

Multi-criteria suitability analysis and spatial interaction modeling of retail store locations in Ontario, Canada

by
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Author's Declaration

I hereby declare that I am the sole author of this 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.

Abstract

GIS-based decision analysis is increasingly used by retailers to address the complexity and cost of investment in retail store location decisions. This study conceptualizes and represents nine criteria in a GIS-based multi-criteria decision analysis of 4.7 million potential retail store locations. From topographic statistics to spatial interaction modelling, the study utilizes criteria of varied complexity to analyze the statistical and spatial distribution of highly suitable locations for a retail store. The study further examines how the spatial representations of criteria based on the Huff model affects the distribution of suitable locations. The results show that although Toronto dominates the retail landscape in Ontario, key regions are found in Guelph, Kitchener-Waterloo and Cambridge. Results show that the incorporation of network-based spatial interaction costs in Huff's model produces more spatially heterogeneous sales estimates than Euclidean-based spatial interactions. Future research efforts in improving various components of the suitability analysis, as well as the scaling and regional parameterization of spatial interaction models are also discussed.

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Chapter 1 – Introduction

Selecting a location for a retail store is said to be both an art and a science (Hernández & Bennison, 2000). While advocates of the art rely on instincts and experience, the science of retail location involves developing and applying systematic methods. In practice, there is a wide variation of what proportions of art and science is used within the retail industry. Despite the tendency to view the scientific approach to retail location as more robust and formalised, scholars admit that the methods employed in the industry are as diverse as the retail industry itself (Davies & Clarke, 1994; Zentes et al. 2012). From simple checklists (e.g., Reynolds & Wood, 2010) and pointing on a map (Reynolds & Woods, 2010), to spatial interaction models (e.g., Huff, 1966) and artificial neural networks (e.g., Wang et al. 2015), the retail industry has a wide variety of tools and understands that formal methods of store location are needed as obvious location decisions are increasingly rare and the numbers of potential locations become overwhelming. Moreover, the cost and commitment of time required for a store location decision has increased (Hernández et al. 1998; Hernández & Thrall, 2007). The raft of methods produced by the science of retail location is extensive, and examples of their implementation into a single cohesive application for a retail company are few.

In this thesis, I am pleased to present a two-part study that performs a complete decision analysis for a dominant retail corporation seeking locations for new stores in Ontario. The second chapter of the thesis completes a multi-attribute decision analysis (MADA), evaluating 4.7 million potential sites based on nine attributes associated with each potential site. The chapter describes the implementation and results of a suitability analysis, with a discussion of the relevance to researchers and the retail industry. The third chapter of the thesis draws on a criterion from Chapter 2, and is a detailed examination of how different spatial representations of components in a spatial interaction model (SIM) affect the distribution of suitable outcomes in Waterloo, Ontario. The methods and results of the third chapter lead to a discussion on how to proceed with improving various components of the SIM, and outlines a specific method to efficiently scale the model across large spatial extents for potential store location assessments.

Retail location theory draws on a diverse set of fields, including economic geography, operations research, computational geometry, geographic information science, market analysis, and spatial statistics. Guided by this rich literature and an energetic research team, a set of criteria were selected that would conceptually represent the suitability of a potential retail store location. I made extensive use of geographic information systems (GIS or GISystems) to store, manipulate, visualise, integrate, and analyse the diverse spatial representations (i.e., models) of all criteria (Church, 2002; Malczewski, 2006). Many of the challenges to the research presented in this thesis arose from the desire to represent more complete and accurate (and consequently, more spatially complex) conceptualisations of criteria at the cost of the computational resources needed to complete the criteria in a reasonable time. The additional complexity of the criteria also raises questions that are well-established in the literature, such as the degree of acceptable aggregation of geographic features (Goodchild, 1984), and the challenges associated with managing and analysing ‘big data’.

