value-added information can be extracted from

food outlet datasets with varying available information using spatial and spatio-temporal statistical approaches, and provide evidence for food planning and interventions.

Table 1-3: Research objectives and questions

Chapter #	Objective	Research questions	Gaps to fill
Chapter 2	Analyze spatio-temporal variations of RHFA	<ol style="list-style-type: none"> 1. Is there an overall trend of RHFA (significant increasing/decreasing or insignificant change) in the Region of Waterloo at the neighborhood level? 2. What are the local (area-specific) trends of RHFA? Neighborhoods could experience different local trends compared with the regional trend. 3. Are there neighborhoods where RHFA decreases significantly faster than the regional trend? 	Relative measure of RFE + temporal dimension of RFE + modeling approach
Chapter 3	Explore the association between marginalization dimensions and neighborhood RFE 'healthfulness'	Do marginalized neighborhoods experience less healthy RFE? In other words, does the deprivation amplification hypothesis in the context of food access hold for the Region of Waterloo?	Relative measure of RFE + primary food outlet dataset + modeling approach
Chapter 4	Assess NRE 'healthfulness' with a multi-dimensional approach	<ol style="list-style-type: none"> 1. Which neighborhoods in the city of Kitchener have the least healthy NRE? In other words, which neighborhoods simultaneously suffer from deprived availability, affordability, and facilitator/barrier of healthy eating? 2. What is the indicator that contributes the most to (or most relevant with) the NRE healthfulness? 	Relative measure of RFE + consumer nutrition environment + primary food outlet dataset + modeling approach

1.3. Thesis outline

This dissertation is composed of five chapters. Specifically, Chapters 2 to 4 present three articles that have been published or submitted for publication on the subject of spatial

and spatio-temporal analyses of neighborhood RFE. Each article addresses specific limitations of current neighborhood RFE assessment.

Chapter 2 analyzes spatio-temporal variations of RHFA in the Region of Waterloo with a four-year RFE dataset. The focus is to explore the regional trend and local trends of RHFA (i.e., how RHFA varies over the region and at specific neighborhoods, respectively). This chapter extends the definition of food swamps by incorporating a temporal dimension and identifies spatio-temporal food swamps, neighborhoods where RHFA decreases faster than the average regional trend, using a hierarchical spatio-temporal model. Temporal variations of RHFA that cannot be revealed by descriptive statistics and/or multi-map comparison are also discussed.

Chapter 3 explores the association between marginalization dimensions and RFE healthfulness at the neighborhood level using hierarchical models. A primary RFE dataset collected in 2010, which contains the information of both community and consumer nutrition environments, is analyzed. In contrast to similar past studies, this paper differentiates ‘healthy’ and ‘less healthy’ food outlets based on NEMS scores rather than food outlet types, explores the entire instead of a partial RFE dataset, models RFE healthfulness (i.e., relative measure of healthy food access) with probability distributions rather than descriptive statistics (i.e., crude proportions of healthy food outlets of all accessible food outlets), and derives marginalization dimensions using spatial statistical approaches. This study sheds light on how the deprivation amplification hypothesis should be interpreted in the context of RFE and provides policy implications for improving the balance between healthy and less healthy food access in the Region of Waterloo.

Chapter 4 focuses on assessing NRE with a multi-dimensional approach in the city of Kitchener. A Bayesian spatial factor analysis approach is used to construct a composite index that represents NRE healthfulness, which is a weighted combination of three restaurant assessment indicators: availability, affordability, and facilitator/barrier of healthy eating. Such a modeling approach quantifies uncertainties associated with the mean NEMS-R score that result from masking the total number of accessible restaurants and variations of in-restaurant features, and ignoring NRE in adjacent neighborhoods. This study advances the understanding of NRE by introducing uncertainties in NRE assessment,

and informs food planning and interventions in terms of what in-restaurant features to prioritize and where the interventions should be targeted.

Chapter 5 concludes this dissertation by summarizing key findings and highlighting major conceptual, methodological, and empirical contributions. Policy implications and future research directions are also discussed in this chapter.

Chapter 2: Identifying food deserts and swamps based on relative healthy food access: a spatio-temporal Bayesian approach ⁷

2.0. Overview

Obesity and other adverse health outcomes are influenced by individual- and neighborhood-scale risk factors, including the food environment. At the small-area scale, past research has analyzed spatial patterns of food environments for one-time period, overlooking how food environments change over time. Further, past research has infrequently analyzed relative healthy food access (RHFA), a measure that is more representative of food purchasing and consumption behaviors than absolute outlet density. This research applies a hierarchical model to analyze the spatio-temporal patterns of RHFA in the Region of Waterloo, Canada, from 2011 to 2014 at the small-area level. RHFA is calculated as the proportion of healthy food outlets (healthy outlets/healthy + unhealthy outlets) within 4-km from each small-area. This model measures spatial autocorrelation of RHFA, temporal trend of RHFA for the study region, and spatio-temporal trends of RHFA for small-areas. For the study region, a significant decreasing trend in RHFA is observed (-0.024), suggesting that food swamps have become more prevalent during the study period. For small-areas, significant decreasing temporal trends in RHFA were observed for all small-areas. Specific small-areas located in south Waterloo, north Kitchener, and southeast Cambridge exhibited the steepest decreasing spatio-temporal trends, thus are classified as spatio-temporal food swamps. This research demonstrates a hierarchical spatio-temporal model to analyze RHFA at the small-area scale. Results suggest that food swamps are more prevalent than food deserts in the Region of Waterloo. Analyzing spatio-temporal trends of RHFA improves understanding of local food environment, highlighting specific small-areas where policies should be targeted to increase RHFA and reduce risk factors of adverse health outcomes such as obesity.

⁷ This chapter is adapted from the article entitled “Identifying food deserts and swamps based on relative healthy food access: a spatio-temporal Bayesian approach”, which has been published in *International Journal of Health Geographics*, 2015, 14:37.

2.1. Introduction

Past research has demonstrated that the food environment is an important factor in health outcomes. Several studies have shown that residents with higher access to healthy foods have healthier diets (Gustafson et al., 2013), lower risk of overweight/obesity (Cerin et al., 2011), and lower risk of high blood pressure (Dubowitz et al., 2012). Obesity, in particular, is a major risk factor for chronic diseases including heart diseases, stroke, and diabetes (WHO, 2013).

Acknowledging the role of healthy food access in shaping food consumption and related health outcomes, policymakers have prioritized increasing healthy food access. In Canada, for example, the Ontario Professional Planners Institute has issued a call for action on planning for healthy food systems and engaging planners with food relevant issues (OPPI, 2011). Furthermore, the municipalities of Vancouver (Seeton, 2012) and Toronto (Toronto Food Policy Council, 2014) have developed local programs to increase healthy food access by establishing healthy corner stores that sell fresh produce and instituting mobile grocery stores.

2.1.1. Measuring the food environment

Various measures have been developed for assessing the food environment and have been summarized (Charreire et al., 2010; Gustafson et al., 2012; Kelly et al., 2011; Ohri-Vachaspati & Leviton, 2010) and compared (Mercille et al., 2013; Minaker et al., 2014) in extant literature. While these measures can be categorized based on a number of different criteria such as community or consumer nutrition environments (Kelly et al., 2011), one important distinction is between absolute and relative measures.

The absolute and relative measures capture different aspects of the food environment (Mercille et al., 2013). Absolute metrics (e.g., the density of supermarkets within a census tract) measure access to one type of food outlet whereas relative metrics assess the relative accessibility of two types of food outlets, including healthy and unhealthy (Zenk, Powell, Rimkus, Isgor, & Barker, 2014). Recent research has demonstrated that relative healthy food access (RHFA), as measured by the percentage of

healthy food outlets (= healthy outlets / healthy + unhealthy outlets), better represents food purchasing and consumption behaviors (Clary et al., 2015; Mason et al., 2013) compared to absolute densities of healthy food outlets. This may be because RHFA measures the balance between healthy and unhealthy food outlets, while absolute measures assess only a portion of the total food environment. While analyzed in past research, relative measures have been shown to provide more consistent and expected associations with health outcomes. In a meta-analysis of 61 studies, Zenk et al. (2015) observed four studies that employ relative food environment measures, and all of these studies had consistent and expected findings (e.g., higher RHFA linked to lower odds of obesity), whereas mixed findings were identified in studies using absolute food environment measures. Relative measures also have methodological advantages since incorporating both absolute measures of healthy and unhealthy food outlets in regression models could lead to multi-collinearity as these two measures are usually positively correlated (Mason et al., 2013).

Capturing both healthy and unhealthy food outlets in one measure allows for a more comprehensive analysis of different dimensions of the food environment (Lucan, 2015), and enables conceptualizing food deserts and food swamps on a continuous scale. Food deserts are areas lacking access to nutritious and affordable food (i.e., 0% RHFA), and food swamps are areas that with relatively few healthy options (i.e., small RHFA) (Centers for Disease Control and Prevention, 2011) or where “large relative amounts of energy-dense snack foods, inundate healthy food options” (Rose et al., 2009, p.2). The modified Retail Food Environment Index (mRFEI) is a relative measure of the food environment that can represent both food deserts and food swamps⁸, where a value equal to zero characterizes a food desert while a small value greater than zero characterizes a food swamp. Food deserts have been extensively investigated in past research, however recent research indicates food swamps may be more prevalent in countries including Canada (Health Canada, 2012; Rose et al., 2009; Strickland, Strategy, & Plan, 2014).

2.1.2. Temporal variation in the food environment

Previous research has indicated that changes in the numbers and types of retail food outlets may lead to changes in food purchasing and consumption behaviors (Filomena et

⁸ This paper follows the mRFEI approach to differentiate food deserts and food swamps.

al., 2013), however little research has analyzed temporal changes in healthy food access, especially RHFA.

Temporal food access can be considered from supply (retail) and demand (consumer) sides. From the supply side, variations in temporal food access occur across years (e.g., new food outlets opening), seasons (e.g., farmers' markets), and weekdays (e.g., opening hours of food outlets) (Chen & Wang, 2014; Chen & Clark, 2013, 2015; Filomena et al., 2013; Widener, Metcalf, & Bar-Yam, 2011). For example, Filomena et al. (2013) investigated annual changes of the food environment in Brooklyn, New York between 2007 and 2011, and observed that changes in absolute healthy food outlets varied between neighborhoods based on income and ethnic composition, where low income and predominately non-white neighborhoods experienced higher variations in healthy food access. Widener et al. (2011) found that poorer neighborhoods have better spatial access to healthy foods in summer than in winter because of seasonal farmers' markets. Also analyzing food environments at the seasonal scale, Lamichhane et al. (2015) explored associations between absolute densities of supermarkets, convenience stores and socio-demographic characteristics. Positive associations were observed between the numbers of both types of food stores and neighborhood poverty. Two recent studies from Chen and Clark (2013, 2015) suggested that socio-economically marginalized neighborhoods have limited temporal access, rather than spatial access, to healthy food outlets due to limited daily opening hours of green retailers. Therefore, interventions such as extending opening hours of green retailers were recommended to reduce healthy food access disparities, complementing conventional interventions such as building new healthy food outlets.

From the demand side, temporal food access is generally measured for individuals because it is largely determined by consumers' time availability. For example, people working non-conventional hours may be constrained by food outlet operating hours (Chen & Clark, 2013). In this case, the space-time prism has been used to quantify food accessibility, incorporating individual mobility and time budgets (Horner & Wood, 2014; Widener et al., 2013). Findings from these studies identify which population rather than which areas have greater or less access to healthy foods. Temporal variations in transportation service (especially public transit) that link supply and demand sides also

influence healthy food access. For example, Farber et al. (2014) found that supermarket accessibility varied for public transit-dependent residents across the day in Cincinnati due to daily fluctuations in transit availability.

This study analyzes annual spatio-temporal variations of RHFA at the small-area scale for the Region of Waterloo, from 2011 to 2014, complementing past research that analyzes only spatial variations and absolute healthy food access. RHFA at a small temporal scale (e.g., annual) merits attention given that changes in the number and type of food outlets are slow, and it probably takes a long time for the food environment to manifest its health effects (Moore & Diez-Roux, 2015). Specifically, this study has three objectives: 1) to estimate temporal trend in RHFA for the study region (regional trend), 2) to identify spatio-temporal RHFA trends at the small-area scale (local trends), and 3) to highlight spatio-temporal food swamps, or small-areas where RHFA is decreasing at a greater rate than the study region.

2.2. Study region and data

2.2.1. Study region

The Region of Waterloo, Ontario, Canada, is composed of three cities, Kitchener, Waterloo, and Cambridge, and four rural townships. It is located approximately one hour west of Toronto, Canada's largest city. For this study, rural townships were excluded from the analysis because retail food outlets are primarily located in urban areas. City boundaries were collected from the Region of Waterloo (Region of Waterloo, 2014).

In total, 655 DAs with a population of 444,681 were analyzed. For reference, DAs are the smallest census units that cover the entirety of Canada and are delineated according to roads and physical boundaries (Statistics Canada, 2012). Average DA population density was 3234/km², ranging between 2/km² in a predominantly industrial DA and 16025/km² in a DA with many apartment buildings. Population data and geographic shapefiles were obtained from Statistics Canada (Statistics Canada, 2015).

2.2.2. Food Outlet Data

Retail food outlet locations were extracted from a food inspection dataset containing all food outlets in the Region of Waterloo. Misclassification of outlets was

detected, which is a common challenge encountered in secondary datasets (Liese et al., 2013; Lucan et al., 2013). Retail food outlets were re-classified based on categories from the Nutrition, Environment in Waterloo Region, Physical Activity, Transportation and Health (NEWPATH) project (Minaker et al., 2013), which surveyed in-store characteristics of all food outlets (e.g., shelf-space dedicated to fruit and vegetables in a supermarket or availability of healthy eating options in a restaurant) in 2009. NEWPATH included nine categories: full-service restaurant, fast-food restaurant, bar/pub, supermarket, specialty food store, convenience store, pharmacy, superstore, and snack stand.

In practice, dichotomously categorizing food outlets as ‘healthy’ or ‘unhealthy’ is contentious because many healthy food outlets supply unhealthy food products. We followed the most common and simplest classification scheme in the literature (Vernez Moudon et al., 2013): only supermarkets/superstores are classified as healthy and only convenience stores and fast-food restaurants are classified as unhealthy. Similar approaches have been employed in recent Canadian (Clary et al., 2015; Engler-Stringer, Shah, Bell, & Muhajarine, 2014) and Australian (Mason et al., 2013) studies.

RHFA was calculated by dividing the number of healthy food outlets by the sum of healthy and unhealthy food outlets within a 4km road network buffering distance from DA centroids. Food outlets that were located outside of the study region, but were inside buffers, were included. This approach alleviates the ‘edge effects’ problem in measuring food access (Sadler, Gilliland, & Arku, 2011). A 4km buffering distance was chosen because RHFA within a DA is likely not representative of food purchasing behaviors, as DAs are small (average area = 0.48 km²) and retail food outlets are often located close to small-area borders (Black et al., 2011). A 4km road network buffer approximates a 5-minute driving distance, which is the primary transportation mode for employment and shopping in the study region (approximately 85% of employed residents either drive to work or are passengers⁹). A 5-minute driving distance also captures local food environments for residents using other forms of transportation, such as public transit and

⁹ The figure was derived based on Census Canada 2011.

cycling. For reference, the longest distance from a DA centroid to the closest healthy or unhealthy food outlet is 3.53km.

Table 2-1 shows the descriptive statistics for healthy and unhealthy food outlets in the study region. Between 2011 and 2014, the number of healthy food outlets slightly declined by three (4.3%), while the number of unhealthy food outlets increased by 34 (3.6%). As a result, RHFA for the study region decreased from 7% to 6.5%. Notably, because the number of convenience stores decreased by 12, the increase in unhealthy food outlets is due to increasing numbers of fast-food restaurants.

Table 2-1: Descriptive statistics of retail food outlets and RHFA by year

		2011	2012	2013	2014
Healthy food outlets		70	69	68	67
Unhealthy food outlets	Total	932	939	942	966
	Convenience store	323	317	306	311
	Fast-food restaurant	609	622	636	655
Total healthy and unhealthy food outlets		1002	1008	1010	1033
RHFA (%)		7	6.8	6.7	6.5

Figure 2-1 shows the geographic distribution of healthy food outlets in the study region from 2011 to 2014. Most healthy food outlets were operational during the four years (green dots), with the exception of two (red dots) in north Kitchener and one (pink dot) in south Cambridge. One healthy food outlet at middle Cambridge (blue dot) was closed in 2012, but a new one was constructed at the same site in 2013.

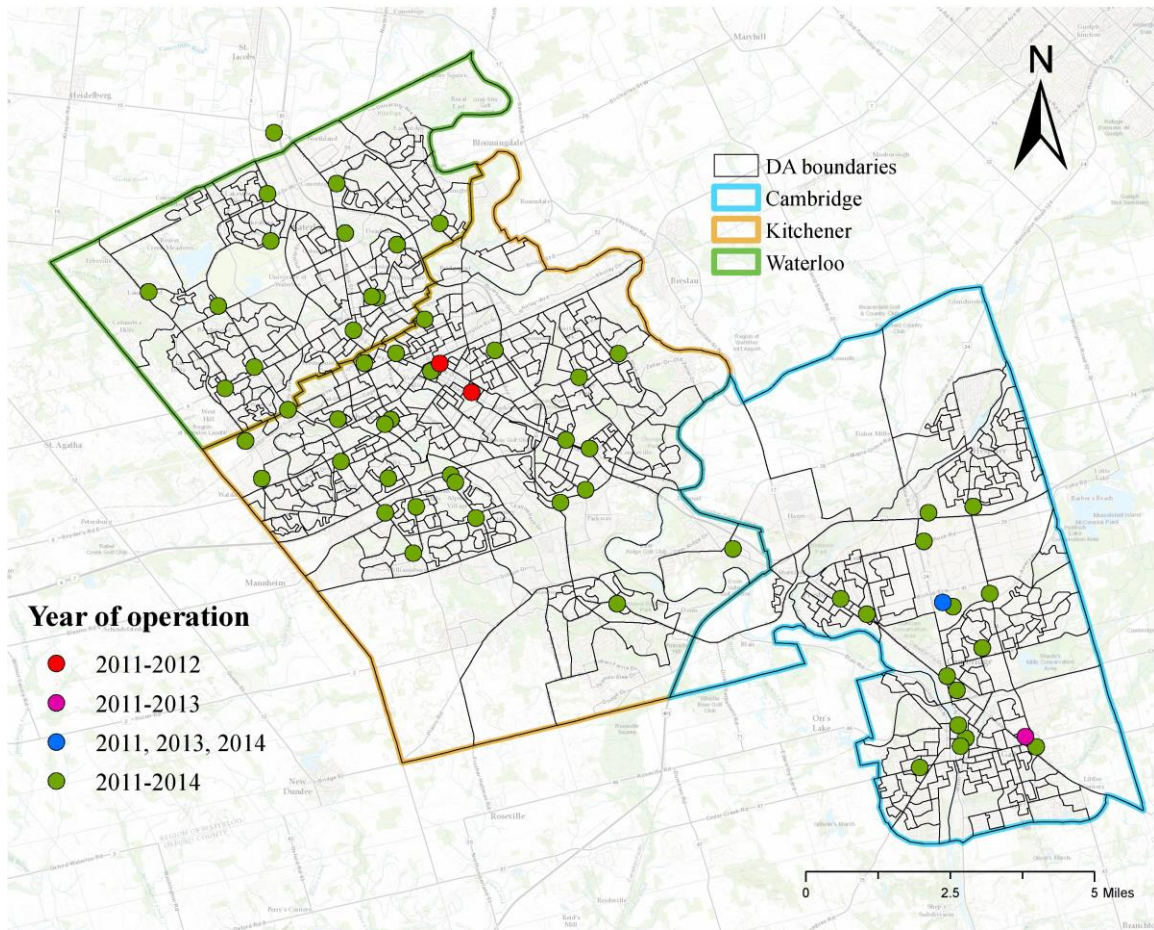


Figure 2-1: Distributions of healthy food outlets in the Region of Waterloo from 2011 to 2014

Figure 2-2 maps the calculated RHFA at the DA-scale for each year. RHFA values range from 0% in all years to 20% in 2012. Areas that have no healthy food outlets within 4km are highlighted with hatched lines.

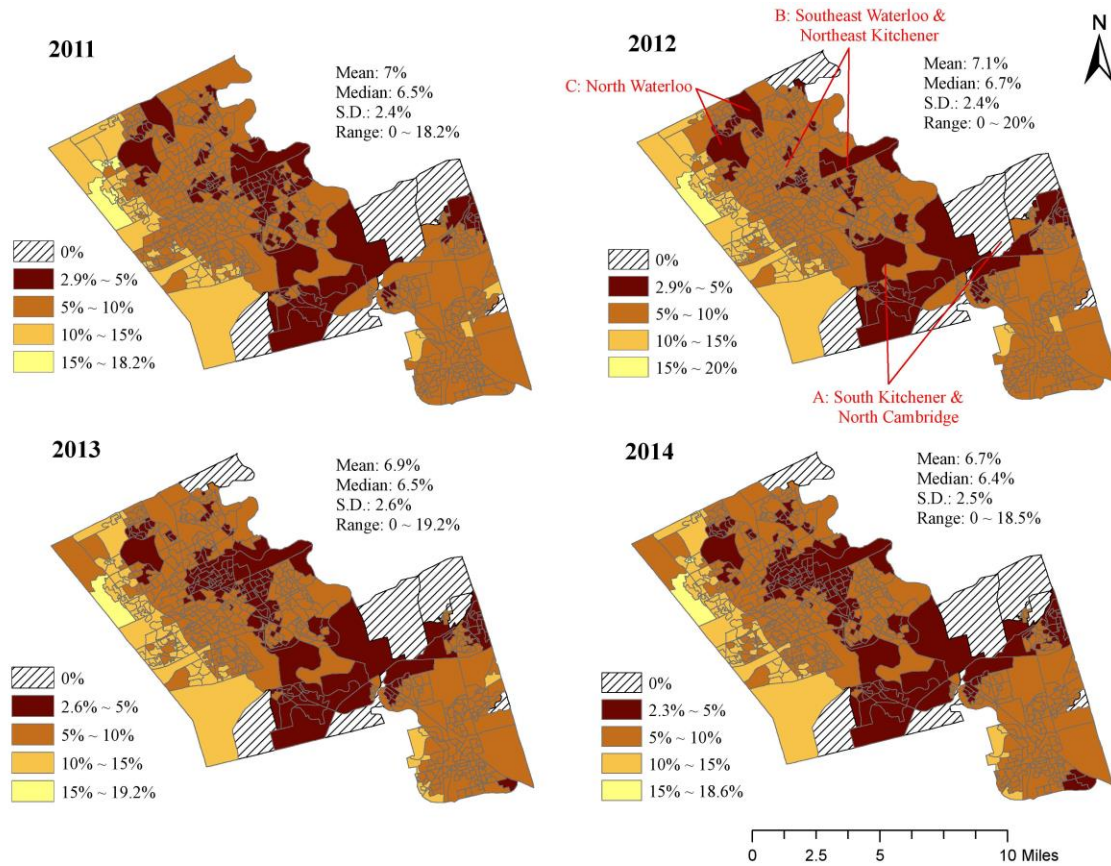


Figure 2-2: Quantile maps of RHFA from 2011 to 2014

While no explicit thresholds have been applied to define food swamps, we assume that they are areas where RHFA is greater than zero and less than 10%. This is based on a recent study that demonstrated that, in areas with more than 10% of healthy food outlets, households had higher odds of purchasing healthier foods (Mason et al., 2013). Most DAs (~ 90%) are identified as food swamps because they have low RHFA (< 10%). Some DAs have RHFA of less than 5% for the duration of the study period and are highlighted in Figure 2-2: south Kitchener and north Cambridge (Location A), southeast Waterloo and northeast Kitchener (Location B), and north Waterloo (Location C).

Notably, one DA in north Waterloo went from a food swamp in 2011 to a food desert in 2012, which was due to road network reconstructions that made supermarkets/superstores inaccessible within 4km. While the RHFA patterns in most

small-areas are similar from 2011 to 2014, RHFA fluctuations in Location B are noticeable. In 2012, RHFA increased in Location B because the number of accessible unhealthy food outlets decreased and the number of supermarkets/superstores was constant. Following closures of two supermarkets in 2013, RHFA decreased in these same areas.

2.3. Methodology

A hierarchical model was used to analyze the spatio-temporal trend of RHFA. This approach was adapted from Bernardinelli et al. (1995) and has been widely used in spatio-temporal analysis of count data (Law, Quick, & Chan, 2013, 2014; Li, Haining, Richardson, & Best, 2014). Bayesian approaches combine prior knowledge and observed data (i.e., accessible healthy food outlets) to estimate posterior distributions of unknown parameters (i.e., regional RHFA trend).

The spatio-temporal model consists of two levels. Level 1 (in Equation (1)) assumes that the count of healthy food outlets within 4km of DA i at time j follows a binomial distribution, where Y_{ij} is the observed number of healthy food outlets, T_{ij} is the sum of healthy and unhealthy food outlets, and p_{ij} is the probability of a food outlet being healthy. Of note, p_{ij} can be considered as an estimated RHFA and while different than calculated RHFA, they are both representative of the risk of low RHFA. The distinction will be detailed in the discussion section.

$$Y_{ij} \sim \text{Binomial}(p_{ij}, T_{ij}) \quad (1)$$

Using a logit link function, p_{ij} is decomposed into parameters measuring purely spatial variation, purely temporal variation, and spatio-temporal interaction at the second level (Equation (2), from Model I).

$$\text{logit}(p_{ij}) = \alpha + u_i + s_i + (\gamma + \delta_i)t_j \quad (2)$$

Purely spatial variation is represented by an intercept α (average RHFA for the study region), u_i (unstructured random effects), and s_i (spatially structured random

effects). Random effects (u_i and s_i) deal with overdispersion (greater variance than expected based on a probability distribution), which occurs when modeling count data at the areal level. Sources of overdispersion in small-area studies include intra-area heterogeneity, which may be due to the presence of missing covariates or measurement errors in covariates (Haining, Law, & Griffith, 2009; Law & Haining, 2004; Law et al., 2014). The spatially structured random effects, s_i , model the spatial autocorrelation of RHFA. Because RHFA is calculated using a buffering approach, it is likely to be spatially autocorrelated such that nearby areas exhibit similar RHFA.

In Equation (2), purely temporal variation of RHFA for the study region is captured by γ . We assumed a linear regional trend over a four-year period considering that the opening and closure of food outlets occur infrequently over time (compared to epidemiological cases that likely vary rapidly at small-area levels over four years, for example) (Figure 2-2). The spatio-temporal interaction term δ_i models local differential trends (the difference between regional trend and local trends) in RHFA after accounting for purely spatial and temporal effects. Notably, t_j is the centered time, calculated by subtracting the empirical mean from each time value, which has been suggested for better model convergence (D. Lunn, Jackson, Best, Thomas, & Spiegelhalter, 2012).

Equation (2) can be extended to include other covariates (Equation (3), from Model II). Specifically, \mathbf{X}_i^T is a vector of covariates that could be included in the modeling, and $\boldsymbol{\beta}$ is a vector of corresponding coefficients. An example of covariates to be included is population density to explore the possibility that food outlets are located in highly populated areas.

$$\text{logit}(p_{ij}) = \alpha + u_i + s_i + (\gamma + \delta_i)t_j + \mathbf{X}_i^T\boldsymbol{\beta} \quad (3)$$

The posterior probability (PP_i) of δ_i being less than zero measures the strength that the local trend negatively departs from the regional trend (γ) (Law et al., 2013, 2014). Spatio-temporal food swamps are small-areas that exhibit a decreasing RHFA trend and a

high probability of local RHFA trend being less than regional RHFA trend. Specifically, they are areas that have a negative local trend ($\gamma + \delta_i < 0$) (i.e., decreasing RHFA from 2011 to 2014) and high PP_i of δ_i less than zero (i.e., local RHFA trend strongly differs from the study region trend).

We specified an improper uniform prior $U(-\infty, +\infty)$ for the intercept α . Priors for spatial random effect s_i and spatio-temporal interaction δ_i were specified by the intrinsic (Gaussian) conditional autoregressive (ICAR) (Besag, York, & Mollie, 1991) distribution. Under the ICAR distribution, the expected mean of s_i and δ_i of the i^{th} DA is the mean of adjacent s_i 's and δ_i 's, respectively, where adjacency is defined as areas sharing at least one common vertex (Law et al., 2013). Variances of s_i and δ_i is controlled by hyperparameters¹⁰ σ_s^2 and σ_δ^2 , respectively, and is inversely proportional to the number of neighbors of the i^{th} DA. It should be noted that there are other prior specifications for spatial parameters, for example the proper (Gaussian) conditional autoregressive distribution. ICAR is appropriate for data that exhibits high spatial autocorrelation (Law & Haining, 2004; D. Lee, 2011) and strong spatial autocorrelation of RHFA has been identified using Moran's I^{11} (≥ 0.8).

A non-informative prior $Normal(0, 1000)$ was given to the regional trend parameter γ and covariate coefficients β , respectively, while a prior of $Normal(0, \sigma_u^2)$ was assigned to u_i . Non-informative hyperpriors of $Gamma(0.5, 0.0005)$ were given to the reciprocal of hyperparameters σ_s^2 , σ_u^2 , and σ_δ^2 (denoted as τ_s , τ_u , and τ_δ). To determine the degree to which hyperparameter specification influenced results, we performed sensitivity analysis using three alternative priors: 1) $Gamma(0.001, 0.001)$ for τ_s , τ_u , and τ_δ , 2) a

¹⁰ In Bayesian approaches, hyperparameters are the parameters of priors. Priors assigned to hyperparameters are called hyperpriors.

¹¹ Moran's I is a statistical method to quantify spatial autocorrelations. A value of Moran's I approaching 1 indicates strong positive autocorrelations.

uniform prior $U(0, 100)$ (Law et al., 2013) for σ_s , σ_u , and σ_δ , and 3) a half normal prior $\text{Normal}_{+\infty}(0,10)$ ¹² (Gelman, 2006; Li et al., 2014) for σ_s , σ_u , and σ_δ .

We fitted the models using the WinBUGS software (Lunn, Thomas, Best, & Spiegelhalter, 2000) with two parallel chains. Convergence was checked by visually examining trace plots, history plots, autocorrelation plots, and Gelman-Rubin plots. Deviance Information Criterion (DIC) (Spiegelhalter, Best, Carlin, & van der Linde, 2002) was used to identify the model best fitting the data. The better model is the one with a smaller DIC value.

2.4. Results

Models I and II were compared in Table 2-2 to identify the model that better represents the spatio-temporal variation (rather than covariates) of RHFA, which is the main goal of this study. Model II extended Model I by testing the association between RHFA and population density, one of the major driving factors of the distribution of food outlets (Chen & Wang, 2014; Zenk et al., 2005). This association was found to be insignificant. A DIC difference of 1.2 (10,162.5 versus 10,163.7) does not indicate remarkable improvement of model fitting, so we selected Model I based on the principle of parsimony.

Table 2-2: Spatio-temporal analyses results of Model I and Model II

	Model I	Model II
Population density β (95% Credible Interval)*	NA	0.003 (-0.015, 0.022)
Regional trend γ (95% Credible Interval)	-0.024 (-0.036, -0.011)	-0.024 (-0.037, -0.011)
DIC	10,162.5	10,163.7

* The 95% Credible Interval is the range in which there is a 95% probability that the posterior mean occurs.

¹² $+\infty$ means that only positive values from the normal distribution will be sampled.

For Model I, convergence occurred by 10,000 iterations (thinned by 10). We ran a further 10,000 iterations for both chains to obtain 20,000 samples of the posterior distribution. Regional trend (γ) was negative (-0.024) and statistically significant at the 95% credible interval, indicating a decreasing trend of RHFA at the region-scale from 2011 to 2014. The sensitivity analysis using the alternative hyperpriors discussed above obtained nearly identical results, suggesting that results are insensitive to the selection of hyperpriors.

Figure 2-3a shows the area-specific differential trend, which indicates the degree to which local area-specific trends deviate from the regional trend. The map is smoothed because of the buffering approach used to calculate RHFA and the addition of spatially structured random effects.

Since the regional trend (γ) is -0.024 and the largest differential trend (δ_i) is 0.004, no DAs exhibit a positive trend in RHFA (i.e., maximum trend is $-0.024 + 0.004 = -0.02$). A negative differential trend (δ_i) indicates a steeper decreasing trend than the regional trend while a positive one indicates a gentler decreasing trend. Areas in the lowest quantile ($-0.004 \sim -0.002$) have the steepest decreasing trend and are located in south Waterloo, north Kitchener, and southeast Cambridge.

Figure 2-3b shows PP_i , or the strength that area-specific trend negatively deviates from the regional trend. Because food outlet closures and openings are slow, PP_i s are relatively small with the maximum 0.63. We assumed 0.55, the fifth quintile threshold of PP_i s, to be a reasonable threshold for defining a “high” PP_i although higher thresholds have been used in other contexts (Law et al., 2013; Li et al., 2014). This threshold enables the top 20% DAs to be identified as having a “high” PP_i . As mentioned, areas with high PP_i and negative ($\gamma + \delta_i$) are spatio-temporal food swamps. In Figure 2-3b, areas in the lowest quantile (0.55 \sim 0.63, Figure 2-3b) are identified as spatio-temporal food swamps given that all small areas had a decrease trend of RHFA. As shown by Figure 2-3, areas with high PP_i coincide with areas with the steepest area-specific differential trends. This is expected as there is more evidence that these areas have a trend that negatively deviates from the regional trend. Notably, in Figure 2-3b we highlight DAs that are not in the quantile with

lowest RHFA (based on Figure 2-2) but experienced a significant steeper decreasing trend of RHFA (more in the discussion).

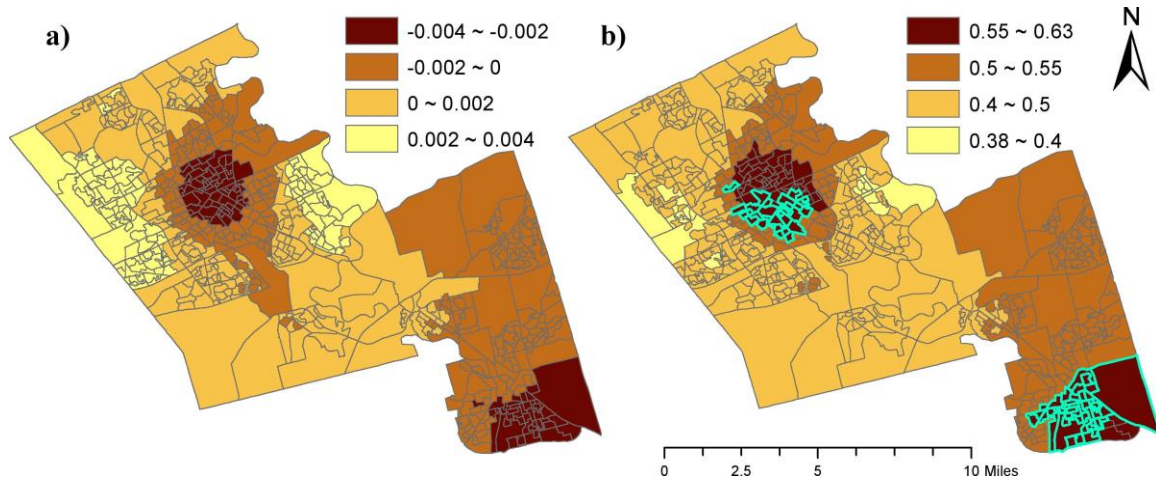


Figure 2-3: a) Local differential trends (δ_i) and b) the posterior probability of a local trend less than the regional trend (PP_i)

2.5. Discussion

Consistent with previous findings in the Canadian context, this paper reveals that food swamps are more prevalent than food deserts in the study region. Using a hierarchical model that accounts for spatial autocorrelation and spatio-temporal interaction, this paper also shows that food swamps are becoming more prevalent during the study period.

2.5.1. Interpreting spatio-temporal modeling results

Past research evaluating the food environment is predominantly spatial, thus providing limited insight into how RHFA is changing over time at the local scale. For example, spatial analysis of the food environment shows that Locations A, B, and C (Figure 2-2) have similar RHFA (<5%). Results of this spatio-temporal model, however, show that there is strong evidence (high PP_i) that some DAs in Location B exhibited steeper decreasing trend of RHFA ($\delta_i < -0.002$), and can be categorized as spatio-temporal food swamps. Locations A and C had relatively stable RHFA and are not spatio-temporal food

swamps ($0 < \delta_i < 0.002$). It is noteworthy that a spatio-temporal food swamp could attribute to decreases of accessible healthy food outlets and/or increases of accessible unhealthy food outlets during the study period. For example, two DAs that are both identified as spatio-temporal food swamps in our analysis and have the same increase in fast-food restaurants; however, one exhibits an increase in convenience stores (unhealthy) and the other exhibits a decrease in supermarkets/superstores (healthy).

This study has also identified areas that were not in the quantile of lowest RHFA based on only spatial and descriptive approaches, but have decreasing trends of RHFA that are steeper than the regional decreasing trend (highlighted in Figure 2-3b). If the trend continues, these highlighted DAs could become new areas that have the lowest RHFA. Such temporal information cannot be quantified through visual comparison of multiple maps (Figure 2-2) and can help policy makers prioritize specific areas for interventions. For instance, the spatio-temporal food swamps at south Waterloo, north Kitchener, and southeast Cambridge should be prioritized since RHFA decreases faster in these areas.

As mentioned, estimated RHFA is different from calculated RHFA. Calculated RHFA is simply the number of healthy food outlets divided by the sum of healthy and unhealthy food outlets. Estimated RHFA is the probability of a food outlet being healthy (p_{ij} in Equation (2)) and is based on calculated RHFA in a given DA and the average of calculated RHFA's in adjacent areas (via the spatial random effects in Equation (2)). In this case, estimated RHFA helps to account for the realistic assumption that people could travel beyond DA or buffering zone boundaries to procure food; therefore, the RHFA value is smoothed (Figure 2-4b). In contrast, calculated RHFA constraints food access within the DA or buffering zones. Two DAs with the same calculated RHFA could have varied estimated RHFA if the averages of calculated RHFA's in their adjacent areas are different. To exemplify the difference between calculated RHFA and estimated RHFA, we selected two pairs of DAs (highlighted in Figure 2-4) with the same calculated RHFA but differing estimated RHFA in 2014: one pair are food deserts (Areas 1 and 2 have calculated RHFA = 0%) and the other pair are food swamps (Areas 3 and 4 have calculated RHFA = 4.76%). Area 1 has a higher average of calculated RHFA's among adjacent areas (3.58%) compared to Area 2 (2.08%), leading to Area 1 having a greater estimated RHFA. Similarly, Area 3

has adjacent areas with a higher average of calculated RHFA's than Area 4, leading to Area 3 having a greater estimated RHFA. Practically, these results suggest that Area 2 is a more serious food desert than Area 1, and that Area 4 is a more serious food swamp than Area 3. When identifying small-areas for food policy interventions, this information helps to continuously categorize food deserts and food swamps, suggesting that Area 2 should be prioritized first because it has the lowest estimated RHFA, followed by Area 1, Area 4, and Area 3 (Table 2-3).

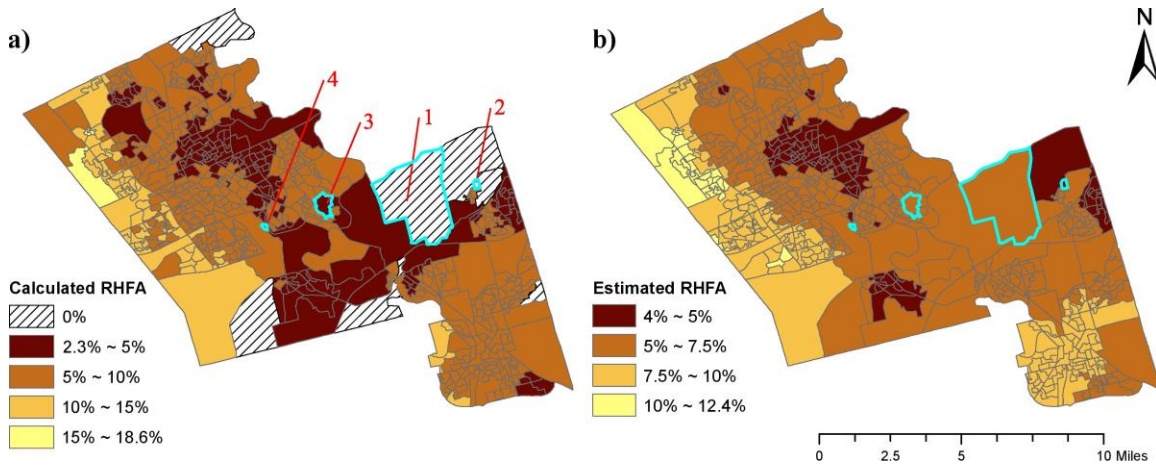


Figure 2-4: a) RHFA in 2014 and b) estimated RHFA in 2014 (p_{14} in Model I)

Table 2-3: Calculated RHFA and estimated RHFA in 2014

Area ID	Calculated RHFA (%)	Average calculated RHFA in neighbouring areas (%)	Estimated RHFA(%)* (95% credible interval)
1	0	3.58	5.2 (4.1, 6.5)
2	0	2.08	4.9 (3.5, 6.6)
3	4.76	6.72	6.0 (5.0, 7.0)
4	4.76	5.31	5.3 (4.1, 6.7)

* p_{14} in Model I indicates the estimated RHFA in 2014

2.5.2. Limitations and future research

There are several limitations to this research. First, we employed a 4km buffer for calculating RHFA. Different buffer sizes could be used depending on policy targets (e.g., improve the RHFA within a walking distance), study region characteristics (e.g., compactness), and characteristics of the local population (e.g., car ownership). The buffering size could also be altered accordingly based on food outlet types, which may be linked to the behaviors underlying travel patterns to visit specific healthy or unhealthy stores (and subtypes among them). Second, we applied the most common scheme for classifying healthy and unhealthy food outlets. The NEWPATH survey, from which food outlets were classified, measured in-store characteristics of food outlets and indicated that all non-supermarket and non-superstore outlets (e.g., full-service restaurants and pub/bars), with the exception of specialty stores (e.g., bakeries), should be categorized as unhealthy. Moreover, supermarkets/superstores are also sources of unhealthy food options. We completed additional analyses following in-store classification and counting grocery stores as both healthy and unhealthy, but results of regional and local RHFA trends (thus the identification of spatio-temporal food swamps) were similar. Additional RHFA measures based on consumer nutrition environment, for instance, shelf space devoted to healthy foods divided by the total shelf spaces devoted to healthy and unhealthy foods in accessible food outlets (Glanz et al., 2007), should be considered. Lastly, we used 10% as a threshold to define food swamps. Nevertheless, this figure could be tailored for different research contexts depending on the intervention targets for striking balance between healthy and unhealthy food access as well as evidence of the level at which RHFA impacts healthy food purchase, consumption, or health outcomes in specific study regions.

Future research should further apply this Bayesian approach in different contexts (e.g., outside Canada) and with different datasets (e.g., more than 4-year's dataset) to study spatio-temporal variations of the food environment accounting for transportation networks. Of particular interest is the association between changes in public transit and changes to RHFA. Future research could also analyze the association between spatio-temporal patterns of the food environment and health or socio-economic data, when available. Compared to spatial studies that analyze one-time period, spatio-temporal analysis clarifies how changes in the food environment influence health outcomes (e.g., obesity), and how

the food environment may be changing in tandem with increasing or decreasing socioeconomic status.

2.6. Conclusions

This paper explores the spatio-temporal patterns of RHFA in the Region of Waterloo over four years, using a hierarchical spatio-temporal model. This method quantifies regional temporal trend and local spatio-temporal trends of RHFA, which are not available from traditional spatial or descriptive analyses. In particular, this study adds to the literature for investigating relative food access at a small temporal scale (based on annual RHFA changes).