In addressing these questions within the context of existing research and developing future research directions, this thesis serves two broad objectives: to provide the reader with a case study of a GIS-based suitability analysis for retail location across a large number of

potential sites and a large spatial extent. The suitability analysis incorporates a range of criteria in terms of their spatial complexity and conceptual relevance to geographic factors that drive retail store success. The second objective demonstrates how different approaches to representing a criterion within a GIS affect the spatial distribution and structure of suitable locations. Both objectives serve to inform both the research community and the retail industry of conceptual approaches and applied methods for a retail store location. Lastly, this thesis also outlines limitations of the methods used to accomplish the study objectives, using both the established and recent literature to understand why and how the existing research may improve further studies in retail location.

Chapter 2 – Multi-criteria suitability analysis of retail locations in Ontario, Canada

1 – Introduction

The phrase “location, location, location” emphasises the importance of location for a retail business without giving insight on how or where to locate a retail business.¹ Traditionally, the importance of a location decision, and the success or failure of a retail store, was the result of executives and managers making store location decisions (Hernández et al. 1998). Heuristics such as common sense, experience, and intuition are often described as the qualities necessary to bring success to retail location decisions (Hernández, & Bennison, 2000). While these qualities are certainly crucial for a location decision, the complexity of factors driving store success and the seemingly infinite range of potential locations can be overwhelming. The distinctly human tendency to generalise and make fuzzy decisions when faced with a large number of potential options may result in sub-optimal decisions (Greifeneder et al. 2010; Jacoby, 1977).

Since its inception in the 1930s, retail location theory has developed a body of concepts, methods, and tools to improve the accuracy and precision of spatial decision-making for retailers. For instance, the application of a geographic information system (GISystems) to visualize, manage, and manipulate different geographic data types in one integrated system provides a supporting platform for retail location decisions (Church, 2002; Hernández, & Bennison, 2000; Reynolds & Wood, 2010). GISystems have been widely applied in analysing the suitability of specific land uses, with applications in retail (e.g., Roig-Tierno et al., 2013), agriculture (e.g., Kalogirou, 2002), public planning (e.g., Brown & Reed, 2009), and environmental conservation (e.g., Huang et al. 2011). In many applications, and those pertaining to retail in particular, spatial decision-making involves multiple individuals that hold many unique interests in evaluating a set of solutions (Malczewski, 2006). Combining these interests toward the goal of identifying suitable options forms the basis of multi-criteria decision-making and -analysis (MCDM and MCDA).

In the context of a retail location decision, MCDM may be categorised as a site search or a site selection problem. In a site search problem, the boundaries of the site define the solution as potential sites are not explicitly identified for evaluation. Site search methods are therefore referred to as multi-objective decision analysis (MODA) due to the use of objective-based methods such as linear programming, heuristics, and genetic algorithms to search for solutions (Malczewski, 2004). Applications of MODA have included habitat suitability modelling for conservation (e.g., Guerra & Lewis, 2002; Villa et al. 1996) and waste management routing through urban landscapes (e.g., Giannikos, 1998).

A more common problem in retail location is choosing suitable sites from among a set of pre-defined potential options, usually divisions of land such as parcels. In contrast to MODA techniques, site selection problems identify and rank a set of potential sites according to their known relevant site attributes according to a decision rule. An MCDM that ranks sites in terms of attributes or criteria is referred to as a multi-attribute decision analysis (MADA) (Malczewski, 2004). MADA includes a number of decision rules, including weighted summation (e.g., Janssen, 2001), Boolean overlay (e.g., Jiang & Eastman, 2000), the analytical hierarchy process

¹ “There are three things that matter in property: location, location, location.” – Harold Samuel

(AHP; Saaty, 1977), ideal and reference point methods (e.g., Janssen, 2008), and outranking (Roy, 1991).