Results of our study are consistent with previous findings in the Canadian context that food swamps are more prevalent than food deserts. While food deserts should be prioritized, food swamps (especially spatio-temporal food swamps) should not be overlooked by public health practitioners and policy-makers. In general, food swamps have become more prevalent during the study period, given that RHFA has decreased at the regional level, and all DAs (most are food swamps in the starting year 2011) at the local level show significant decreasing trend of RHFA. Areas located at south Waterloo, north Kitchener, and southeast Cambridge have the steepest RHFA decreasing gradient (Figure 2-3) thus are spatio-temporal food swamps and should be prioritized for interventions.

Chapter 3: Do marginalized neighborhoods have less healthy retail food environments? An analysis using spatial latent factor and hurdle models¹³

3.0. Overview

Findings of whether marginalized neighborhoods have less healthy Retail Food Environments (RFE) are mixed across countries, in part because inconsistent approaches have been used to characterize RFE ‘healthfulness’ and marginalization, and researchers have used non-spatial statistical methods to respond to this ultimately spatial issue. This study uses in-store features to categorize healthy and less healthy food outlets. Spatial hierarchical models are applied to explore the association between marginalization dimensions and RFE healthfulness (i.e., relative healthy food access that modeled via a probability distribution) at various geographical scales. Marginalization dimensions are derived from a spatial latent factor model. Zero-inflation occurring at the walkable-distance scale is accounted for with a spatial hurdle model. Neighborhoods with higher residential instability, material deprivation, and population density are more likely to have access to healthy food outlets within a walkable distance from a binary ‘have’ or ‘not have’ access perspective. At the walkable distance scale however, materially deprived neighborhoods are found to have less healthy RFE (lower relative healthy food access). Food intervention programs should be developed for striking the balance between healthy and less healthy food access in the study region as well as improving opportunities for residents to buy and consume foods consistent with dietary recommendations.

3.1. Introduction

A growing body of literature has shown that neighborhood Retail Food Environment (RFE) has a role in shaping residents’ food shopping and consumption behaviors (C. Black et al., 2014; Caspi et al., 2012; Engler-Stringer, Le, et al., 2014; Kirkpatrick et al., 2014; Kimberly B. Morland, 2015c). Identifying and modifying

¹³ This chapter is adapted from the article entitled “Do marginalized neighborhoods have less healthy retail food environments? An analysis using spatial latent factor and hurdle models”, which has been published in *International Journal of Health Geographics* 2016, 15:29.

characteristics of neighborhood RFE could therefore be an important step in promoting population-wide healthy eating and reducing diet-related chronic diseases. An extensively explored research question is whether the RFE is less healthy in marginalized¹⁴ neighborhoods, wherein residents are more vulnerable to adverse health outcomes. The exploration is largely motivated by the deprivation amplification hypothesis, which postulates that residents living in deprived neighborhoods tend to have fewer health-promoting resources such as healthy foods (Macintyre, 2007). In light of Lytle’s conceptual model of eating behaviors (Lytle, 2009), the more people are constrained by individual (e.g., disability) and social (e.g., income) factors, the more their eating behaviors are explained by the food environment. In other words, Lytle’s model posits that marginalized residents are particularly at risk of poor diet and subsequent nutrition-related chronic disease if they live in a less healthy RFE.

Nevertheless, findings in terms of the association between marginalization and RFE are mixed across countries. Studies from the U.S. consistently indicate that neighborhoods with lower income and higher proportions of minority residents have reduced healthy food access, but the evidence is weak in other developed countries including Canada (Beaulac et al., 2009; Larson et al., 2009; Minaker et al., 2016). These inconsistent findings in past studies do not conclusively answer the question of whether marginalized neighborhoods have a less healthy RFE, in part because of limitations in the approaches used to characterize the ‘healthfulness’ of neighborhood RFE and neighborhood marginalization as well as deficiencies in the statistical methods used.

3.1.1. Characterizing neighborhood RFE healthfulness

The ‘healthfulness’ of the neighborhood RFE has been characterized using numerous methods. For example, focusing on absolute densities or numbers of so-called healthy food outlets such as supermarkets represents a focus on a single dimension of the complex RFE and thus could be biased. As reported, densities of healthy and less healthy food outlets are positively correlated, indicating that a neighborhood could simultaneously have high densities of healthy and less healthy food outlets (Mason et al., 2013). Recent

¹⁴ Marginalization occurs “when people are systematically excluded from meaningful participation in economic, social, political, cultural and other forms of human activity in their communities and thus are denied the opportunity to fulfil themselves as human beings” (Rao, 2007, p.223).

studies have attempted to characterize the RFE healthfulness using relative healthy food access metrics, such as the proportion of healthy food outlets of all accessible food outlets, see for example the modified Retail Food Environment Index (CDC, 2011).

These relative measures however, ignore in-store characteristics (i.e., the quality and price of available foods as well as in-store marketing), which could vary within outlet types. For instance, the literature has suggested variations in shelf-space devoted to fruits and vegetables or healthy eating options, which have been proven relevant to healthy eating, within the same outlet types across neighborhoods (Franco et al., 2008; Zenk et al., 2006). Moreover, using outlet types to categorize healthy and less healthy food outlets has the potential to misclassify outlets and exclude outlets (e.g., specialty food stores) whose category is undetermined with a dichotomous classification scheme (Vernez Moudon et al., 2013). Another limitation associated with crude proportions for estimating neighborhood RFE healthfulness is its uncertainty. Two areas with the same crude proportions, say 0.5, but different total number of accessible food outlets, say 2 and 20, respectively, are regarded to have a RFE with the same level of healthfulness.

3.1.2. Characterizing neighborhood marginalization

Much of the extant research is also limited by inadequate characterizations of neighborhood marginalization. Most studies, in particular those in the U.S., have explored the association between individual socio-demographic and/or socio-economic indicators (i.e., proportions of low-income and minority residents) and the neighborhood RFE. These individual indicators represent but a small fraction of marginalization, which is a multi-faceted construct. Hence, many previous conclusions regarding these associations are actually based on associations between an oversimplified metric of the neighborhood RFE and specific indicators of marginalization rather than multi-dimensional marginalization. The literature suggests that representing an overall construct such as marginalization by selecting a particular facet of the construct could “reduce strength of the intended signal and thus underestimate its association with the outcome of interest” (Shishehbor & Litaker, 2006, p.781). In addition, selecting individual socio-economic or socio-demographic indicators is problematic since they may correlate with another indicator belonging to the same marginalization dimension, such that it could act as a proxy of its related indicator in

the regression analysis and consequently the association. While the regression analysis could include all marginalization indicators, the multicollinearity problem is likely to occur.

Alternatively, marginalization can be measured with a composite index (Matheson, Dunn, Smith, Moineddin, & Glazier, 2012). For instance, Larsen and Gilliland (2008) calculated deprivation for London, Ontario by adding the standardized scores of percentage of lone-parent families, prevalence of low income, percentage of low educational attainment, and percentage of unemployment. Such a composite index may also be subject to arbitrary inclusion of marginalization indicators. Compared with the London case, a study conducted in Montreal, Quebec (Apparicio et al., 2007) included an additional indicator, the percentage of recent immigrants in the past five years, to operationalize deprivation.

Another limitation of current composite marginalization indices is that the included indicators are unweighted, an approach that assumes each indicator contributes evenly to marginalization. This assumption is problematic given that population structures vary across neighborhoods (Hogan & Tchernis, 2004). To weight each indicator, statistical approaches implemented in the frequentist framework such as Principal Component Analysis and Factor Analysis have been applied to construct the composite indices (Borrell, Mari-Dell'Olmo, Serral, Martinez-Beneito, & Gotsens, 2010; Matheson et al., 2012; Polsky et al., 2014; Zadnik & Reich, 2006). These approaches are flawed in presuming that indicators (and the associated constructs they purport to measure) in adjacent areas are independent, an assumption usually violated in spatial studies at a small-area level.

3.1.3. Statistical methods in neighborhood RFE studies

Methodologically, with few exceptions, most studies use non-spatial statistical approaches to analyze the association between neighborhood RFE and marginalization. For example, non-spatial versions of Ordinary Least Square (OLS) and Poisson/Negative Binomial regression approaches have been applied to model the continuous (e.g., distance to the nearest food outlet) (Black et al., 2011; Daniel, Kestens, & Paquet, 2009) and discrete (e.g., count of accessible food outlets) (Black et al., 2011; Polsky et al., 2014; Smoyer-Tomic et al., 2008) measures of neighborhood RFE, respectively. Residuals from regression analyses could be spatially auto-correlated given that spatial dependence is

likely to exist between RFE measures at small-area levels with adjacent areas having similar RFE, a phenomenon rooted in the understanding that socioeconomic processes occur systematically and spatially across metropolitan areas (McKenzie, 2014). Ignoring spatial autocorrelation renders conclusions regarding the association potentially invalid. The mixed findings in the literature could also be partly attributed to this methodological limitation. A recent meta-analysis of 54 papers revealed that although the spatial nature is widely acknowledged in RFE studies, very few adopted appropriate spatial statistical approaches (Lamb, Thornton, Cerin, & Ball, 2015).

Of the few studies that did use spatial approaches, Baker et al. (2006) applied a spatial scan method to model the counts of fast-food restaurants and supermarkets in urban areas of St. Louis, Missouri. Their research found that mixed-race or white high-poverty communities and all-black communities regardless of poverty are less likely to have access to healthy foods compared to their predominantly white high-income counterparts. McKenzie (2014) assessed neighborhood disparities in supermarket access for Portland, Oregon region with a spatial error model. Findings revealed that in comparison to their counterparts in urban areas, neighborhoods in suburban areas, either poor or non-poor, have longer travel distance and time to the nearest supermarket. Within suburban neighborhoods however, the study found that deprivation was associated with shorter travel distance but longer travel time. Applying and comparing both spatial and non-spatial regression techniques, Wang et al. (2016) analyzed the relationship between spatial proximity to fresh food retailers and socioeconomic status in Saskatoon and Regina, Saskatchewan, Canada at the dissemination area level. In addition to identifying significant associations between healthy food access and socio-economic variables, their research reported that in comparison with spatial regression approaches, OLS overestimated the magnitude of the associations. Lamichhane et al. (2013) analyzed the relationship between access to supermarkets as well as fast-food outlets and neighborhood characteristics with a spatial Bernoulli model for the State of South Carolina at the census block group level. Several characteristics including income, housing value, and educational attainment were found to have a positive association with access to both supermarkets and fast-food outlets, whereas a negative association was identified for characteristics such as percentage of minority and population living under poverty after accounting for geographic location (e.g., urban, rural,

etc.) and population density. Finally, Lamichhane et al. (2015) applied a spatio-temporal Poisson model to analyze the relationship between sociodemographic characteristics and densities of supermarkets and convenience stores for four U.S. cities at the Census Tract level. Results indicated that poorer neighborhoods have better access to both supermarkets and convenience stores after controlling for covariates including population density.

3.1.4. Study objectives

To address the limitations in past studies, this research uses measures of the consumer nutrition environment (a Canadian adaptation of the widely-used NEMS-S (Glanz et al., 2007) and the NEMS-R (Saelens et al., 2007)) to classify “healthy” vs. “less healthy” food outlets rather than assuming invariance in the consumer nutrition environment within outlet types.

Second, this study constructs four composite indices representing the four different dimensions of marginalization for the study region, namely residential instability, material deprivation, dependency, and ethnic concentration, using a spatial latent factor model. A recent study reported that compared to its non-spatial counterpart, the spatial latent factor model provides more precise estimation for composite dimension scores, which thus enables more accurate assessment of the association between dimensions of neighborhood environment and health outcomes (Nethery et al., 2015). Specifically, each marginalization dimension is derived from a number of relevant indicators, which are theoretically informed and have been empirically validated (Matheson et al., 2012). These dimensions have been proven to be strongly and significantly associated with several public health outcomes derived from the nationally-generalizable Canadian Community Health Survey.

Finally, using hierarchical spatial models, this research investigates whether marginalized neighborhoods experience less healthy RFE. Healthfulness of neighborhood RFE is represented as relative healthy food access, which is modeled via probability distributions rather than crude proportions of healthy food outlets. Various buffering sizes are used to characterize neighborhood RFE, accounting for potential transportation modes. More details regarding the datasets and methodologies are given in the following sections.

3.2. Study region and data

3.2.1. Study Region

Our study was conducted in the Regional Municipality of Waterloo (Figure 3-1), Ontario, specifically the cities of Waterloo, Kitchener, and Cambridge, which include 625 dissemination areas (DA). For reference, a DA is the smallest census area in Canada that covers the entire territory and follows roads and physical boundaries (Statistics Canada, 2015). DAs are delineated such that the population size is generally between 400 and 700 (Statistics Canada, 2015). The average population density in the study region was 3273.37 /km², ranging from 1.26 /km² to 16754.11/km².

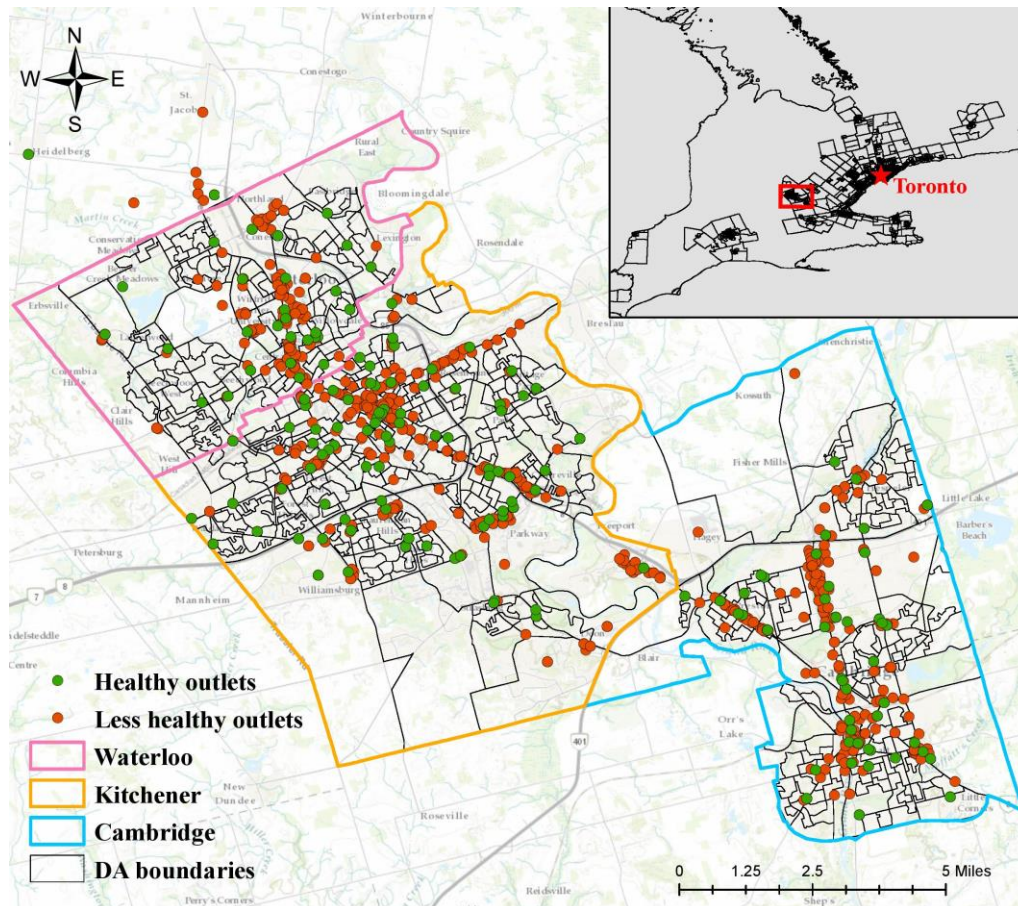


Figure 3-1: Boundaries of Region of Waterloo and food outlet distributions, 2010

3.2.2. Marginalization indicators

Guided by contemporary theories regarding marginalization in Canadian societies (Curtis, Grabb, & Guppy, 2004; MacLeod & Eisenberg, 2006) and the selection of characteristics for constructing areal deprivation indices in previous studies (Atkinson, Salmond, & Crampton, 2014; Pampalon et al., 2012; Townsend, Phillimore, & Beattie, 1988), we followed Matheson et al.'s approach (2012) to include 18 indicators from 2006 Canadian census that belong to four marginalization dimensions: residential instability, material deprivation, dependency, and ethnic concentration (Table 3-1). The inclusion of these indicators enables a comprehensive depiction of neighborhood marginalization, which involves diversified social problems relevant to health. The hypothesized loading sign of the indicator and its corresponding marginalization domain, which indicates the direction of correlation, is also presented. For example, percentage of living alone (R1) is assumed to be positively associated with residential instability, whereas percentage of dwellings that are owned (R6) is presumed to have a negative loading.

Table 3-1: Variables used to measure marginalization dimensions, with hypothesized sign of loadings

ID	Indicator	Hypothesized loading sign
Residential Instability		
1	% of living alone (R1)	+
2	% of youth population aged 5-15 (R2)	-
3	Crowding: Average number of persons per dwelling (R3)	-
4	% of multi-unit housing (R4)	+
5	% of the population that is married/common-law (R5)	-
6	% of dwellings that are owned (R6)	-
7	% of residential mobility (same house as 5 years ago) (R7)	+
Material Deprivation		
8	% 25+ without certificate, diploma, or degree (M1)	+
9	% of lone-parent families (M2)	+
10	% of government transfer payment (M3)	+
11	% of unemployment 15+ (M4)	+
12	% of below low income cut-off (M5)	+
13	% of homes needing major repair (M6)	+
Dependency		
14	% of seniors (65+) (D1)	+
15	Dependency ratio [(0-14)+(65+)]/(15-64) (D2)	+
16	Labor force participation rate (aged 15+) (D3)	-
Ethnic Concentration		
17	% of 5-year recent immigrants (E1)	+
18	% of visible minority (E2)	+

3.2.3. Measures of neighborhood RFE

Food stores and restaurants were categorized as healthy if their Nutrition Environment Measures Survey (NEMS-S or NEMS-R) score fell within the highest two quartiles. The NEMS-S (Glanz et al., 2007) and NEMS-R (Saelens et al., 2007) are inventory-type measures of food stores and restaurants, respectively, that score outlets according to the quality, relative affordability, availability, and marketing of foods and beverages that comprise a large proportion of caloric intake at the population level. Data collection methods employed in the current study have been reported in detail elsewhere (Minaker et al., 2013, 2014). Briefly, the Region of Waterloo's public health inspection database was used to identify food outlets, and systematic direct observation was used to identify additional outlets and remove non-existent food outlets within the three cities from the sampling frame. One of each chain convenience store, pharmacy and superstore, and each grocery store and independently owned convenience store, pharmacy, and specialty store in the three cities were assessed using the NEMS-S adapted for Canada (n=422 stores). One of each chain restaurant and each independently-owned restaurant was assessed using the NEMS-R (n=912). NEMS food outlet scores ranged from 0 to 43 for food stores and from -11 to 37 for restaurants. Data were collected in 2010.

The numbers of accessible healthy and total food outlets within 1km, 4km, and 8km network buffering zones were calculated from each DA's centroid. The first cut-off represents a walkable distance (10~15 min) which has been widely used in Canadian studies (Apparicio et al., 2007; Black et al., 2011; Larsen & Gilliland, 2008; Smoyer-Tomic, Spence, & Amrhein, 2006), while the second, which has been used in past research for the same study region (Luan, Law, & Quick, 2015), represents a 5-min driving distance and also represents accessibility for people who use alternative transportation modes such as bicycling and public transit. A third buffering size which approximately represents a 10-min driving distance, 8km, is used for testing the sensitivity in terms of how the relationships change under the assumption that residents own cars. Descriptive statistics of accessible healthy and total food outlets are shown in Table 3-2.

Table 3-2: Descriptive statistics of accessible food outlets within 1km, 4km, and 8km from DA centroids

Buffering size	Food outlets	Mean	Min	Max	S.D.
1km	Healthy	5.1	0	48	7.6
	Total	11.6	0	117	17.5
4km	Healthy	82.1	2	208	51.4
	Total	178.6	3	478	119
8km	Healthy	249.3	32	414	94.9
	Total	527.5	52	859	199.4

The count and crude proportion of accessible healthy food outlets are mapped in Figure 3-2. Areas without access to food outlets within a walkable distance are highlighted using hatch lines in Figure 3-2b. Within 1km, the central parts of the three cities have access to higher number of healthy food outlets. The spatial pattern becomes more distinct at the 4km and 8km scales, with south Cambridge and north Kitchener having highest number of accessible healthy food outlets. In contrast, areas with higher crude proportions of healthy food outlets locate at peripheral parts of the cities, probably attributable to the relatively low number of total accessible food outlets. This pattern suggests that uncertainties exist in using the crude proportion to estimate the healthfulness of neighborhood RFE.

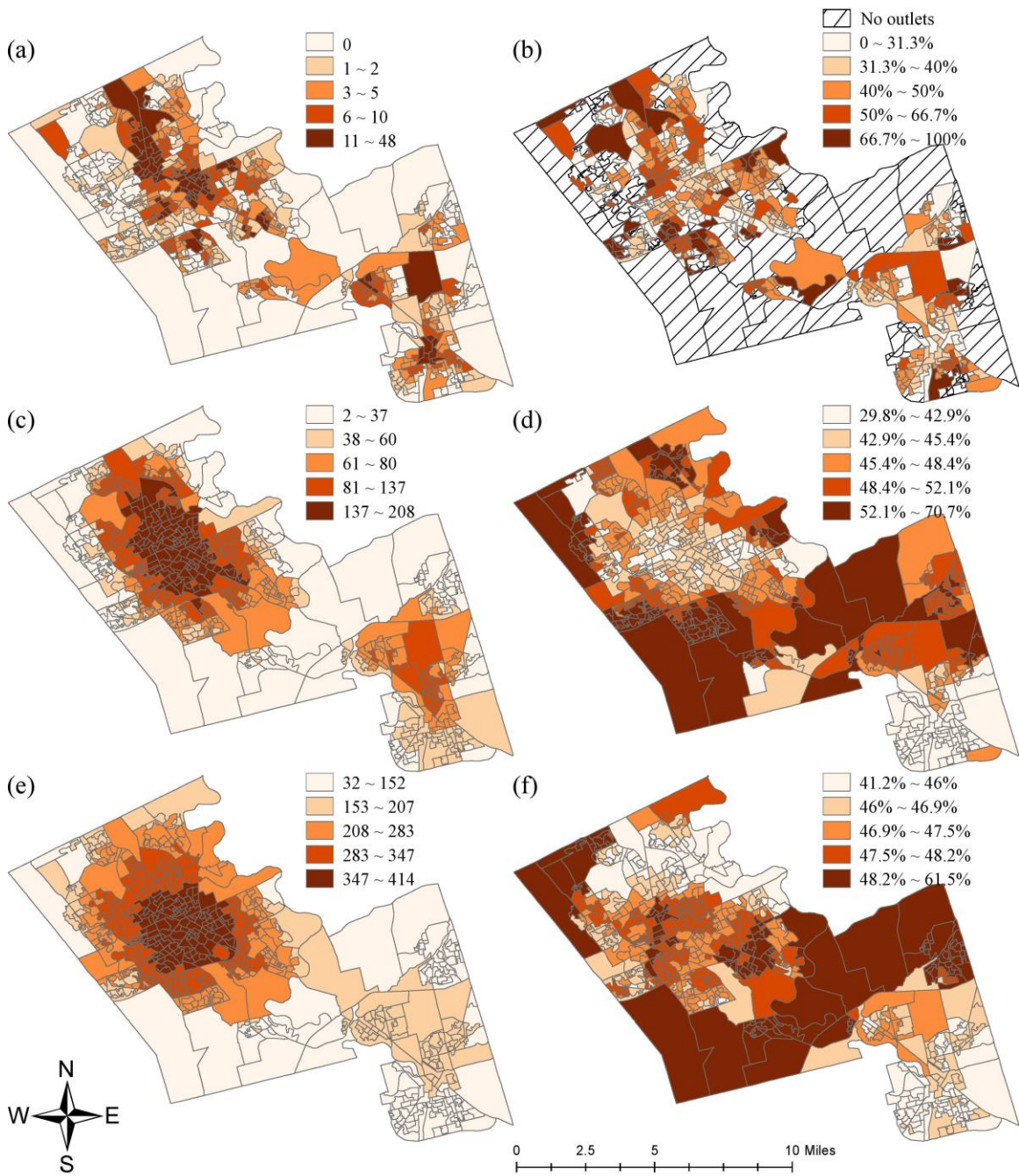


Figure 3-2: Quantile maps of count and crude proportion of healthy food outlets

(a) Count of healthy food outlets, 1km; (b) Proportion of healthy food outlets, 1km;

(c) Count of healthy food outlets, 4km; (d) Proportion of healthy food outlets, 4km;

(e) Count of healthy food outlets, 8km; (f) Proportion of healthy food outlets, 8km;

3.3. Methodology

We use Moran's I statistic to test spatial autocorrelation within each marginalization indicator and RFE measures including counts and crude proportions of healthy food outlets. A Moran's I value approaching 1/-1 indicates strong positive/negative spatial autocorrelation, indicating that adjacent neighborhoods have similar/dissimilar values of marginalization indicators and RFE. In contrast, a value equal to or close to zero suggests spatial randomness. In other words, values of marginalization indicators and RFE are randomly distributed over space. Spearman's rank correlation analysis is applied to examine the correlations between indicators belonging to the same marginalization domain. Below we detail the spatial latent factor model for constructing marginalization domains and spatial regression models for exploring the association between RFE healthfulness and marginalization dimensions as well as population density. All models are implemented in the Bayesian framework. For reference, Bayesian approaches combine prior knowledge and observed data to estimate posterior distributions of unknown parameters.

3.3.1. Spatial latent factor model

Given that each marginalization indicator is theoretically linked to a specific dimension (Matheson et al., 2012), the confirmatory rather than the exploratory factor model is used. Except for the dimension an indicator belongs to, the factor loadings of this indicator on other dimensions are set to zero. Similar approaches have been applied in Congdon (2008, 2011, 2016). Specifically, the normalized marginalization indicator j at area i (denoted as V_{ij}) is assumed to follow a Normal distribution with mean $(\alpha_j + \delta_j * X_{ni})$ and variance σ_j^2 (Equation (1)), where X_{ni} is the n^{th} marginalization dimension at area i (that V_{ij} belongs to); α_j is the intercept representing the average of indicator j over the study region; and δ_j is the factor loading of V_{ij} on X_{ni} . For reference, the constructed factors X_{1i} , X_{2i} , X_{3i} , and X_{4i} represent residential instability, material deprivation, dependency, and ethnic concentration, respectively.

$$V_{ij} \sim \text{Normal}(\alpha_j + \delta_j * X_{ni}, \sigma_j^2) \quad (1)$$

An improper flat prior $Uniform(-\infty, +\infty)$ is specified to the intercept α_j . To avoid the “flip-flop” problem (i.e., $\delta_j * X_{ni} = (-\delta_j) * (-X_{ni})$) and to achieve identifiability, we set δ_1 ,

$\delta_8, \delta_{14}, \delta_{17}$ – the factor loading of the first indicator of corresponding marginalization dimensions – as one (P. Congdon, 2011). Alternatively, we can specify a prior distribution for these factor loadings to restrict their values to be positive (Abellan, Fecht, Best, Richardson, & Briggs, 2007; Peter Congdon, 2016; Marí-Dell’Olmo et al., 2011). A vague prior $Normal(0, 1000)$ is assigned to all other δ_j ’s. An intrinsic Conditional Autoregressive (ICAR) prior is assigned to marginalization dimensions X_{ni} . Under this prior distribution, the expected mean of X_{ni} is the mean of X_n ’s in adjacent areas, and the variance of X_n , denoted as $\sigma_{X_n}^2$, is inversely proportional to the number of adjacent areas to area i . Adjacency is defined as areas sharing at least one vertex, a common approach used in spatial analysis studies (Haining et al., 2009). To address the identifiability issue between the scales of δ_j and X_{ni} , we set the variance of \mathbf{X}_n to 1, equivalent to standardizing \mathbf{X}_n (Skrondal & Rabe-Hesketh, 2007). A non-informative prior $Gamma(0.5, 0.0005)$ is given to the reciprocal of $\sigma_{X_n}^2$ and the variance of indicator j , σ_j^2 .

3.3.2. Spatial regression models

3.3.2.1. Model for the 1km dataset: spatial hurdle model

Considering that ~30% of DAs (178 out of 625) had no access to healthy food outlets within a walkable distance and adjacent areas have similar healthy food access, we used a spatial hurdle model to analyze the 1km dataset, accounting for the potential zero-inflation and spatial autocorrelation. Similar spatial hurdle models have been applied to model emergency department visits (Neelon, Chang, Ling, & Hastings, 2014; Neelon, Ghosh, & Loeb, 2013) and adult mortality (Kazembe, 2013) with excess zeros. An alternative to the hurdle model for accounting for zero-inflation is the zero-inflated model (Amek et al., 2011), which assumes zeros arise from two sources – the “structural” zeros and “chance” zeros. The hurdle model is appropriate for this study because cases of zero accessibility are fully observed rather than latent – a DA either can or cannot access healthy food outlets within a walkable distance, and this access is not dependent on chance. Using a Binomial hurdle model (more details given in Appendix 1), zero counts and positive counts are modeled via a Bernoulli distribution with probability parameter π_i and a truncated Binomial distribution with probability parameter p_i , respectively. Specifically, π_i represents the likelihood of a binary indicator – whether or not a DA has access to healthy

food outlets, while p_i is the probability of a food outlet being healthy in DA_i , which represents the prevalence of healthy food outlets (thus the healthfulness of neighborhood RFE). Notably, p_i is equivalent to a modeled version of the relative healthy food access (Luan et al., 2015). Compared with calculated or crude proportions of healthy food outlets, p_i is a more robust metric to reflect RFE healthfulness. Using a sampling distribution (i.e., Binomial) to model empirical counts (e.g., the number of accessible healthy food outlets) that occur as proportions (i.e., the proportion of healthy food outlets), the uncertainty associated with crude proportions of healthy food outlets as shown in Figure 3-2 can be accounted for by incorporating the sample size (i.e., the total number of accessible food outlets).

Logistic regression was further performed for π_i and p_i (Equations (2) and (3)), where α_1 and α_2 are intercepts for the Bernoulli and truncated Binomial components and represent the average (logit) probability to access healthy food outlets and the (logit) average RFE healthfulness (or relative healthy food access) over the region, respectively. \mathbf{X}^T is a 1x5 vector of covariates (with corresponding regression coefficient vectors $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ for Bernoulli and truncated Binomial components, respectively). In particular, these coefficients represent the four marginalization dimensions (X_{1i} , X_{2i} , X_{3i} , and X_{4i}) estimated from Equation (1) and population density – a major driving factor of food outlet distributions (Chen & Wang, 2014; Zenk et al., 2005). The parameter vectors \mathbf{u} (u_{1i} and u_{2i}) and \mathbf{s} (s_{1i} and s_{2i}) are unstructured and spatial random effects (a.k.a., heterogeneity), respectively. These random effects are included to account for unmeasured, spatial or non-spatial, covariates and overdispersion (Haining et al., 2009).

$$\text{logit}(\pi_i) = \alpha_1 + \mathbf{X}_i^T \boldsymbol{\beta}_1 + s_{1i} + u_{1i} \quad (2)$$

$$\text{logit}(p_i) = \alpha_2 + \mathbf{X}_i^T \boldsymbol{\beta}_2 + s_{2i} + u_{2i} \quad (3)$$

An improper flat prior $Uniform(-\infty, +\infty)$ is given to the intercepts α_1 and α_2 . Regression coefficients $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are specified with a vague prior $Normal(0, 1000)$. Considering the potential correlation between the binary and positive outcomes, for example, areas more likely to have access to healthy food outlets (higher π_i) also have healthier RFE (higher p_i), we specify multivariate distributions for the random effects.

Specifically, the unstructured random effects were assumed to follow a bivariate normal distribution $(u_{1i}, u_{2i})^T \sim MVN(0, \Omega)$ with means 0 and a 2x2 variance-covariance matrix Ω . A bivariate ICAR (BICAR) distribution is assigned to the spatial random effects such that $\mathbf{s}_i = (s_{1i}, s_{2i})^T | \mathbf{s}_{-i} \sim \text{BICAR}(\frac{1}{n_i} \sum_{j \in m_i} \mathbf{s}_j, \frac{1}{n_i} \Sigma)$, where n_i and m_i are the number and the set of adjacent areas of DA_i , respectively, and again, Σ is a variance-covariance matrix. We specify an inverse Wishart prior with 2 degrees of freedom to Ω and Σ .

3.3.2.2. Model for the 4km and 8km datasets: spatial Binomial model

A regular spatial Binomial model is used for the 4km and 8km datasets because all DAs have access to healthy food outlets within the 4km and 8km buffers. Specifically, the number of accessible healthy food outlet is assumed to follow a Binomial distribution with probability parameter p_i . Similarly, a logistic regression model is fitted for p_i (Equation (4)). Symbols in Equation (4) refer to the same variables in Equations (2) and (3).

$$\text{logit}(p_i) = \alpha + \mathbf{X}_i^T \boldsymbol{\beta} + s_i + u_i \quad (4)$$

$Uniform(-\infty, +\infty)$ and $Normal(0, 1000)$ are assigned to α and $\boldsymbol{\beta}$, respectively. We give an ICAR prior with variance σ_s^2 to the spatial random effect s_i and a prior of normal distribution with mean 0 and variance σ_u^2 to the unstructured random effect u_i . The reciprocals of σ_s^2 and σ_u^2 are further specified with a prior $Gamma(0.5, 0.0005)$.

3.3.3. Model fit and implementation

Models were implemented with the WinBUGS software (MRC Statistics Unit, 2015). The spatial latent factor model (Equation (1)) was jointly implemented with spatial hurdle model (Equations (2) and (3)) and spatial Binomial model (Equation (4)), respectively, accounting for uncertainties associated with the constructed marginalization dimensions. Two parallel chains were fitted for the models, starting with diverging initial values. We checked model convergence by visually examining trace plots, history plots, autocorrelation plots, and Gelman-Rubin statistic plots. Model selection was based on the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002). The best model is the one with lowest DIC. We ran each chain for 600,000 iterations, discarded the first 200,000

as burn-ins, and kept every 40th sample, resulting in a total of 20,000 samples for posterior estimates. Sensitivity analysis of prior specification was performed with alternative vague priors for parameters in the models. Similar results were obtained and DIC difference is smaller than 5, indicating that modeling results are insensitive to prior selections.

3.4. Results

3.4.1. Moran's I analysis of marginalization indicators and RFE measures

Results of Moran's I analysis for marginalization indicators are presented in Table 3-3. Most indicators are found significantly and spatially correlated with the exception of M4 (% of unemployment), D2 (dependency ratio), and E1 (% of 5-year recent immigrants), indicating the necessity to use spatial statistical approaches to construct the composite marginalization dimensions.

Table 3-3: Moran's I test of marginalization indicators

ID	Indicator	Moran's I
Residential Instability		
1	% of living alone (R1)	0.537***
2	% of youth population aged 5-15 (R2)	0.467***
3	Crowding: Average number of persons per dwelling (R3)	0.588***
4	% of multi-unit housing (R4)	0.371***
5	% of the population that is married/common-law (R5)	0.497***
6	% of dwellings that are owned (R6)	0.396***
7	% of residential mobility (same house as 5 years ago) (R7)	0.221***
Material Deprivation		
8	% 25+ without certificate, diploma, or degree (M1)	0.488***
9	% of lone-parent families (M2)	0.11***
10	% of government transfer payment (M3)	0.384***
11	% of unemployment 15+ (M4)	0.066**
12	% of below low income cut-off (M5)	0.157***
13	% of homes needing major repair (M6)	0.362***
Dependency		
14	% of seniors (65+) (D1)	0.278***
15	Dependency ratio [(0-14)+(65+)]/(15-64) (D2)	0.038*
16	Labor force participation rate (aged 15+) (D3)	0.233***
Ethnic Concentration		
17	% of 5-year recent immigrants (E1)	0.099***
18	% of visible minority (E2)	0.325***

Note: (1) p-value: <0.001, ***; <0.01, **; <0.05, *; (2) the smaller the p-value, the less likely that the correlation occurs by chance.

Table 3-4 shows results of Moran's I test of count and crude proportions of healthy food outlets. All RFE measures at the three scales are significantly auto-correlated with

high autocorrelation except the crude proportion at the 1km scale, which has a moderate autocorrelation. This finding indicates that adjacent areas have similar absolute and relative healthy food access thus again demonstrates the necessity to apply spatial statistical approaches.

Table 3-4: Moran's I test of count and crude proportions of healthy food outlets

Buffering size	RFE measures	
	Count	Crude proportion
1km	0.709***	0.295***
4km	0.917***	0.805***
8km	0.957***	0.701***

Note: (1) p-value: <0.001, ***; <0.01, **; <0.05, *; (2) Crude proportion = (number of accessible healthy food outlets/total number of accessible food outlets) * 100

3.4.2. Bivariate correlation analysis of marginalization indicators

Results of bivariate analysis of marginalization indicators are shown in Table 3-5. As expected and consistent with previous findings (Matheson et al., 2012), indicators belonging to the same marginalization dimension are significantly and highly or moderately correlated. Exceptions are R2 and R7, M1 and M4, and M4 and M6, which have significant but weak correlations.

Table 3-5: Bivariate correlation analysis between indicators belonging to the same marginalization dimension

Residential Instability							
	R1	R2	R3	R4	R5	R6	R7
R1	1						
R2	-0.66***	1					
R3	-0.83***	0.78***	1				
R4	0.61***	-0.28***	-0.57***	1			
R5	-0.71***	0.55***	0.74***	-0.71***	1		
R6	-0.67***	0.39***	0.66***	-0.82***	0.78***	1	
R7	0.37***	-0.08*	-0.24***	0.56***	-0.35***	-0.52***	1
Material Deprivation							
	M1	M2	M3	M4	M5	M6	
M1	1						
M2	0.33***	1					
M3	0.57***	0.46***	1				
M4	0.1**	0.24***	0.27***	1			
M5	0.23***	0.45***	0.49***	0.3***	1		
M6	0.29***	0.31***	0.27***	0.17***	0.25***	1	
Dependency							
	D1	D2	D3				

D1	1					
D2	0.75***	1				
D3	-0.59***	-0.43***	1			
Ethnic Concentration						
	E1	E2				
E1	1					
E2	0.46***	1				

Note: p-value: <0.001, ***; <0.01, **; <0.05, *.

3.4.3. Spatial latent factor modeling

Factor loadings from the spatial latent factor model (Equation (1)) are presented in Table 3-6. All indicators significantly load on their corresponding marginalization dimensions, with the expected positive or negative sign shown in Table 1. The posterior mean as well as the 95% credible interval (CrI) of factor loadings ascertain indicators that most central to defining corresponding marginalization dimensions. For example, the level of material deprivation, dependency, and ethnic concentration seem to be mainly driven by the percentage of government transfer payment, percentage of seniors (65+), and percentage of visible minority, respectively, whereas all indicators of residential instability similarly relate to the constructed factor, with the exception of the percentage of residential mobility (same house as 5 years ago), which has a relatively low impact.

Table 3-6: Loadings of indicators on corresponding marginalization dimensions from Equation (1)

ID	Indicator	Parameter	Posterior mean (95% credible interval)
Loadings on Residential Instability			
1	% of living alone (R1)	δ_1	1
2	% of youth population aged 5-15 (R2)	δ_2	-0.984 (-1.081, -0.889)
3	Crowding: Average number of persons per dwelling (R3)	δ_3	-1.164 (-1.253, -1.078)
4	% of multi-unit housing (R4)	δ_4	0.972 (0.872, 1.074)
5	% of the population that is married/common-law (R5)	δ_5	-1.081 (-1.178, -0.987)
6	% of dwellings that are owned (R6)	δ_6	-1.116 (-1.212, -1.025)
7	% of residential mobility (same house as 5 years ago) (R7)	δ_7	0.491 (0.383, 0.604)
Loadings on Material Deprivation			
8	% 25+ without certificate, diploma, or degree (M1)	δ_8	1
9	% of lone-parent families (M2)	δ_9	0.747 (0.621, 0.875)
10	% of government transfer payment (M3)	δ_{10}	1.194 (1.073, 1.319)
11	% of unemployment 15+ (M4)	δ_{11}	0.313 (0.182, 0.447)
12	% of below low income cut-off (M5)	δ_{12}	0.688 (0.559, 0.818)
13	% of homes needing major repair (M6)	δ_{13}	0.738 (0.616, 0.862)
Loadings on Dependency			
14	% of seniors (65+) (D1)	δ_{14}	1

15	Dependency ratio [(0-14)+(65+)]/(15-64) (D2)	δ_{15}	0.727 (0.597, 0.859)
16	Labor force participation rate (aged 15+) (D3)	δ_{16}	-0.751 (-0.877, -0.629)
Loadings on Ethnic Concentration			
17	% of 5-year recent immigrants (E1)	δ_{17}	1
18	% of visible minority (E2)	δ_{18}	1.53 (1.352, 1.72)

We map the four marginalization dimensions constructed from the spatial latent factor model (Figure 3-3). Clear spatial patterns of the four marginalization dimensions can be identified from the map: areas with high residential instability locate along the main road – King Street – in the region, mainly concentrating in the central parts of Waterloo, Kitchener, and Cambridge. Highly materially deprived areas locate in central Waterloo, central and northeast Kitchener, and south Cambridge. Five distinct clusters of areas with high levels of dependency are found at south Waterloo, north Kitchener, and west Cambridge. As for areas with high ethnic concentration, they cluster at northeast Waterloo and east Cambridge, and scatter across the region.

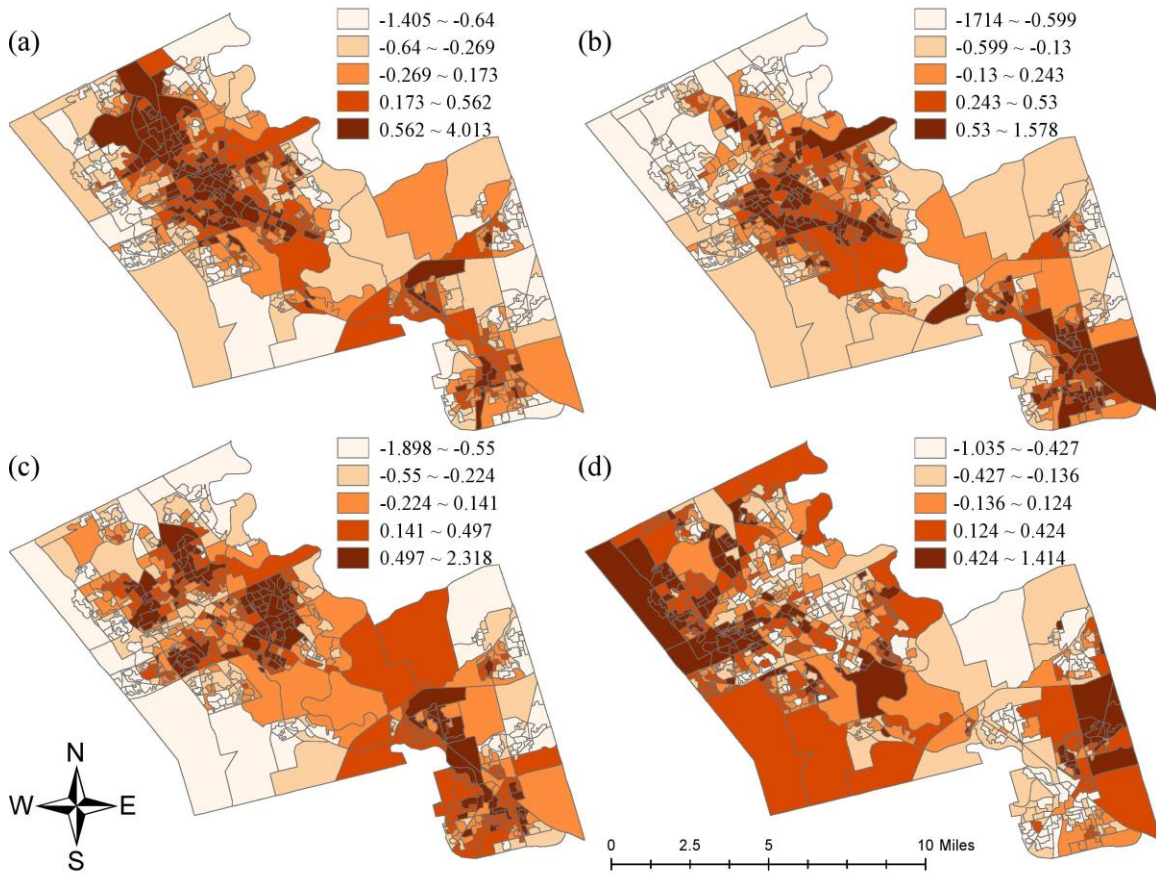


Figure 3-3: Quantile maps of marginalization dimensions at Dissemination Area scale, 2006

(a) Residential instability; (b) Material deprivation; (c) Dependency; (d) Ethnic concentration

3.4.4. Spatial regression

Results regarding the associations between RFE healthfulness and marginalization dimensions as well as population density are presented in Table 3-7. The Bernoulli component of the spatial hurdle model (Equation (2)) shows that residential instability (1.242, 95% CrI: 0.755 - 1.721), material deprivation (0.558, 95% CrI: 0.166 - 0.945), and population density (0.824, 95% CrI: 0.45 - 1.252) are significantly and positively associated with the probability of accessing healthy outlets within a walkable distance. These significant associations are not found in the Binomial component (Equation (3)). Interestingly, a reversed direction is found between material deprivation and RFE healthfulness (-0.109, 95% CrI: -0.216 - -0.004). None of the marginalization dimensions or population density is found significantly related with RFE healthfulness with the 4km

and 8km datasets, with the exception of the negative association between dependency and RFE healthfulness at the 4km scale (-0.022, 95% CrI: -0.042 - -0.002).