By far the most commonly applied decision rules used to obtain criteria weights is the weighted summation approach and related methods such as Boolean overlay. The simplicity and straightforward implementation of Boolean overlay has seen the method used in many applications of MADA (Jiang & Eastman, 2000). Boolean overlay produces criteria as thematic layers and combines the criteria using set operators such as intersection (AND), union (OR), and not (NOT). The application of set theory in MADA incorporates logical operators for combining criteria as factors, constraints, or both. However, Boolean overlays are limited as hard logic operators (such as AND or NOT) may exclude sites that do not meet every single criteria selected for a location decision. AHP offers a more robust method of ranking potential sites over Boolean overlay procedures. In AHP, a pairwise comparison of every combination of criteria is performed to determine weights based on relative importance (Roig-Tierno et al., 2013). Weighted linear combination is often used after Boolean overlay or AHP, standardizing criteria before combining them into a weighted average (Basnet et al. 2001; Greene et al. 2011). Boolean operators such as OR and NOT are then applied to constrain criteria and remove unavailable sites from the suitability analysis. Criteria applied as factors provide more flexibility in assessing site suitability, while constraints narrow the set of potential sites.

While weighted summation, Boolean overlay, and AHP are able to evaluate a large number of sites, these approaches do not identify differences between an ideal set of sites and a set of efficient solutions (Carver, 1991). Compared to these methods, alternative MADA such as ideal/reference point and outranking approaches are designed to address the lack of compromise in identifying optimal sites. Although the ideal site according to the selected criteria will likely not exist, the ideal/reference point method identifies the ideal site as a point of reference for comparison. A site that is a minimum distance from the ideal site with respect to many individual criteria is identified as suitable, with greater distances for more important criteria incurring greater penalties for site suitability (Carver, 1991). Outranking methods (also referred to as concordance-discordance analysis) take a similar though more detailed approach than ideal/reference point methods, and measure how sites and criteria weights confirm or conflict with alternative sites and criteria weights (Carver, 1991; Roy, 1991). Based on a user-defined minimum concordance and maximum discordance index, a dominance matrix can be constructed to show how a site outranks alternatives. Outranking methods therefore advance the ideal/reference point approach using a pairwise comparison of alternatives to identify a site that is the best compromise relative to all other sites. The limitation to both methods is that large numbers of potential sites for comparison quickly become unmanageable from a computational standpoint (Carver, 1991; Malczewski, 2004). Therefore, the number of potential sites and the complexity of comparing weights and criteria among alternatives must be considered when selecting a MADA method for a suitability analysis of retail store location.

In contrast to traditional methods of retail location, implementing a suitability analysis in a GISystem allows retailers to store and describe the characteristics of vast numbers of potential sites across large spatial extents (Roig-Tierno et al., 2013). The application of MADA to potential site criteria further allows retail analysts to consider different scenarios emphasising the importance of a criterion to site suitability. The results of a GIS-based MADA for retail suitability may then be visualised to remove or narrow the number and spatial extent of potential

sites for decision-makers. In this study we first answered the question, what are the dominant criteria influencing retail location suitability in Ontario? Subsequently we answered the question, what is the spatial distribution of the most suitable sites in Ontario? We contextualize our research within the home improvement industry and evaluate site suitability for a new home improvement store within approximately 4.7 million ownership parcels covering the province of Ontario, Canada. The analytical methods and our results provide insight on the application and limitations of GIS-based MADA for retail site selection.

Our research begins by identifying, selecting, and combining criteria into suitability scores using weights derived from a survey of retail industry experts. The study presents the challenges of conceptualizing criteria from available data and methods of spatial analysis. Criteria of varied computational complexity are calculated across a large spatial extent and included in a multi-attribute decision analysis to yield a complete suitability analysis. The suitability analysis is empirically informed and applied across a large spatial extent for a specific retail sector, providing researchers and practitioners of retail location with a spatially and conceptually challenging case study.