Table 3-7: Posterior estimates of coefficients from Equations (2) – (4)

Covariate	Posterior mean (95% credible interval)			
	1km buffer		4km buffer	8km buffer
	Bernoulli	Binomial	Binomial	Binomial
Residential instability	1.242 (0.755, 1.721)	-0.004 (-0.088, 0.08)	-0.017 (-0.038, 0.005)	0.003 (-0.007, 0.013)
Material deprivation	0.558 (0.166, 0.945)	-0.109 (-0.216, -0.004)	-0.018 (-0.042, 0.007)	-0.006 (-0.017, 0.006)
Dependency	0.168 (-0.227, 0.569)	0.019 (-0.067, 0.106)	-0.022 (-0.042, -0.002)	-0.002 (-0.011, 0.008)
Ethnic concentration	-0.249 (-0.584, 0.074)	-0.02 (-0.101, 0.061)	0.006 (-0.013, 0.025)	-0.002 (-0.011, 0.007)
Population density	0.824 (0.45, 1.252)	-0.006 (-0.062, 0.05)	0.002 (-0.013, 0.016)	0.003 (-0.004, 0.011)

Note: Significant coefficients are shown in bold text.

3.5. Discussion

3.5.1. Modeling results interpretations

In the Region of Waterloo’s cities, neighborhoods with higher residential instability and material deprivation are more likely to have access to healthy food outlets (i.e., better absolute healthy food access) within a walkable distance. This makes sense since healthy food outlets (Figure 3-1) as well as residentially instable and materially deprived areas (Figure 3-3) concentrate along the arterial streets of the region. This finding aligns with previous Canadian findings that socio-economically deprived residents have better access to absolute densities of healthy food outlets (Apparicio et al., 2007; J. L. Black et al., 2011; Daniel et al., 2009; Mercille et al., 2013; Minaker et al., 2016; Polsky et al., 2014; Smoyer-Tomic et al., 2008, 2006; H. Wang et al., 2016). A probable explanation is that residents who are socio-economically deprived might be more likely to find affordable housing in highly populated areas (Black et al., 2011; Polsky et al., 2014) where healthy food outlets are located, given that population density is a driving force of food outlet distribution as noted above.

In contrast, modeling the relative healthy food access (via Binomial component from the spatial hurdle model), which represents RFE healthfulness in this study, reveals

that areas with higher material deprivation have a relatively less healthy RFE at the walkable distance scale, despite higher probability to access to healthy food outlets. The finding is contrary to past Canadian studies that explored the relationship between material deprivation and relative healthy food access which is measured with crude proportions. For instance, most materially deprived neighborhoods in Toronto were found to have healthier RFE (i.e., lower crude proportion of less healthy food outlets) (Polsky et al., 2014). Mercille et al. (2013) reported that the poorest areas in Montreal have lower crude proportions of fast-food outlets over all accessible restaurants and higher crude proportions of fruit and vegetable stores over all accessible food stores in comparison to their wealthier counterparts. This inconsistency could be attributed to the differences between our research and previous studies in terms of the methods used for differentiating ‘healthy’ and ‘less healthy’ food outlets, the completeness of RFE datasets, and the appropriateness of statistical modeling approaches. Compared with the two Canadian studies noted above, our study is strengthened by differentiating ‘healthy’ and ‘less healthy’ based on in-store characteristics instead of food outlet types. This approach for defining healthy food outlets enabled all retail food outlets to be included in our dataset, which was a major strength of the current study. Also, in contrast to previous studies, we explicitly accounted for spatial autocorrelation occurring within RFE measures and marginalization indicators as demonstrated above, which increases the reliability of our results. Finally, we modeled the count of healthy food outlets with a Binomial distribution rather than the crude proportion of healthy food outlets, which is associated with uncertainty thus is not a stable estimation of RFE ‘healthfulness’. As mentioned, our modeling approach is more robust to analyze relative healthy food access because it accounts for the underlying total number of accessible food outlets (thus the number of accessible less healthy food outlets), which cannot be reflected by crude proportions.

Not surprisingly, while increasing the buffering size to 4km and 8km (thus increased mobility) based on alternative transportation modes such as bicycling, public transit, and driving, population density and marginalization dimensions are not significantly associated with RFE healthfulness since discrepancies in relative healthy food access between areas decrease with larger travel distances (Figure 3-2b, 3-2d, and 3-2f). An exception is the negative association between dependency and RFE healthfulness at the

4km scale, indicating that neighborhoods with higher proportions of seniors and children have a less healthy RFE; however, this might not be problematic given that these dependent populations may be more likely to walk than to take public transit or bicycle.

3.5.2. Policy implications

Findings from our study are important and informative for food environment planning and interventions for combating adverse diet-related health outcomes. Specifically, rather than improving absolute densities of healthy food outlets, a more pressing mission may be to strike a better balance between healthy and less healthy food access, especially given that increasing evidence shows that residents with higher relative healthy food access have healthier food purchasing (Mason et al., 2013; Thornton et al., 2009) and consumption (Clary et al., 2015; Mercille et al., 2012) behaviors, and lower body weight (Kestens et al., 2012; Mehta & Chang, 2008; Polsky et al., 2016; Spence et al., 2009). Traditional approaches such as building new supermarkets (Cummins, Flint, & Matthews, 2014) have been proposed in the U.S. for improving healthy food access thus the balance, but were found ineffective for promoting healthy eating (Cummins et al., 2014), possibly due to residents' hesitation of relying on a new food store (Morland, 2015a).

Policy and program interventions to improve the food environment in Canada are nascent (Mah et al., 2016). One potentially effective intervention for the Region of Waterloo could be modifying the in-store characteristics of existing food outlets in materially deprived areas, for example, providing fruits and vegetables in less healthy food outlets through intervention programs such as healthy corner stores, which have been implemented in municipalities of Toronto and Vancouver (Seeton, 2012; Toronto Food Policy Council, 2014). This approach, if undertaken, should prioritize food outlets within a walkable distance to areas that fall inside the highest material deprivation quantile (Figure 3-2b). An alternative intervention could be restricting the construction of less healthy food outlets within or around these neighborhoods via zoning bylaws. While Canadian planning laws do not permit discrimination against specific types of food outlets (Grant, MacKay, Manuel, & McHugh, 2010; Quebec Public Health Association, 2011), the Regional Municipality of Waterloo can apply several urban planning tools to limit the establishment of less healthy food outlets, for example, prohibiting fast-food restaurant establishments

and regulating the densities or quotas of less healthy food outlets in materially deprived neighborhoods (Canadian Institute of Planners, 2013; Quebec Public Health Association, 2011).

Modeling results of 4km- and 8km- datasets suggest that increasing mobility might be effective for alleviating the disparities of RFE healthfulness. Yet travelling further to access healthier RFEs could economically burden materially deprived residents. As discussed in LeClair and Aksan (2014), the high travelling costs might outweigh the cost savings from food shopping, thus deterring residents from taking public transit to procure healthy foods. In this sense, improving public transportation to healthy food retailers via interventions such as providing healthy food outlets (e.g., supermarkets) sponsored shuttle services could be potentially effective for encouraging materially deprived residents to travel beyond the walkable zones for food purchasing, complementary to aforementioned interventions.

3.5.3. Methodology implications

Methodologically, this study contributes to the RFE literature by introducing a flexible modeling approach to study the association between neighborhood RFE and marginalization. While the spatial lag (Wang et al., 2016) and spatial error (McKenzie, 2014; Wang et al., 2016) models are inappropriate to model count data (e.g., number of supermarkets accessible to a DA), the applied Bayesian hierarchical approach can model the count of food outlets by following a discrete distribution, for example the Binomial distribution as demonstrated in this study, while simultaneously account for spatial autocorrelation by including spatial random effects. Moreover, this Bayesian approach applied is superior to the spatial scan statistical method (Baker et al., 2006), which is also capable of modeling count data, in terms of its feasibility to incorporate covariates.

Another noticeable advantage of the applied Bayesian approach is its capability to model spatio-temporal RFE datasets, as demonstrated by Lamichhane et al. (2015). Future research could examine how neighborhood RFE might change over time in tandem with varying levels of marginalization. Furthermore, the spatial hurdle model used for analyzing the 1km dataset accounts for zero-inflation, an issue rarely reported by past RFE studies, but could occur in the case that a large portion of neighborhoods in the study region have

no access to (healthy) food outlets within a walkable distance. Not appropriately taking into account zero-inflation may result in biased or imprecise inferences. Although the Negative Binomial model implemented via conventional frequentist approaches can deal with zero-inflation in some cases, it cannot easily address the spatial autocorrelation issue.

3.5.4. Study limitations

Findings of this study are subject to several limitations. First, to create the buffering zones, the geographic centroid rather than the population centroid was used to represent each DA. We consider this approach acceptable considering that most DAs are relatively small so geographic centroids approximate population centroids. Second, we used 1km, 4km, and 8km to represent potential transportation modes; however, a unified travelling distance might not be suitable for all DAs. In reality, residents in different neighborhoods could take different times to travel 4km by bus due to varying public transit availability and routes. More nuanced methods for characterizing transportation-based RFE (see for example Farber et al. (2014)) should be applied in future research. Lastly, ‘healthy’ and ‘less healthy’ were differentiated based on a binary category. Although we observed similar results by conducting sensitivity analysis with a more rigorous definition of healthy food outlets (i.e., outlets falling into the highest tercile instead of the highest two quartiles), this categorization approach should be refined in future studies.

3.6. Conclusion

This paper contributes empirically and methodologically to the RFE literature that explores the association between neighborhood marginalization and RFE healthfulness. Using hierarchical spatial models, this research found that residents in neighborhoods with higher residential instability, material deprivation, and population density are more likely to have absolute access to healthy food outlets within a walkable distance. Materially deprived neighborhoods however, are also more likely to have a relatively less healthy RFE at the walkable distance scale. These findings indicate that a simple ‘yes’ or ‘no’ answer for the deprivation amplification hypothesis in the context of RFE is inappropriate. To infer a relatively unbiased conclusion, incorporating the complete RFE dataset, considering various assessment strategies (i.e., absolute and relative access) of RFE, and applying sound spatial statistical approaches are warranted.

For the Region of Waterloo in particular, striking the balance between healthy and less healthy food outlets in these neighborhoods via interventions such as modifying in-store characteristics, restricting the opening of less healthy food outlets, and improving public transit to healthy food outlets may be warranted. The hierarchical spatial models, including spatial latent factor and spatial hurdle models, as shown in this study can be further explored in other Canadian settings or different countries. Future research could tailor the buffering cut-offs for different types of food outlets, which are potentially linked to behaviors underlying travel patterns to visit specific types of food outlets and subtypes among them.

Chapter 4: Diving into the consumer nutrition environment: a Bayesian spatial factor analysis approach for assessing neighborhood restaurant environment ¹⁵

4.0. Overview

Neighborhood restaurant environment (NRE) is playing a vital role in shaping residents' eating behaviors. Most previous studies, however, evaluate NRE 'healthfulness' based on restaurant types, thus largely ignoring variations of in-restaurant features. Of the few studies that account for in-restaurant characteristics, researchers simply average the composite 'healthfulness' scores of all the restaurants accessible to a neighborhood. This paper assesses NRE healthfulness in the city of Kitchener, Canada using a Bayesian spatial factor analysis approach, which incorporates several in-restaurant characteristics including availability and affordability of healthy eating options. This modeling approach identifies the specific indicator that is most relevant with NRE healthfulness, provides a metric for evaluating NRE healthfulness of neighborhoods without accessible restaurants, and quantifies uncertainties associated with the simple descriptive measure that are attributable to masking total number of accessible restaurants and ignoring NRE in adjacent neighborhoods. Being the first study that applies robust spatial statistical approaches to investigate restaurant consumer nutrition environment at the neighborhood level, this research advances the understanding of NRE from what in-restaurant characteristics should be intervened to what and where the characteristics should be prioritized. Implications for intervention program development and community food planning are discussed.

4.1. Introduction

Neighborhood restaurant environment (NRE) is the place where residents can eat away from home or buy take-out foods. It has become an indispensable component in residents' daily life. For example, in North America, Canadians and Americans spend over 25% and 50%, respectively, of their food expenditures on foods away from home (Statistics

¹⁵ This chapter is adapted from the article entitled "Diving into the consumer nutrition environment: a Bayesian spatial factor analysis approach for assessing neighborhood restaurant environment", which is under review at *Spatial and Spatio-temporal Epidemiology*.

Canada, 2014; United States Development of Agriculture Economic Research Service, 2016). According to the report on Canada's Restaurant Industry, over 35% Canadians rank eating out in a restaurant as their top preferred activity with friends and families, and over 60% Canadians eat out in restaurants at least once per week (Canadian Restaurant and Foodservices Association, 2010). In this context, NRE is playing a vital role in shaping residents' eating behaviors, resulting in the development of numerous measures for assessing NRE healthfulness from researchers in multiple fields including public health, geography, and urban planning.

4.1.1. Evaluating neighborhood restaurant environment

Absolute restaurant density in a neighborhood, represented as total numbers of accessible restaurants (Jeffery, Baxter, McGuire, & Linde, 2006; Polsky et al., 2016) or restaurant density per population or per area (Hollands, Campbell, Gilliland, & Sarma, 2013, 2014; Maddock, 2004; Mehta & Chang, 2008; Moore, Diez Roux, Nettleton, Jacobs, & Franco, 2009), is the most common measure for evaluating NRE. This measure has been extensively applied in public health studies exploring, for example, whether absolute densities of fast-food restaurants contribute to unhealthy eating and excess weights. Mixed findings, however, have been identified (Jeffery et al., 2006; Maddock, 2004; Mehta & Chang, 2008; Polsky et al., 2016), partly attributable to the application of absolute density measures that assess a single dimension of the multi-faceted NRE. While composite measures such as the ratio between unhealthy (e.g., fast-food) and healthy (e.g., full-service) restaurants have been used for NRE assessment (Mehta & Chang, 2008; Mercille et al., 2013; Polsky et al., 2016), such measures ignore restaurants that cannot be simply classified as unhealthy or healthy, which is predominantly the case for restaurants that are independently owned (as opposed to franchised or chains). Furthermore, measures focusing on the community nutrition environment (e.g., restaurant types and numbers) fail to acknowledge differences between in-restaurant features such as availability of healthy eating options between restaurants of the same type in different neighborhoods. Additionally, in-restaurant features other than availability also have a role in defining NRE healthfulness. The presence of healthy eating options in restaurants does not necessarily guarantee a healthy NRE, given that higher prices of healthy eating options and barriers to healthy eating (e.g., overeating encouraged on the menu) could potentially prohibit

consumers from making healthy consumption decisions (Hammond et al., 2013; Haws & Liu, 2016; Nordström & Thunström, 2015). These limitations are problematic either in studies exploring geographical disparities of NRE healthfulness, or in studies examining the association between NRE and diet-related outcomes in that a measure evaluating the partial rather than complete NRE is used.

Recently, in-store audit tools have been developed to assess restaurants. For example, the Nutrition Environment Measure Survey – Restaurant (NEMS-R) (Saelens et al., 2007) assesses in-restaurant features including availability, affordability, and facilitator/barrier of healthy eating, providing a composite measure of overall restaurant healthfulness. This tool allows to account for all restaurants and in-restaurant characteristics for assessing NRE healthfulness. However, the mean NEMS-R score per neighborhood is typically used for subsequent analyses (Duran et al., 2013; J. Wang et al., 2016), for example, exploring its association with neighborhood distress level. Although the mean NEMS-R score provides a simple and intuitive measure for assessing NRE, it suffers from a number of limitations. First, it masks the total number of accessible restaurants to a neighborhood as well as variations of in-restaurant features, leaving the measure unreliable for assessing NRE healthfulness. Second, using the mean NEMS-R score to evaluate NRE healthfulness of a neighborhood ignores information of NRE in adjacent neighborhoods. In reality, people could travel beyond their own neighborhoods to procure foods, making it necessary to account for information of adjacent NRE to strengthen and stabilize the estimation (Luan et al., 2015). Finally, the mean score does not reflect which in-restaurant feature contributes the most to (or most relevant with) NRE healthfulness. Ignoring the difference of importance between in-restaurant features restricts the potential to inform food planning and interventions for promoting healthy eating.

4.1.2. Bayesian spatial factor analysis

To address the limitations associated with the mean NEMS-R score, we propose a Bayesian spatial factor analysis (BSFA) approach for assessing NRE healthfulness. Originated in psychometrics, factor analysis is a statistical approach used to describe the variation and correlation of a set of observable and correlated indicators with a lower number of latent factors that cannot be directly observed or measured (e.g., Brown, 2015).

Conceptually, NRE healthfulness is abstract and unobservable, but manifests in the form of a number of NRE indicators (i.e., availability, affordability, facilitator/barrier, etc.). In this sense, factor analysis is a suitable approach for assessing NRE healthfulness. For example, recognizing the correlation in terms of food provision and quality between different food outlet types, Michimi and Wimberly (2015) applied factor analysis to construct two factors representing the healthy and unhealthy dimensions of the food environment, respectively. In particular, Factor 1 consists of food outlets providing healthy options including supermarkets, snack/coffee shops, and full-service restaurants, while Factor 2 represents unhealthy food outlets including convenience stores and fast-food restaurants.

Traditional factor analysis applied in the spatial context is flawed due to its unrealistic assumptions that the observed indicators are normally distributed and values of these indicators are independent between adjacent areas. Thus, the obtained latent factors of adjacent areas are assumed to be independent as well. In reality, these assumptions are likely invalid in the analysis of spatial data. Hierarchical models implemented with Bayesian approaches for factor analysis have been recently developed to overcome these limitations. Bayesian approaches provide posterior estimation for unknown parameters by combining prior information and observed data. Although hierarchical modeling can also be implemented with frequentist approaches, Bayesian inference via Markov chain Monte Carlo (MCMC) is often the most viable inference technique for complex hierarchical models with non-normal and spatially correlated observations and random effects (Marí-Dell'Olmo et al., 2011; F. Wang & Wall, 2003). Additionally, Bayesian approaches more readily account for parameter uncertainties (Morris & Lysy, 2012). BSFA has been applied in various fields in addition to psychology (Stakhovych, Bijmolt, & Wedel, 2012), especially in estimating deprivation (Abellan et al., 2007; Peter Congdon, 2016; Hogan & Tchernis, 2004; Marí-Dell'Olmo et al., 2011) and spatial and spatio-temporal common risk factors of mortalities and morbidities (Courtemanche, Soneji, & Tchernis, 2015; Lawson, 2013; Mezzetti, 2012; Tzala & Best, 2006; F. Wang & Wall, 2003). These studies demonstrate that BSFA is capable of quantifying uncertainties, tackling spatial autocorrelation, and assessing neighborhoods without observations. A recent study from Congdon (2016) exemplifies the only application in the literature that applies BSFA to

assess the food environment. His study constructs a healthy food access index at the Metropolitan county level in the U.S., and then uses the index as a predictor for explaining geographical variations of obesity. The ratio between convenience stores and grocery stores was identified as the central indicator in defining healthy food access. Nevertheless, Congdon's study does not take into account variances of food outlets' in-store features, but focuses on outlet types only. Further, his index was created at a relatively large-area (i.e., county) level; therefore, heterogeneity of the food environment is largely dissimulated.

4.1.3. Research questions

This study aims to answer two research questions. First, which neighborhoods have the least healthy NRE (simultaneously suffer from deprived availability, affordability, and facilitator/barrier of healthy eating)? A BSFA approach is used to create a composite NRE index at the neighborhood level. Being a combination of weighted restaurant assessment indicators, this index reflects the underlying NRE 'healthfulness'. Neighborhoods with an index value in the lowest quintile are identified as neighborhoods with least healthy NRE. Two metrics are applied for quantifying uncertainties associated with the composite index thus NRE healthfulness: one, the 95% credible interval (CrI) of the index; and two, the posterior probability of the index falling into the lowest quintile.

Second, what is the indicator (availability, affordability, or facilitator/barrier) that contributes the most to (or most relevant with) NRE 'healthfulness'? Statistically, the indicator is the one with the highest factor loading on the composite NRE index. Its variance is also best explained by the NRE index. Overall, this specific indicator should be targeted for intervention to improve NRE in the study region.