2 – Study Area

Located in the centre of Canada, the province of Ontario (51°15'13" N, 85°19'23" W) is home to 13.6 million (38.3%) of the 35.5 million people across the country (Figure 2.1; Statistics Canada, 2014a). The majority of Ontario's population and economic activity occur in the southern region of the province, with 88.7% of the 2011 population living inside census metropolitan areas or census agglomerations such as Ottawa-Gatineau, Toronto, Hamilton, and Kitchener-Cambridge-Waterloo (Statistics Canada, 2012). Key regions in Ontario for population growth include Milton, Whitchurch-Stouffville, Ajax, Brampton, and Vaughan, with percent growth of between 20.7 and 56.5% from 2006 to 2011 (Statistics Canada, 2012).



Figure 2.1: Ontario (centre) is one of the ten provinces of Canada.

Along with the largest population, Ontario is also the largest economy in Canada with a GDP of \$695 billion (CDN), nearly twice that of the second largest provincial economy, Quebec (Statistics Canada, 2014b). Although the 2008 economic crisis has slowed economic growth in Ontario, the province presents an opportunity for a prospective retail company seeking to expand into the Canadian market. While construction began on an average of 60,000 homes in 2013, the number of housing starts was below the long-term average of 64,000 units from 2008 to 2012 (IHS Global Insight, 2013). Despite the slowed economy, Ontario remains a key market for the home improvement retail sector (IHS Global Insight, 2013). As of 2012, the professional and consumer market of home improvement products was estimated at \$15.5 billion and is expected to increase to \$18.8 billion in 2017 (IHS Global Insight, 2013). Given that population growth is a major driver of demand in economic sectors such as housing and home improvement products, demand estimates and the identification of suitable sites for home improvement retail stores are of interest.

3 – Methods

3.1 – Overview of Suitability Analysis

Conceptually, the MADA begins by defining the spatial representation of potential sites, as well as the potential site criteria for evaluation. A potential site is defined as any individual ownership parcel, with the spatial extent of potential sites identified as all parcels within the province of Ontario (Figure 2.2).

We conceptually categorised the selected criteria relative to their spatial definition as either site or situational characteristics. Site criteria are characteristics of a potential site found along or within the boundary of an individual property parcel, while situational criteria are characteristics that describe the potential site relative to geographic features outside the parcel. Examples of site criteria include the parcel slope or area, while situational criteria may include the travel time of the parcel to the nearest highway ramp. Suitability characteristics belonging to each potential site were selected according to the organisational goals of a home improvement retail company using a site-and-situation concept of the real estate, logistical, developmental, and market requirements on and surrounding the potential sites. Criteria were identified from mixed sources, including a review of relevant literature (e.g., Jankowski, 1995; McGoldrick, 2002; Roig-Tierno et al., 2013; Zentes, 2012), industry consultations, and expert opinions.

Once the criteria were calculated for all parcels, criteria values were normalized for comparison and weighing (Figure 2.2). A survey distributed among a selection of retail industry experts informed the weight of each criterion in terms of importance in affecting the suitability of a potential site for a retail store. Following the application of criteria weights using a weighted linear combination, constraints were applied to eliminate parcels unavailable for retail development. The remaining parcels constituted a solution set to the MADA, with each individual parcel assigned a suitability score.

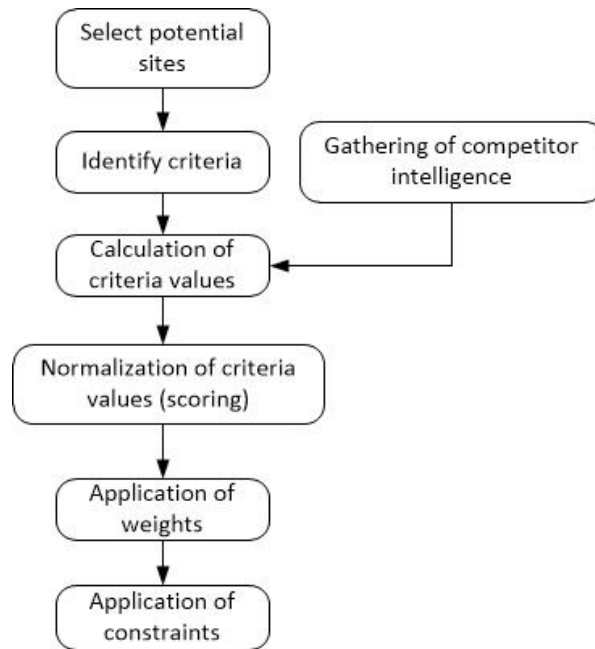


Figure 2.2: the process of developing a suitability analysis for retail location.