4.2. Study area and data

4.2.1 Study area

The analysis was conducted for the city of Kitchener at the dissemination area (DA) level. Kitchener is composed of 299 DAs and is located at the center of the Region of Waterloo, a municipality seated approximately one-hour west of Toronto. DA is the smallest census unit that covers the entirety of Canada (Statistics Canada, 2012). The population size of a DA generally ranges from 400 to 700. Considering the inconsistency

of neighborhood definitions, we used DAs to represent neighborhoods, an approach that benefits policy implementation and planning because local governments have jurisdiction over administrative areas (Health Canada, 2012). Figure 4-1 displays the DA boundaries of Kitchener city and spatial distributions of restaurants in 2010. Generally, restaurants concentrate at downtown Kitchener along the arterial road (i.e., King Street). NEMS-R scores of restaurants accessible to Kitchener are presented with proportional dots.

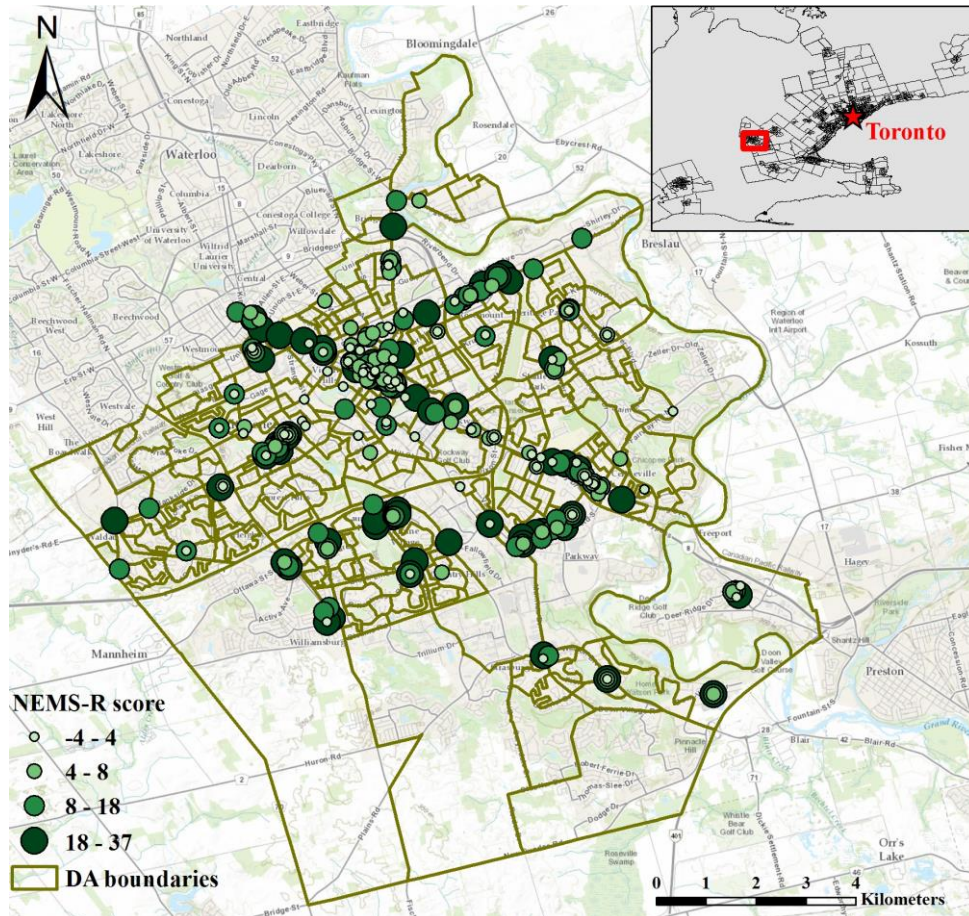


Figure 4-1: DA boundaries of Kitchener city and distributions of restaurants, 2010

4.2.2. Restaurant assessment indicators

Three correlated restaurant assessment indicators were used for constructing the composite index: availability of healthy eating options, affordability of healthy eating, and facilitators or barriers to healthy eating (hereafter called *availability*, *affordability*, and *facilitator/barrier*, respectively). These indicators were collected in 2010 based on adapted

NEMS-R for Canadian food environment studies. More details are provided elsewhere (Minaker et al., 2013, 2014). Specifically, *availability* of a restaurant is assessed with a score that measures the availability of healthy food items such as main-dish salads with low calorie; *affordability* indicates the comparative pricing between ‘healthy’ and ‘unhealthy’ foods; and a score of *facilitator/barrier* reflects whether a restaurant includes measures for facilitating (e.g., providing nutrition information on the menu) or prohibiting (e.g., encouraging larger portions on the menu) healthy eating. For all three indicators, a restaurant with a higher score is deemed healthier. Scores of *availability*, *affordability*, and *facilitator/barrier* range from -1 to 21, -3 to 3, and -9 to 24, respectively (Table 4-1). We performed correlation analyses for the indicators using Spearman’s rho. Results indicate that *availability*, *affordability*, and *facilitator/barrier* are significantly correlated. In particular, *availability* is positively associated with *facilitator/barrier* while *affordability* is negatively associated with *availability* and *facilitator/barrier*, suggesting that a restaurant with higher scores of *availability* and *facilitator/barrier* usually have a lower score of *affordability* (higher prices of healthy eating). In this sense, assuming that high *availability* is a positive contributor to NRE healthfulness, the three indicators used to construct the index represent high *availability*, low *affordability*, and high/low *facilitator/barrier*, respectively.

Table 4-1: Descriptive statistics of in-store indicators for all restaurants accessible to Kitchener

Indicator	Mean	Min	Max	S.D.
Availability	8.15	-1	21	4.64
Affordability	-1.48	-3	3	1.78
Facilitator/barrier	4.5	-9	24	6.46

A 1km road network buffer was created around each restaurant using ArcGIS 10.2 to identify neighborhoods that can access to this specific restaurant (i.e., the centroid of the neighborhood falls inside the buffering zone of the restaurant). The distance demarcation, 1km, represents a 10~15 mins walking distance, which has been widely used in Canadian food environment studies (Apparicio et al., 2007; J. L. Black et al., 2011; Larsen & Gilliland, 2008; Luan, Minaker, & Law, 2016; Smoyer-Tomic et al., 2006). Another reason for choosing a walkable distance for NRE assessment is that active transportation including walking is essential for creating healthy communities and combating obesity epidemics

(Ontario Professional Planners Institute, 2014). The number of neighborhoods that can access a specific restaurant ranges from 1 to 19, and the number of restaurants accessible to a neighborhood within 1km ranges from 0 to 87.

4.3. Statistical modeling

With BSFA, the unobservable concept, NRE healthfulness, can be inferred by multiple observable restaurant assessment indicators at the consumer nutrition environment level. In the model (denoted as Model I), the j^{th} restaurant indicator (normalized scores of *availability*, *affordability*, or *facilitator/barrier*) of the k^{th} restaurant, Y_{jk} , is assumed to follow a Normal distribution with mean $\frac{1}{n_k} \sum_{m \in N_k} \mu_{mj}$ and variance σ_j^2

(Equation (1)), where n_k is the number of neighborhoods whose centroids fall inside into the 1km buffering zone of the k^{th} restaurant, N_k is the ID set of the n_k neighborhoods, and μ_{mj} is the latent value of indicator j at neighborhood m . μ_{ij} is decomposed into an intercept α_j (the average of indicator j over the study region), a product of factor loading δ_j (the loading of indicator j on the index) and index θ_i (restaurant environment index at neighborhood i), and indicator-specific random noise ε_{ij} (Equation (2)). Notably, several neighborhoods do not have direct access to any restaurant within a walkable distance such that corresponding μ_{ij} are not connected directly to the data via Equation (1). Their composite index θ_i however, can be imputed via specifying an intrinsic Conditional Autoregressive (ICAR) distribution (Besag et al., 1991) to θ . Specifically, θ_i follows a normal distribution with conditional mean that equals to the average of neighboring θ_j 's and conditional variance that is inversely proportional to the number of neighbors, n_i (Equation (3)). For reference, two areas are defined as neighbors if they share at least one common vertex, a common approach used in spatial statistical studies (Law et al., 2013). Note that $w_{ij} = 1$ if DA i and DA j are neighbors; otherwise, $w_{ij} = 0$. Under the ICAR distribution, NRE healthfulness of a neighborhood without accessible restaurants is estimated by 'borrowing' information from adjacent neighborhoods.

$$Y_{jk} \sim \text{Normal}\left(\frac{1}{n_k} \sum_{m \in N_k} \mu_{mj}, \sigma_j^2\right) \quad (1)$$

$$\mu_{ij} = \alpha_j + \delta_j \theta_i + \varepsilon_{ij} \quad (2)$$

$$\theta_i | \theta_{-i} \sim Normal\left(\sum_{j \neq i} \frac{w_{ij} \theta_j}{n_i}, \frac{\sigma_\theta^2}{n_i}\right) \quad (3)$$

To estimate the parameters of Model I, we employed a Bayesian MCMC sampling approach, which begins by specifying priors on all the model parameters. An improper uniform prior on the whole real line was given to α_j . To avoid the “flip-flop” problem ($\delta_j * \theta_i = (-\delta_j) * (-\theta_i)$) and allow feasible identification, we constrained δ_1 to be positive. Similar approaches have been applied in past studies (Abellan et al., 2007; Peter Congdon, 2016; Mari-Dell’Olmo et al., 2011). δ_1 was assigned a prior of a log-normal distribution with mean zero and variance 100, and a vague prior of normal distribution with mean zero and variance 1000 was assigned to δ_2 and δ_3 (Abellan et al., 2007). For identification purposes, the variance of θ (denoted as σ_θ^2) is set to 1, equivalent to index standardization (Skrondal & Rabe-Hesketh, 2007). The random noise ε_{ij} was given a prior $Normal(0, \tau_j^2)$. A vague prior $Gamma(0.5, 0.0005)$ was specified to the reciprocal of variance parameters σ_j^2 and τ_j^2 .

To test whether the spatial structure of restaurant assessment indicators is adequately captured by θ_i , we also fitted a model (Model II) by modifying Equation (2) to include a spatial random effect (φ_{ij}), making $\mu_{ij} = \alpha_j + \delta_j \theta_i + \varepsilon_{ij} + \varphi_{ij}$. Similarly, an ICAR prior with variance ζ_j^2 was specified to φ_{ij} , and the prior distribution of $Gamma(0.5, 0.0005)$ was given to the reciprocal of ζ_j^2 .

In addition to the unknown parameters in the model, we also monitored the posterior probability that θ_i falls inside the lowest quintile (denoted as PP_{θ_i}) as a measure for identifying neighborhoods that have least healthy NRE. Complementary to the point estimate of θ_i (i.e., posterior mean), PP_{θ_i} quantifies the uncertainty associated with θ_i via taking into account the sampling variance of θ_i and making use of the full posterior

distribution of θ_i (Richardson, Thomson, Best, & Elliott, 2004). Each neighborhood was given a binary indicator at each iteration (one if θ_i falls into the lowest 20%; otherwise zero). PP_{θ_i} is the fraction of one's of all iterations. The higher the value of PP_{θ_i} , the stronger evidence that neighborhood i has a least healthy NRE.

To determine which restaurant indicator is most relevant with NRE healthfulness, we calculated the ratio (ρ_j) between the empirical variance of θ_i (denoted as s_{θ}^2) and the sum of s_{θ}^2 and the indicator-specific variance τ_j^2 ($\rho_j = s_{\theta}^2 / (s_{\theta}^2 + \tau_j^2)$) (Abellan et al., 2007), apart from examining the magnitude of factor loadings δ_j . A higher value of ρ_j suggests stronger relevance between the restaurant indicator and NRE healthfulness.

Both models were fitted in WinBUGS (D. J. Lunn et al., 2000) with two parallel chains. Trace plots, history plots, autocorrelation plots, and Gelman-Rubin plots were visually examined for checking convergence. Models converged after 50,000 iterations. We ran each chain for another 100,000 iterations and retained every 10th sample, resulting in an acceptable Monte Carlo error (<5% of sample posterior deviation). A final 20,000 samples were obtained for posterior estimations. Model comparison was based on Deviance Information Criteria (DIC) (Spiegelhalter et al., 2002). A model best fitting the dataset is the one with lowest DIC. We conducted sensitivity analysis by specifying a prior of Uniform(0, 100) directly to variance parameters (σ_j^2 and τ_j^2) in the best-fitting model. Similar results were obtained and DIC difference is smaller than 5, indicating that inferential results are essentially insensitive to prior selections.

4.4. Results

Table 4-2 shows the values of DIC and pD (effective parameters) from the two fitted models. Although Model II has a higher pD, the DIC difference is only $2937.88 - 2937.36 = 0.52$, indicating that the two models fit the dataset equally well. Thus, the parsimonious Model I was chosen as the final model. We report below results from Model I.

Table 4-2: DIC and pD values from two fitted models

Model	DIC	pD
Model I: Without spatial residuals (φ_{ij})	2937.88	39.004
Model II: With spatial residuals (φ_{ij})	2937.36	42.24

4.4.1. Factor loadings

Loadings of *availability*, *affordability*, and *facilitator/barrier* on the common factor (the composite index θ_i) are presented in Table 4-3. All three indicators are significantly associated with the composite index since the 95% CrI of the factor loadings do not cover zero, suggesting that each indicator is a meaningful manifestation of the underlying concept – the ‘healthfulness’ of NRE. *Facilitator/barrier* (1.036, 95% CrI: [0.525, 1.715]) has the highest magnitude of loading factor, followed by *availability* (0.823, 95% CrI: [0.321, 1.443]) and *affordability* (-0.675, 95% CrI: [-1.127, -0.280]). While *availability* and *facilitator/barrier* are positively associated with the index, a negative association was found between *affordability* and the composite NRE index, indicating that the low affordability as noted above is discounting NRE healthfulness. The calculated ratio (ρ_j) as explained above for *availability*, *affordability*, and *facilitator/barrier* are 0.955, 0.906, and 0.980, respectively, which are in agreement with the factor loadings of each indicator on the index.

Table 4-3: Factor loadings (δ_j) on and the ratio (ρ_j) from Model I

Indicator	Factor loading (95% CrI)	The ratio (ρ_j)
Availability of healthy eating option	0.823 (0.321,1.443)	0.955
Affordability of healthy eating	-0.675 (-1.127, -0.280)	0.906
Facilitator/barrier of healthy eating	1.036 (0.525, 1.715)	0.980

4.4.2. Posterior estimations of the composite NRE index

Posterior means and 95% CrI of the composite index θ_i , which represents NRE healthfulness, are plotted in Figure 4-2. Varying NRE ‘healthfulness’ is observed among neighborhoods. Notably, neighborhoods with similar posterior means (shown in red dots) could have different 95% CrI thus associated with different degrees of uncertainty in identifying neighborhoods with least healthy NRE. Such uncertainties are also reflected by the fraction of the 95% CrI that falls within the lowest quintile (Figure 4-2). Posterior means of θ_i are further mapped (Figure 4-3a). Four distinct clusters of neighborhoods locating at west, northwest, north, and northeast Kitchener are identified as having least healthy NRE. These areas simultaneously suffer from deprived *availability*, *affordability*, and *facilitator/barrier*, or in other words, lower relative availability of healthy eating options, higher relative prices of healthy eating, and higher/lower levels of facilitators/barriers to healthy eating.

We also map the posterior probability of θ_i that falls inside the lowest quintile, PP_{θ_i} (Figure 4-3b). Following Mari-Dell’Olmo et al.’s (2011) approach for classifying deprivation and considering that the maximum of PP_{θ_i} is 0.634, we categorized PP_{θ_i} into three groups, representing neighborhoods that ‘probably suffer from least healthy NRE’ ($PP_{\theta_i} > 0.5$), ‘probably do not suffer from least healthy NRE’ ($0.05 < PP_{\theta_i} \leq 0.5$), and ‘have low probability of least healthy NRE’ ($PP_{\theta_i} \leq 0.05$). Two clusters of neighborhoods locating at west and towards northwest Kitchener as well as several neighborhoods scattering across the region are identified as ‘probably suffer from least healthy NRE’. These neighborhoods all fall inside the lowest quintile based on the posterior mean of θ_i (Figure 4-3a). Compared with their counterparts in the same quintile, they have a NRE that is more likely to be least healthy, which, again, shows the unreliability of using a point estimate (i.e., posterior mean) to evaluate NRE healthfulness.

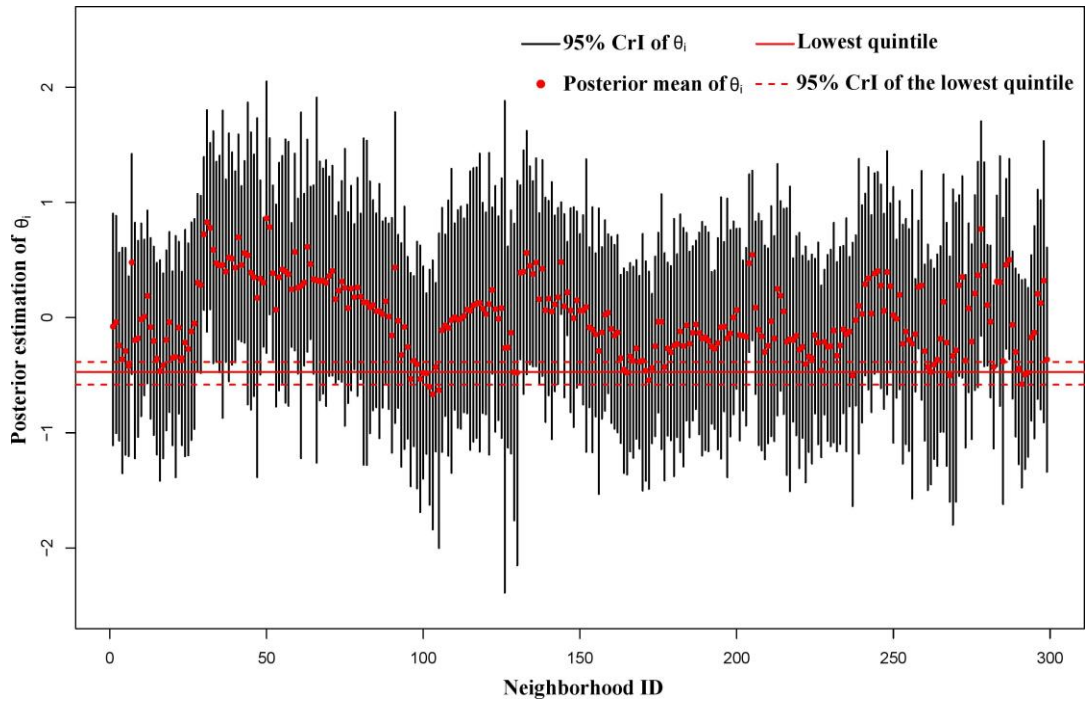


Figure 4-2: Caterpillar plot of the posterior mean and 95% credible interval of composite index (θ_i)

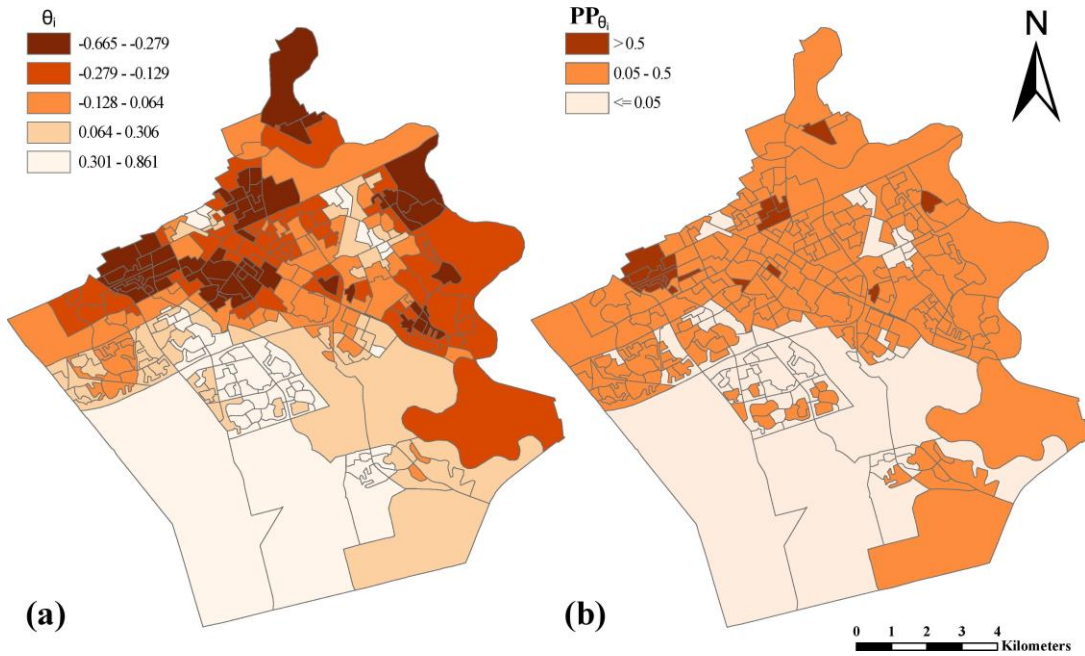


Figure 4-3: Quantile map of (a) the composite NRE index (θ_i) and (b) the posterior probability of θ_i falling into the lowest quintile (PP_{θ_i})

4.5. Discussion

4.5.1. Dissecting uncertainties associated with descriptive measures for quantifying NRE 'healthfulness'

As noted above, using just the mean NEMS-R score to quantify NRE healthfulness ignores the variability associated with this statistic, and thus has limited ability to address the following questions. First, do two neighborhoods with the same mean NEMS-R score but different numbers of accessible restaurants have the same level of healthfulness (scenario A)? Second, is a neighborhood with higher mean NEMS-R score but lower number of accessible restaurants necessarily healthier than a neighborhood with lower mean NEMS-R score but higher number of accessible restaurants (scenario B)? Lastly, which neighborhood of the two has a healthier NRE: a neighborhood without accessible restaurants or a neighborhood with accessible restaurants that have low scores of *availability*, *affordability*, and *facilitator/barrier* (scenario C)? The mean NEMS-R score of accessible restaurants for each neighborhood is mapped in Figure 4-4. Neighborhoods without accessible restaurants are highlighted with hatch lines. We also highlight and label three groups of neighborhoods, and demonstrate how the applied BSFA approach quantifies the aforementioned uncertainties.