Although constraints are conventionally applied before the calculation and normalisation of criteria values (e.g., Jankowski, 1995; Malczewski, 2004; Chang et al. 2008), this suitability analysis applies constraints after the suitability of each parcel has been calculated. This methodological approach has important implications for the capability, performance, cost, and flexibility of the suitability analysis. As a result of applying the constraints after the calculation of suitability scores, the criteria and suitability of all parcels (i.e., regardless of availability) are calculated and consequently imposes much higher computational costs on the analysis. The benefit to the approach used in this thesis is that the analysis can quickly accommodate the addition and removal of constraints, allowing decision-makers to change the assumptions determining parcel availability without repeating the suitability analysis on a subset of newly available parcels. The approach also allows decision-makers to consider significantly more potential sites and to evaluate the coincidence of highly suitable yet unavailable parcels. Simultaneously, the method of applying constraints used here has important impacts on the normalisation of criteria values (see 3.5.1 – Normalisation of Criteria Values).

3.2 – Selection of Criteria

The importance of site criteria to parcel suitability informs the cost of site development (e.g., parcel slope) or the site availability for retail development (e.g., parcel area or constraints). Of the site criteria selected (Table 2.1), the parcel area, land cover, and spatial relationships with exclusive land uses such as protected parks or public infrastructure provided the basis for constraining site availability.

Table 2.1: Site criteria selected and developed for retail location.

Site criteria	Relevance to suitability
Slope	Summary statistics such as minimum, maximum, mean, and range of slope over the parcel area represent topographic attributes that can affect the cost of site development.
Area	Parcels that are too small in area (7432m ²) constrain site development for a potential store with a minimum retail area.
Land cover	Proportions of forest cover (>50%) constrain site development.
Constraints	Constraints include parcel characteristics such as area, or environmental characteristics such as the presence of forest cover, wetlands, and water bodies or courses. Other constraints include parcels that intersect or contain railways, schools, First Nations reserves, national or provincial parks, and other areas banned from development.

Relative to the site criteria, situational criteria allow for the conceptualisation and representation of more complex spatial relationships between parcels and features relevant to site suitability. The spatial interactions between parcels and features via a street network provided the basis for the majority of spatial relationships represented by the situational criteria (Table 2.2). For instance, the travel time to the nearest highway ramp measures the accessibility of the site to highway roads, as more accessible sites are more likely to be preferred by consumers to avoid congestion and reduce travel time. For retail operations, a potential site located nearer to a highway ramp or distribution warehouse is more economical for logistical access (Jakubicek, & Woudsma, 2011). Other situational criteria such as trade area characteristics (i.e., the density of competing chain stores and retailers) and potential or competitive expenditures at a potential site location provide more complex representations of site suitability.

Table 2.2: Situational criteria selected and developed for retail location.

Situational criteria	Relevance to suitability
Access to nearest highway ramp	The shortest travel time of a parcel to a highway ramp increases the accessibility of the parcel.
Proximity to traffic volumes	The proximity of a parcel to highways with high traffic flows will increase visibility.
Density of competing chain stores in trade area	Parcels with trade areas of high competitor density are less suitable due to high competition.
Density of retail stores in trade area	Parcels with trade areas of high retail density present more shopping opportunities for consumers.
Potential and competitive expenditures	The demand available to a potential store location in the presence and absence of competition.
Distance to distribution warehouse	The shortest network-based distance or travel time of a parcel to a distribution warehouse minimizes logistical costs.