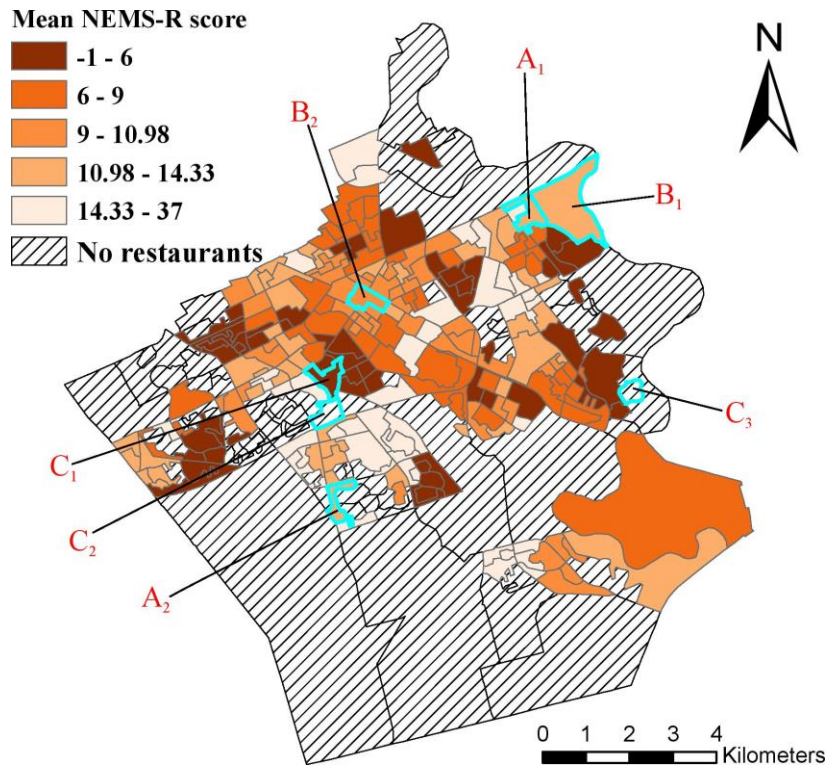


Figure 4-4: Mean NEMS-R scores at the dissemination area level, 2010

Table 4-4 presents the descriptive statistics and posterior estimates for selected neighborhoods. Under scenario A, the mean NEMS-R scores of neighborhoods A₁ and A₂ are the same (14); however, the posterior means for A₁ and A₂ are -0.185 and 0.245, respectively. This difference is not surprising given that the estimations incorporate NEMS-R information from adjacent neighborhoods, which are usually different, thus enabling the differentiation between two neighborhoods with the same mean NEMS-R score. ‘Borrowing strength’ from neighbors is reasonable since it strengthens NRE healthfulness assessment via accounting for the possibility that residents could walk beyond their own neighborhoods (Luan et al., 2015). Furthermore, the uncertainty associated with varied total number of accessible restaurants is reflected by the 95% CrI of the index. The index of neighborhoods with smaller numbers of accessible restaurants usually has a wider 95% CrI range. For example, the range for A₁ (only one accessible restaurant) is 1.613 (=0.621+0.992), wider than that (1.076, =0.255+0.821) of A₂ (5 accessible restaurants), suggesting that there is greater uncertainty associated with the

assessment for A_1 . With smaller sample size (i.e., observed accessible restaurants) providing limited information, the posterior estimation is largely determined by the prior distribution, which in our case is vague, leaving the posterior estimation with a wide 95% CrI.

Under scenario B, neighborhood B_1 has a higher mean NEMS-R score (12) than B_2 (9.94). However, the former can access to one restaurant only while the latter 87. Not surprisingly, the 95% CrI for B_1 is wider than that of B_2 (1.529 versus 1.377), indicating greater uncertainty of NRE healthfulness assessment for B_1 for the same reason as mentioned above. Interestingly, B_1 has a lower posterior mean of the composite index θ_i and a higher PP_{θ_i} than B_2 (-0.291 versus -0.270 and 0.324 versus 0.276, respectively), suggesting that B_1 has a less healthy NRE although its mean NEMS-R score is higher.

Comparing the posterior estimations of C_1 and C_2 , we found that neighborhoods without access to restaurants do not necessarily have a lower composite index or a higher PP_{θ_i} (i.e., NRE is more likely to be least healthy) compared to neighborhoods with accessible restaurants. Nevertheless, according to the 95% CrI of θ_i , greater uncertainties are associated with the posterior estimation for neighborhoods without accessible restaurants. Additional comparison between C_2 and C_3 (both do not have access to restaurants) highlights the impact of spatial lag¹⁶ on posterior estimations for neighborhoods without access to restaurants. Neighborhoods with a higher spatial lag have a higher composite index, and are less likely to have least healthy NRE (i.e., lower PP_{θ_i}).

Table 4-4: Dissecting uncertainties under different scenarios

ID	# of accessible restaurants	Mean NEMS-R score	Spatial lag	Posterior mean (95% CrI)	PP_{θ_i}
Scenario A: Neighborhoods with the same mean NEMS-R score but different number of accessible restaurants					
A_1	1	14	11.64	-0.185 (-0.992, 0.621)	0.247
A_2	5	14	18.59	0.245 (-0.255, 0.821)	0.003
Scenario B: Neighborhoods with low number of accessible restaurants have higher mean NEMS-R score than neighborhoods with higher number of accessible restaurants					
B_1	1	12	7.56	-0.291 (-1.068, 0.461)	0.324
B_2	87	9.94	10.51	-0.270 (-0.967, 0.410)	0.276
Scenario C: Neighborhoods with and without accessible restaurants					
C_1	2	-0.5	8.54	-0.087 (-0.834, 0.658)	0.163

¹⁶ Spatial lag refers to the mean NEMS-R score in adjacent neighborhoods.

C ₂	0	NA ^a	13.98	0.352 (-0.522, 1.227)	0.037
C ₃	0	NA	2	-0.226 (-1.57, 1.107)	0.359

^a NA: not available

4.5.2. From community to consumer nutrition environment: policy and planning implications

Findings from our study are informative for developing in-restaurant feature based interventions for planning and improving NRE. Past restaurant interventions are predominantly implemented at the community nutrition environment level, for example, banning the construction of fast-food restaurants to encourage establishments of restaurants with more healthy eating options (Mair et al., 2005; Stephens, 2007), probably attributable to the lack of primary consumer nutrition environment data that support sound spatial statistics for NRE assessment. Our modeling however, provides information in terms of what indicator to prioritize and where the interventions should be targeted.

In general, our findings suggest that Kitchener should increase availability and facilitator, and decrease prices and barriers of healthy eating because all three indicators are meaningful manifestations of NRE healthfulness (Table 4-3). Increasing/decreasing facilitator/barrier could be an intervention priority in that facilitator/barrier is most relevant with NRE healthfulness (i.e., highest values of factor loading (δ_j) and the ratio (ρ_j), Table 4-3). This finding suggests that interventions such as implementing the regulation of menu labeling (e.g., labeling calorie, nutrient, and sodium) in Kitchener's restaurants could potentially be effective for improving NRE healthfulness and promoting population-wide healthy eating. Mandatory menu labeling regulations have been implemented in several U.S. cities including New York City (Dumanovsky, Huang, Bassett, & Silver, 2010), but not in Ontario until January 01, 2017 (Ontario's Regulatory Registry, 2016). Nevertheless, menu labeling has been found effective in reducing calorie and sodium intake and increasing awareness of healthy eating in the Region of Waterloo (Hammond et al., 2013) and other Canadian contexts (Girz et al., 2012; Scourboutakos et al., 2014; Vanderlee & Hammond, 2014). Such labeling regulations might need to couple with additional interventions, for example, removing barriers to healthy eating, to take effect since multiple facilitators and/or barriers could interact to impact eating behaviors (Haws & Liu, 2016).

Interestingly, regulating calorie- and nutrition-labeling also has the potential to affect other indicators of NRE healthfulness, for example, motivating restaurants to provide more healthy eating options (Namba, Auchincloss, Leonberg, & Wootan, 2013) and improve signage for promoting healthy eating (Saelens et al., 2012), as evidenced by recent studies.

Neighborhoods with least healthy NRE (lowest quintile with darkest color in Figure 4-3a) should be prioritized for interventions in *availability*, *affordability*, and *facilitator/barrier* because they simultaneously suffer from these indicators as explained above. If resources are limited, priorities should be placed on the neighborhoods with higher PP_{θ_i} (i.e., > 0.5) (Figure 4-3b), where stronger evidence of least healthy NRE is present. The identification of neighborhoods with least healthy NRE is beneficial for community food planning, which has recently emerged as a tool for improving the food environment and facilitating healthy eating. Although planners cannot control the food prices and what to sell in restaurants (Minaker et al., 2011), they can greatly contribute to restaurant environment improvement via zoning and licensing regulations. For example, Raja et al. (2008) suggested that fast-food restaurants should be required to provide a ‘healthy offerings check’, which certifies that healthy foods will be offered, from the local public health agency in the licensing process, when they are applying for a food establishment permit. In a similar fashion for Kitchener, municipalities and planners could request checks for *availability*, *affordability*, and *facilitator/barrier* from pending restaurants that are accessible to the neighborhoods with least healthy NRE (Figure 4-3), ensuring that the new establishments could improve the NRE or at least maintain the healthfulness level in specific neighborhoods.

Interventions for neighborhoods without access to restaurants within a walkable distance, especially those with a high estimated composite index and low PP_{θ_i} , require special attentions. The population density of these neighborhoods (64 in total; areas with hatch pattern, Figure 4-4) ranges from 87.86 to 5553.85 per km² (median: 2855.86), indicating that restaurants are inaccessible by walking to a substantial amount of residential neighborhoods in Kitchener. This inaccessibility probably results from zoning ordinances that prohibit the establishment of food outlets in residential neighborhoods or within a pre-designated distance (J. L. Black et al., 2011; Raja et al., 2008). The NRE healthfulness for

these neighborhoods is estimated by pooling information from adjacent neighborhoods, which is usually associated with high uncertainties as noted above. While this approach is reasonable from a spatial statistical perspective since food access is a continuous phenomenon (Charreire et al., 2010), the estimation might not reflect the underlying needs of people residing in these neighborhoods, especially in the context that active transportation such as walking could be potentially effective for facilitating physical activity, thus reducing obesity rates. Future (qualitative) research surveying residents' interests and desires in dining away from home within a walkable distance should therefore be warranted. Survey results could be incorporated in the community food planning process for these neighborhoods.

4.5.3. Study strengths and limitations

Our research has several notable strengths. Instead of focusing on a proportion of restaurants such as fast-food restaurants and full-service restaurants, this study analyzes all restaurants, franchised, chain, or independent, in the study region. The analysis gives a holistic and more nuanced picture of NRE in Kitchener, which is essential for accurately targeting neighborhoods for interventions. In addition, rather than concentrating on the community nutrition environment, we explore the consumer nutrition environment. Compared with other measures based on restaurant types (e.g., number of fast-food restaurants), the composite index constructed in this paper could be more meaningful and useful for determining NRE healthfulness, and evaluating opportunities for procuring and consuming healthy foods away from home, given that *affordability* and *facilitator/barrier* also influence residents' eating behaviors other than *availability* as noted above. Finally, to our knowledge, our study is the first of its kind to analyze spatial patterns of NRE 'healthfulness' with in-restaurant indicators using a robust spatial statistical approach. This modeling approach advances the understanding of NRE by providing a more reliable measure of NRE healthfulness, which quantifies uncertainties associated with NRE assessment and could benefit food planning and interventions.

Several limitations of this study should be acknowledged. First, we used geographic centroids to determine whether a DA has access to a specific restaurant. This approach might result in the 'positional discrepancy' problem due to the discrepancies between

residents' actual addresses and DA centroids (Healy & Gilliland, 2012). Second, the uncertainty of NRE healthfulness assessment might be greater for periphery neighborhoods where the estimation cannot borrow strength from adjacent neighborhoods (which are outside Kitchener and not included in our dataset). Third, only *availability*, *affordability*, and *facilitator/barrier* are used to construct the composite index. Beyond these in-restaurant features collected via NEMS-R, additional consumer nutrition environment indicators could be incorporated in the model to refine the index. For example, when the index is intended to reflect NRE healthfulness for a specific group of population (e.g., Chinese, vegan, etc.), availability of culturally acceptable healthy foods should be included. Lastly, exploring the spatial patterns of NRE healthfulness is inherently exploratory. Socio-economic and socio-demographic environments should be incorporated into future NRE assessment in that residents with similarly healthful NRE but different socio-economic status could experience disparate eating patterns.

4.5.4. Future research

Future research could apply the proposed approach to the whole Region of Waterloo and other cities inside and outside Canada for assessing the healthfulness of NRE or the entire retail food environment. The derived composite NRE index could be further tested in terms of its usefulness for explaining geographical disparities of eating behaviors or diet-related health outcomes. The proposed approach is also useful for validating other indicators purported to measure the healthfulness of restaurants or food stores, especially given that increasing indicators are available for food environment measurement but validation approaches are lacking (Minaker et al., 2014).

Additionally, future research could analyze dynamic NRE healthfulness via spatio-temporal factor analysis by incorporating a temporal dimension. *Availability*, *affordability*, and *facilitator/barrier* change over short-term temporal scales including hours and weekdays due to restaurant opening-hour variations, and over long-term temporal scales including seasons and years attributable to the opening and closing of restaurants. Yet spatio-temporal analyses of the NRE require repeated assessment of in-restaurant features, which is costly and time-consuming. Alternative assessment tools, for example, the reduced-item audit tools (Partington, Menzies, Colburn, Saelens, & Glanz, 2015) and

mobile phone applications (Kanter, Alvey, & Fuentes, 2014) could be applied for rapid data collection in future research. Such spatio-temporal analyses could also be computationally challenging, for which fast but approximate inference methods for latent factor models, for example, the Integrated Nested Laplace Approximation approach (Blangiardo, Cameletti, Baio, & Rue, 2013; Carroll et al., 2015; Rue & Martino, 2009), might be required. Finally, while this paper analyzes objective food environment and identifies neighborhoods with less healthy NRE from a statistical modeling perspective, future research could investigate how residents perceive the restaurant environment in their neighborhoods (Barnes et al., 2015) or how they are truly exposed to the restaurant environment based on activity space (Sadler & Gilliland, 2015).

4.6. Conclusion

This research illustrates a BSFA approach for assessing the healthfulness of restaurant environment at the neighborhood level, where healthfulness is a latent factor derived from three correlated restaurant assessment indicators: *availability*, *affordability*, and *facilitator/barrier* of healthy eating. Methodologically, uncertainties associated with the descriptive statistic (i.e., mean NEMS-R score) are modeled by accounting for the varying total number of accessible restaurants between neighborhoods, borrowing information of NRE healthfulness in adjacent neighborhoods, and incorporating variations of in-restaurant features within neighborhoods. These uncertainties are quantified with posterior estimates including the range of 95% CrI and the posterior probability of the composite index falling into the lowest quintile.

The applied modeling approach enables to identify neighborhoods with least healthy NRE and the in-restaurant feature that is most relevant with NRE healthfulness. Such information guides community food planning and interventions in terms of where and what restaurant indicators to intervene. In particular, neighborhoods with a composite NRE index in the lowest quintile (i.e., those with the darkest color and locate at west, northwest, north, and northeast Kitchener, Figure 4-3a) should be targeted for interventions, with prioritization of two clusters of neighborhoods at west and towards northwest Kitchener and several individual neighborhoods across the city (Figure 4-3b). The identification of *facilitator/barrier* with highest loading (compared to *availability* and

affordability) on NRE healthfulness supports implementing interventions for increasing/decreasing facilitator/barrier of healthy eating such as mandatory menu labeling. While the applied modeling approach provides a tool for assessing NRE healthfulness of neighborhoods without accessible restaurants within a walkable distance, interventions for these neighborhoods warrant special attentions.

Chapter 5: Conclusion

Using spatial and spatio-temporal statistical approaches, this research illustrates how new and value-added information can be extracted from the food outlet datasets that are associated with geographical and temporal information. Although with different foci, the three articles presented in Chapters 2 to 4 significantly contribute to the common theme, neighborhood RFE assessment. They demonstrate how neighborhood RFE can be assessed with varying availability of food outlet information, for example, whether food outlets are inspected for multiple years or whether in-store features are measured. Results are informative for planners who can substantially contribute to the construction of healthy communities, of which healthy RFE is an indispensable component. Key findings and major contributions are briefly summarized in Table 5-1, in correspondence with the research questions proposed in Table 1-3 and the limitations of past RFE studies that are highlighted in Figure 1-4 and discussed in section 1.1.3.7, respectively. More details are given in the following sections.

Table 5-1: Key findings and major contributions

	Key findings	Major contributions
Chapter 2 (Article 1)	<ol style="list-style-type: none"> 1. Food swamps are more prevalent than food deserts in the Region of Waterloo; 2. Food swamps are becoming more prevalent during the study period; 3. Spatio-temporal food swamps are identified at south Waterloo, north Kitchener, and southeast Cambridge. 	<ol style="list-style-type: none"> 1. Applies a spatial modeling approach for analyzing RHFA; 2. Provides an empirical study for analyzing the temporal dimension of RFE; 3. Extends the definition of food swamps by incorporating a temporal dimension.
Chapter 3 (Article 2)	<ol style="list-style-type: none"> 1. Neighborhoods with higher residential instability, material deprivation, and population density are more likely to have access to healthy food outlets within a walkable distance; 	<ol style="list-style-type: none"> 1. Applies a spatial latent factor model for deriving neighborhood marginalization dimensions; 2. Applies a spatial hurdle model for accounting for zero-inflation occurring in

	<p>2. At the walkable distance scale, materially deprived neighborhoods are found to have less healthy RFE (i.e., lower RHFA).</p>	<p>RFE studies at the walkable distance scale;</p> <p>3. Analyzes a primary RFE dataset which contains the information of both community and consumer nutrition environments;</p> <p>4. Provides insights into food interventions for balancing healthy and less healthy food access;</p> <p>5. Provides empirical evidence that the deprivation amplification hypothesis holds only at specific geographic scales with specific RFE measures.</p>
<p>Chapter 4 (Article 3)</p>	<p>1. Neighborhoods located at west, northwest, north, and northeast Kitchener are found to have least healthy NRE. These neighborhoods simultaneously suffer from lower relative availability, higher prices, and lower/higher facilitator/barrier of healthy eating;</p> <p>2. Two clusters of neighborhoods located at west and towards northwest Kitchener as well as several individual neighborhoods across the city are more likely to have least NRE, thus should be prioritized for interventions;</p> <p>3. Facilitator/barrier of healthy eating is found most relevant with NRE healthfulness.</p>	<p>1. Provides an empirical application of the multi-dimensional approach in NRE assessment;</p> <p>2. Proposes a spatial factor analysis model for assessing NRE healthfulness;</p> <p>3. Dissects uncertainties associated with the mean NEMS-R score for assessing NRE;</p> <p>4. Provides a modeling approach for analyzing relative measures of the consumer nutrition environment;</p> <p>5. Informs the development of food intervention programs that focus on modifying in-restaurant features.</p>

5.1. Key findings

Consistent with previous findings in the Canadian context, the second chapter (article 1) reveals that food swamps are more prevalent than food deserts in the Region of Waterloo since most neighborhoods in the region have access to supermarkets within a 4km buffering zone from 2011 to 2014. The spatio-temporal modeling also shows that food swamps are becoming more prevalent during the study period, evidenced by the decreasing trend of RHFA during the study period. These results support interventions for ‘fixing’ food swamps such as limiting the establishments of fast-food restaurants or convenience stores via zoning bylaws, or increasing the relative availability of healthy foods (e.g., fruits and vegetables) via programs such as Healthy Corner Store. Spatio-temporal food swamps, neighborhoods that experience a steeper decreasing trend of RHFA than the average trend at the regional level, are identified at south Waterloo, north Kitchener, and southeast Cambridge, where interventions should be prioritized.

The third chapter (article 2) reports that residentially instable, materially deprived, and highly populated neighborhoods are more likely to have access to healthy food outlets within a walkable distance when RFE is measured by the presence/absence of healthy food outlets. However, neighborhoods with higher material deprivation are found to have a less healthy RFE (i.e., lower RHFA) at the walkable distance scale. Such results are in contradictory with two existing Canadian studies that measure neighborhood RFE with crude proportions of healthy/unhealthy food outlets of all accessible food outlets rather than probability distributions. These findings partially support the deprivation amplification hypothesis, suggesting that a simple ‘yes’ or ‘no’ answer for this hypothesis does not exist in the context of food access in the Region of Waterloo.

The fourth chapter (article 3) indicates that neighborhoods with least healthy NRE cluster at west, northwest, north, and northeast Kitchener. These neighborhoods simultaneously suffer from lower relative availability, higher prices, and lower/higher facilitator/barrier of healthy eating. Accounting for uncertainties associated with the point estimate (i.e., posterior mean) of NRE healthfulness, two clusters of neighborhoods located at west and towards northwest Kitchener as well as several individual neighborhoods scattered across the region are identified as ‘probably have least healthy NRE’ (i.e., more

likely to have least healthy NRE), thus should be prioritized for interventions. Compared with availability and affordability, facilitator/barrier of healthy eating is more relevant with NRE healthfulness. Hence, increasing/decreasing healthy eating facilitator/barrier is a higher priority, when food intervention programs that focus on modifying in-restaurant features are developed.

5.2. Major contributions

This research has significant conceptual, methodological, empirical, and policy implication contributions, which are detailed below.

5.2.1. Conceptual contributions

Conceptually, this research illustrates how the concept of food swamp can be extended to include a temporal dimension, resulting in the identification of spatio-temporal food swamps. To my knowledge, this is the first study in the RFE literature that explores temporal variations of RHFA. This concept refinement acknowledges that RFE research should be conducted from both the spatial and temporal perspectives, provides opportunities for further research (e.g., why RHFA in several neighborhoods decreases faster than the average trend of the study region, and how does this change impact on the diet of residents living in these neighborhoods), and informs which neighborhoods should be prioritized for increasing RHFA.

An additional conceptual contribution results from the empirical evidence that in a mid-sized Canadian region such as the Region of Waterloo, the deprivation amplification hypothesis holds only at the walkable distance scale, when RFE ‘healthfulness’ is measured with the relative strategy (i.e., modeled via probability distributions). This finding supports Macintyre et al.’s (2008) conclusion that in modern societies, marginalized neighborhoods are not always disadvantaged with poorer access to health-promoting resources. In the RFE context specifically, it largely depends on how the RFE healthfulness is characterized (absolute versus relative, and descriptive versus modeling), what statistical approach is used (spatial versus non-spatial), and whether the entire RFE dataset is used.

Moreover, this research advances the understanding of the concept of RFE ‘healthfulness’. In particular, the uncertainty associated with descriptive RFE assessment

measures is challenged. As demonstrated throughout this dissertation, measuring RFE ‘healthfulness’ with the commonly applied descriptive statistics such as mRFEI and mean NEMS scores is associated with uncertainties that arise from three sources: one, the total number of accessible food outlets is masked; two, in-store features are largely ignored; and three, RFE in adjacent neighborhoods are overlooked. Accounting for these uncertainties, the present research provides a more rigorous approach for interpreting the concept of neighborhood RFE ‘healthfulness’.

Finally, this research proposes a framework for neighborhood RFE assessment (Figure 1-4), which includes five essential elements: strategy, dimension, data, scale, and methodology. Along with Glanz et al.’s conceptual framework (Figure 1-5) of the food environment, the proposed framework serves as a base for comprehensive evaluations of neighborhood RFE. It emphasizes diversified aspects that should be considered in RFE assessment, and could be applied in other RFE studies conducted elsewhere (inside or outside Canada).

5.2.2. Methodological contributions

This research also has substantial methodological contributions. The presented Bayesian spatial and spatio-temporal statistical approaches have been widely applied in a variety of research fields, especially spatial epidemiology, but not necessarily in RFE studies. As noted above, such methodologies provide a flexible analytical framework for analyzing discrete and continuous measures of neighborhood RFE with the presence of spatial autocorrelation. In particular, these methodologies strengthen and stabilize the estimation of RFE ‘healthfulness’ when the total number of accessible food outlets is small, provide a modeling approach for the evaluation of NRE with a multi-dimensional approach (i.e., integrating community and consumer nutrition environments), enable the quantification of the uncertainties associated with the descriptive estimation of RFE ‘healthfulness’, and take into account potential zero-inflation that occurs at the walkable distance scale.

Additionally, this research presents a spatial statistical approach (i.e., spatial latent factor model) for constructing marginalization dimensions, which are proven relevant with several public health outcomes in the Canadian society, at a small-area level (Matheson et

al., 2012). Compared with the recently released and widely used Canadian Marginalization Index (Matheson et al., 2012) (developed with non-spatial factor analysis), the marginalization indices constructed from the spatial model retains the spatial structures and uncertainties associated with marginalization dimensions, thus benefiting subsequent analyses such as exploring the association between marginalization and food access or health outcomes.

Lastly, the Bayesian spatial factor analysis approach is proposed to assess NRE healthfulness in Chapter 4. This is the first study in the RFE literature that uses a spatial statistical model to assess NRE with multiple relative measures of the restaurant consumer nutrition environment. Accounting for uncertainties associated with the mean NEMS-R score as noted above, this modeling approach identifies neighborhoods where the NRE is more likely to be least healthy. It also reveals the indicator most relevant with NRE healthfulness, thus enabling to differentiate the importance of different restaurant assessment indicators (i.e., availability, affordability, and facilitator/barrier). This approach can be further adopted for validating RFE measures that purport to represent the underlying concept, RFE ‘healthfulness’. For example, RFE assessment indicators that do not significantly load on the composite index (e.g., the composite NRE index constructed in Chapter 4) are not valid measures for evaluating neighborhood RFE.

5.2.3. Empirical contributions

This research empirically contributes to the RFE literature by analyzing a primary RFE dataset (Chapters 3 and 4), which includes all validated food outlets (i.e., food stores and restaurants) in the Region of Waterloo, and contains the information of both community and consumer nutrition environments. Compared with past RFE studies that use secondary RFE datasets, results from this research are more reliable for informing food planning and interventions.

In particular, the empirical evidence strengthens the finding that “food swamps seem to be a more appropriate metaphor for urban Canada than food deserts” (Minaker et al., 2016, p.eS10) and partially supports the deprivation amplification hypothesis in the urban area of a mid-sized Canadian city. A further empirical contribution results from the analysis of a multi-year RFE dataset, of which the results indicate that local neighborhoods

could experience differing trends of RHFA. Finally, diving into the consumer nutrition environment, this research provides an empirical example that different restaurant assessment indicators could have varying contributions to NRE ‘healthfulness’, a finding that is informative for developing food intervention programs.

5.2.4. Policy implications

This research also has substantive contributions that have crucial policy implications. Studies in Chapters 2 and 3 demonstrate that food interventions in the Region of Waterloo should focus on striking the balance between healthy and less healthy food access. In other words, improving relative rather than absolute healthy food access is a priority. This goal can be achieved by implementing food intervention programs focusing on modifying either the community or the consumer nutrition environment. The Healthy Corner Store program exemplifies an intervention that modifies in-store features of existing food outlets to improve RHFA. Compared with traditional intervention programs such as opening new healthy retailers including supermarkets and grocery stores, working with existing retailers to increase the availability of fresh produce is less challenging, financially and functionally. Limiting the establishment of less healthy food outlets such as fast-food restaurants and convenience stores via zoning policies is another option for increasing RHFA. In contrast with the Healthy Corner Store program, this intervention concentrates on changing the community nutrition environment instead, and can be implemented by regulating the number or density of less healthy food outlets. Moreover, improving transportation, especially those supported by the food outlets such as supermarket-sponsored shuttles, to enable (materially deprived) residents to travel beyond their neighborhoods can also increase RHFA, as suggested by Chapter 3. This finding implies that it might be necessary to include food as an element in other plans such as transportation plans and official plans.

Results from chapter 4 are informative for developing intervention programs with a focus on modifying in-restaurant features for improving NRE. In general, the city of Kitchener should increase the relative availability, reduce the price, and increase/decrease the facilitator/barrier of healthy eating, given that *availability*, *affordability*, and *facilitator/barrier* have significant positive, negative, and positive associations with NRE

healthfulness, respectively. Moreover, it might be necessary to require a check for in-restaurant features in the licensing process from pending restaurants that will operate in neighborhoods where residents suffer more from *availability*, *affordability*, and *facilitator/barrier*, in particular those with a higher probability of having a least healthy NRE. This intervention could be effective for improving the NRE in specific neighborhoods, at least maintaining the current level of ‘healthfulness’. Lastly, the identification of *facilitator/barrier* being most relevant with NRE healthfulness supports the implementation of the menu labeling legislation in Ontario, which will take effect on January 1, 2017 as noted above. This legislation might be effective for promoting population-wide healthy eating in the Region of Waterloo.

5.3. Future research

5.3.1. Continuing spatio-temporal analyses of neighborhood RFE

Future research should continue spatio-temporal analyses of neighborhood RFE in the following two ways. First, extending the work presented in Chapter 2, future studies could analyze RHFA at other temporal scales apart from annual RHFA variations. For example, it would be worthwhile investigating whether several neighborhoods experience reduced RHFA at specific seasons, specific days of a week, or specific times of a day. Results from these investigations are informative for developing food intervention programs other than incentivizing or restricting the construction of specific types of food outlets, for example, extending opening hours of supermarkets or establishing farmers’ markets in specific neighborhoods. Second, the research conducted in Chapters 3 and 4 can be expanded to include a temporal dimension, answering spatio-temporal research questions such as (i) *how does the RFE vary over time in tandem with changing neighborhood marginalization*, and (ii) *are there neighborhoods that experience significant increasing/decreasing trends of NRE healthfulness*.

5.3.2. Comparing objective and subjective, and place-based and people-based RFE measures

Another potential topic for future research concerns the comparison between objective and subjective assessments of neighborhood RFE. Depending on the research contexts, objective and subject RFE measures might not align well with each other (Barnes

et al., 2015; Health Canada, 2012; Moore, Diez Roux, & Brines, 2008). Identifying which RFE assessment approach, objective, subject, or both, contributes to eating behaviors and subsequent health outcomes have important and distinct policy implications. For instance, if objective RFE measure is a stronger predictor of residents' eating patterns, increasing RHFA at the neighborhood level might be an effective step for improving population-wide eating behaviors; otherwise, intervention programs with an emphasis on strengthening residents' awareness of neighborhood RFE and nutrition knowledge are warranted.

Future research should also compare place-based and people-based (in particular activity space) RFE measures. In contrast to place-based measures that quantify potential food exposures of a neighborhood, activity space captures individuals' movements via travel surveys (Crawford, Jilcott Pitts, McGuirt, Keyserling, & Ammerman, 2014; Kestens et al., 2012; Kestens, Lebel, Daniel, Thériault, & Pampalon, 2010) or geospatial technologies including the Global Positioning System (Christian, 2012; Sadler, Clark, Wilk, O'Connor, & Gilliland, 2016; Zenk et al., 2011) such that it usually returns a larger value of food exposures. Measuring activity space has important policy implications because it helps to examine whether residents with restricted mobility cluster in specific neighborhoods, where food interventions should be prioritized.

5.3.3. Implementing and evaluating food interventions

An important direction for future research is to implement the recommended food interventions as noted above. From a planning perspective, these interventions can be implemented via stand-alone food system plans or official plans that includes 'food' as an element. As food is not in the purview of any single department, implementing these interventions require multi-sector collaborations (e.g., planners and local public health agency), and the role that each sector plays should be made clear (Raja et al., 2008). For example, when planners use performance zoning to regulate restaurant constructions and require 'healthy offering' certifications from pending restaurants in the licensing process, nutritionists could assist planners in defining what constitutes a 'healthy offering'. Notably, each food intervention should be accompanied with clear benchmarks that enable to gauge progress after the implementation of these plans (Raja et al., 2008).

Evaluating food interventions is another important area of future research, which also requires multi-sector and multi-disciplinary collaborations, especially between researchers from institutions (e.g., universities) and practitioners from local governments (e.g., professional planners and public health professionals). For example, assessing the impact of public transit availability changes (attributed to transit constructions such as Light Rail Transit) on neighborhood food access requires the collaboration between geographers, transportation researchers, and public health practitioners; examining whether the implementation of food interventions (e.g., the Healthy Corner Store program and the menu labeling legislation) improves residents' eating behaviors necessitates a partnership between public health researchers who are capable of characterizing 'healthy diet' with appropriate measures and (spatial) statistician who can guide robust statistical analyses.

5.3.4. Advancing the application of up-to-date spatial statistical approaches in RFE studies

Up-to-date spatial and spatio-temporal statistical approaches should be applied in future RFE studies. The application includes not only the statistical models, but also the algorithms used to implement the models. All the models fitted in this dissertation were implemented using the MCMC algorithm, which is computationally inefficient and time consuming, especially when the applied statistical model is highly complex or big datasets are analyzed (Banerjee, Carlin, & Gelfand, 2014). For example, it approximately took two weeks to run the joint spatial latent factor and spatial hurdle models in Chapter 3 on an IBM ThinkPad with relatively high configuration (2.4 GHz processor and twelve gigabytes RAM). This computational inefficiency also makes it difficult to compare different assumptions of the priors for the unknown parameters in the model. Future research could employ a more efficient alternative, the Integrated Nested Laplace Approximation (INLA) algorithm (Rue & Martino, 2009), for Bayesian analysis of spatial and spatio-temporal RFE datasets. INLA approximates posterior probability distributions via numerical integration rather than an iterative process (Blangiardo et al., 2013). Compared with MCMC-based algorithms, INLA dramatically reduces computational time while retaining reliable parameter estimates (Carroll et al., 2015).

Balancing the soundness of statistical assumptions and the appropriateness of RFE measures is a relevant area of future research that explores the RFE with spatial statistical models. As noted above, compared with administrative boundaries, buffering zones better identify food outlets accessible to a neighborhood, especially when the neighborhood is a relatively small area such as a DA and food access is characterized based on transportation modes. A food outlet accessible to multiple neighborhoods (say, N), however, correspond to multiple Y_{ij} (Chapter 2) or Y_i (Chapter 3) specified by different models, such that it is healthy with different probabilities p_1, p_2, \dots, p_N , which is possible only when $p_1=p_2=\dots=p_N$. Such models are invalid from a data-generating perspective, resulting in severely limited statistical inferences. When there is no data-generating mechanism $p(\text{data}|p_i)$, the concept of posterior distribution $p(p_i|\text{data})$ is meaningless. Thus, the distribution of p_i is some function of the data. This issue has been addressed by the model developed in Chapter 4. A conceptually flawed model (i.e., a model without valid data-generating mechanism, not presented in this dissertation) was also fitted with the same dataset used in Chapter 4. Specifically, this model assumed that a restaurant accessible to multiple neighborhoods (DAs) correspond to different models, the same issue existing in Chapters 2 and 3. Very similar results, however, were obtained from the invalid and valid models, indicating that this statistical drawback is unlikely to have much influence on the inferential results. Nevertheless, more statistically sound models should be developed and applied in future RFE studies. For example, the spatio-temporal model from Chapter 2 can be improved as follows (Equations (1) and (2)), where $I_{kj} = 1$ if the k^{th} food outlet is healthy at time j ; otherwise, $I_{kj} = 0$. Using a logit function, the probability that $I_{kj} = 1$, p_{kj} , can be linked with the latent RFE ‘healthfulness’ for DA i at time j , μ_{ij} . Similar with Chapter 4’s approach, N_{kj} is the set of DA’s that can access to the k^{th} food outlet at time j , and the weight w_{kij} denotes this accessibility. μ_{ij} can be further modeled with relevant covariates including time and socio-economic indicators.

$$I_{kj} | \boldsymbol{\mu} \stackrel{\text{ind}}{\sim} \text{Bernoulli}(p_{kj}) \quad (1)$$

$$\text{logit}(p_{kj}) = \sum_{i \in N_{kj}} w_{kij} \mu_{ij} \quad (2)$$

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Appendix 1: Formulation of a Binomial hurdle model

A Binomial hurdle model is a two-component mixture model that consists of a point mass at zero with a Bernoulli model accounting for the zero counts and a truncated Binomial model accounting for the positive counts. The form of a Binomial hurdle model is given in Model (A1), where π_i is the probability that a DA has access to healthy food outlets; Y_i and N_i are the number of accessible healthy food outlets and total number of accessible food outlets of DA_i , respectively; and p_i is the probability of a food outlet being healthy in DA_i .

$$\Pr(y = Y_i) = \begin{cases} 1 - \pi_i & (Y_i = 0) \\ \pi_i * \frac{\text{Binomial}(Y_i | p_i, N_i)}{1 - \text{Binomial}(0 | p_i, N_i)} & (Y_i > 0) \end{cases} \quad (\text{A1})$$

Appendix 2: WinBUGS code for the analyses conducted in Chapters 2 to 4

A2.1. WinBUGS code for Chapter 2

```
model
{
  for(j in 1:Time)
  {
    t[j] <- j
  }

  m_t <- mean(t[1:Time])

  for(i in 1:N)
  {
    for(j in 1:Time)
    {
      O[i,j] ~ dbin(p[i,j], T[i,j])
      logit(p[i,j]) <- alpha + s[i] + u[i] + gamma*(t[j]-m_t) + delta[i]*(t[j]-m_t)
    }
    u[i] ~ dnorm(0, prec.u)
    hotspot[i] <- step(-delta[i])
  }

  s[1:N] ~ car.normal(adj[], weights[], num[], prec.s)
  delta[1:N] ~ car.normal(adj[], weights[], num[], prec.delta)

  alpha ~ dflat()
  gamma ~ dnorm(0,0.001)

  prec.s ~ dgamma(0.5, 0.0005)
  prec.u ~ dgamma(0.5, 0.0005)
  prec.delta ~ dgamma(0.5, 0.0005)

  for(k in 1:sumNumNeigh)
  {
    weights[k] <- 1
  }
}
```

A2.2. WinBUGS code for Chapter 3

A2.2.1. Spatial latent factor model

```
model
{
  ##Number of marginalization dimensions
  for(n in 1:D)
  {
    ##Loading of the first indicator restricted to 1
    for(i in 1:N)
    {
      ind[startID[n],i] ~ dnorm(mu[startID[n],i],tau[startID[n]])
      mu[startID[n],i] <- alpha[startID[n]] + index[n,i]
    }

    ##Factor loadings of other indicators follow Normal(0,1000)
    for(j in (startID[n]+1):(startID[n+1]-1))
    {
      for(i in 1:N)
      {
        ind[j,i] ~ dnorm(mu[j,i], tau[j])
        mu[j,i] <- alpha[j] + loading[j]*index[n,i]
      }
      loading[j] ~ dnorm(0,0.001)
    }

    index[n,1:N] ~ car.normal(adj[], weights[],num[], 1)
  }

  ##M: Total number of marginalization indicators
  for(j in 1:M)
  {
    alpha[j] ~ dflat()
    tau[j] ~ dgamma(0.5, 0.0005)
  }

  for(k in 1:sumNumNeigh)
  {
    weights[k] <- 1
  }
}
```

A2.2.2. Spatial hurdle model for 1km dataset


```

model
{
  K <- 100000

  for(i in 1:N)
  {
    p[i] <- max(0.00001, min(0.99999, q[i]))

    ##Logistic regression: Bernoulli
    logit( $\pi$ [i]) <- alpha[1] + beta[1,1]*Resi[i] + beta[1,2]*Mate[i]
      + beta[1,3]*Depen[i] + beta[1,4]*Eth[i] + beta[1,5]*popu_dense[i] + s[1,i] + u[i,1]
    ##Logistic regression: Truncated Binomial
    logit(p[i]) <- alpha[2] + beta[2,1]*Resi[i] + beta[2,2]*Mate[i]
      + beta[2,3]*Depen[i] + beta[2,4]*Eth[i] + beta[2,5]*popu_dense[i] + s[2,i] + u[i,2]

    u[i,1:2] ~ dnorm(mean[], prec.u[,])

    z[i] <- step(y[i]-1)

    ##Base distribution: Binomial
    psi[i] <- max(0.00001, min(0.99999, p[i]))

    ##Log-likelihood of Binomial distribution
    ll[i] <- (1-z[i])*log(1-p[i]) + z[i]*(log(p[i]) + loggam(n[i]+1)
      - loggam(y[i]+1) - loggam(n[i]-y[i]+1) + y[i]*log(psi[i])
      + (n[i]-y[i])*log(1-psi[i]) - log(1-pow((1-psi[i]), n[i])))

    ##Zero-tricks
    zeros[i] <- 0
    zeros[i] ~ dpois(phi[i])
    phi[i] <- -ll[i] + K
  }

  for(i in 1:2)
  {
    alpha[i] ~ dflat()
    for(j in 1:betaNum)
    {
      beta[i,j] ~ dnorm(0, 0.001)
    }
  }

  s[1:2, 1:N] ~ mv.car(adj[], weights[], num[], prec.s[,])
  prec.s[1:2, 1:2] ~ dwish(Omega.s[,], 2)

  prec.u[1:2, 1:2] ~ dwish(Omega.u[,], 2)

  for(k in 1:sumNumNeigh)
  {
    weights[k] <- 1
  }
}

```

A2.2.3. Spatial Binomial model for 4km and 8km datasets

```
model
{
  for(i in 1:N)
  {
    O[i] ~ dbin(p[i],N[i])
    logit(p[i]) <- alpha + beta[1]*Resi[i]+beta[2]*Mate[i]
    +beta[3]*Depen[i]+beta[4]*Eth[i] +beta[5]*popu_dense[i] + s[i] + u[i]
    u[i] ~ dnorm(0, prec.u)
  }

  prec.u ~ dgamma(0.5, 0.0005)

  s[1:N] ~ car.normal(adj[], weights[], num[], prec.s)
  prec.s ~ dgamma(0.5, 0.0005)

  alpha ~ dflat()
  for(k in 1:betaNum)
  {
    beta[k] ~ dnorm(0, 0.001)
  }

  for(k in 1:sumNumNeigh)
  {
    weights[k] <- 1
  }
}
```

A2.3. WinBUGS code for Chapter 4

```
model
{
  ##Number of indicators: 3
  for(j in 1:M)
  {
    ##Number of restaurants: 351
    for(k in 1:K)
    {
      for(m in START[k):(START[k+1]-1))
      {
        sub[j,m] <- mu[j,ID[m]]
      }

      mu2[j,k] <- sum(sub[j,START[k):(START[k+1]-1)])/TOTAL[k]
      Y[j,k] ~ dnorm(mu2[j,k], tau[j])
    }

    for(i in 1:N)
    {
      mu[j,i] <- alpha[j]+delta[j]*theta[i] + u[j,i]
      u[j,i] ~ dnorm(0,tau.u[j])
    }

    alpha[j] ~ dflat()

    ##Random noise
    tau.u[j] ~ dgamma(0.5,0.0005)
    sigma.u[j] <- sqrt(1/tau.u[j])

    ##Indicator precision
    tau[j] ~ dgamma(0.5, 0.0005)
    sigma[j] <- sqrt(1/tau[j])

  }
  delta[1] ~ dlnorm(0,0.01)
  delta[2] ~ dnorm(0,0.001)
  delta[3] ~ dnorm(0,0.001)

  ##Identify the posterior probability that ith neighborhood falls into the lowest quantile
  for(j in 1:N)
  {
    darank[j] <- rank(theta[,j])
    hotspot[j] <- step(-darank[j]+60)
  }
  ##the value of the 20% threshold
  ranked60 <- ranked(theta[, 60])
}
```

```
##variance explained
for(j in 1:M)
{
  var.theta[j] <- pow(delta[j],2)*pow(sd(theta[]),2)
  var.noise[j] <- 1/tau.u[j]
  theta.explain[j] <- var.theta[j]/(var.theta[j]+var.noise[j])
}

theta[1:N] ~ car.normal(adj[], weights[], num[], 1)
for(k in 1:sumNumNeigh)
{
  weights[k] <- 1
}
}
```