Situational criteria	Relevance to suitability
Market representation	Measures representation of retail sector within trade area relative to representation of retail sector within the study area.
Viewshed analysis	Viewshed analysis will allow for the selection of parcels that offer high visibility based on elevation

The conceptualization and spatial representation of situational criteria often affected the computational complexity and consequently the feasibility of the criteria (Figure 2.3). Therefore the process of criteria development was iterative, with improved conceptual models requiring numerous revisions of computational workflows. The spatial extent and resolution of the criteria often required enormous computational resources, and highly intensive methods required revisions of the spatial representation or even the inclusion of a criterion. For example, the visibility of a parcel to large volumes of pedestrian or automobile traffic is widely viewed to be important to retail store success. However, a viewshed analysis of individual parcels consumed prohibitive resources², and so the criterion was simplified to measure the proximity of parcels to traffic volumes.

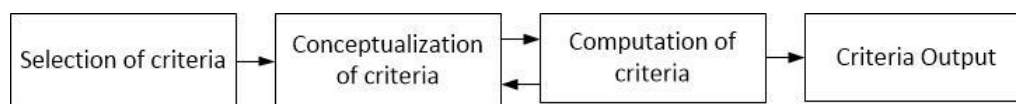


Figure 2.3: the process of criteria development shows how computational limitations may modify or limit the concept or representation of a criterion.

3.3 – Data

The criteria selected were implemented in a GIS³ based on datasets obtained from a variety of government and private sources (Table 2.3). Provincial roads, land cover, and geographic census areas were obtained from Ontario government ministries and Statistics Canada. Proprietary datasets of consumer points of origin to retail store locations were provided by a dominant retail corporation. A database of retail chain store locations and retail areas was also constructed to inform situational criteria such as the analysis of trade areas and competitive expenditures (Table 2.2).

Table 2.3: Provincial datasets for all criteria included in the suitability analysis

Description	Data Type	Size	Source
Annual average daily traffic	Vector line	2,225 lines	Ontario Ministry of Transportation, 2010
Canadian Business	Integer	19,964 rows	Statistics Canada, 2011

² Performance testing on a subset of parcels showed that a viewshed analysis of all 4.7 million parcels would require approximately 2.7 years of computing time on a computer equipped with a Core i7 processor.

³ ESRI's ArcGIS 10.1 SP1, GME (Beyer, 2012), Python 2.7, and R 3.1 (R Core Team, 2015; Wickham, 2009) were used throughout the study.

Description	Data Type	Size	Source
Patterns			
Census dissemination areas	Vector polygon	19,964 polygons	Statistics Canada, 2013
Census subdivisions	Vector polygon		Statistics Canada, 2013
Census divisions	Vector polygon	49 polygons	Statistics Canada, 2013
Census metropolitan areas	Vector polygon	43 polygons	Statistics Canada, 2013
Consumer points of origin	Vector point	495,956 points	Proprietary source.
Digital elevation model	Raster	10m resolution	Ontario Ministry of Natural Resources
Land Cover Database	Raster	25m resolution	Ontario Ministry of Natural Resources, 2008
Retail chain stores	Vector point	1,591 points	Unpublished data
Ownership property parcels	Vector polygon	4,756,562 polygons	TeraNet Inc., 2010
Ontario road network	Vector line	581,093 lines	Ontario Ministry of Transportation, 2013
Road classes (road type)	String	581,093 rows	Ontario Ministry of Transportation, 2013
Road speed limits	Integer	581,093 rows	Ontario Ministry of Transportation, 2013

Note: All spatial datasets were projected to the Ontario MNR Lambert Conformal Conic projection throughout the study.

Several datasets were used for spatial representations across multiple criteria. The provincial ownership property parcels provided the basis for the spatial representation of potential sites and their associated criteria throughout the study. The Ontario road network (ORN) was integrated with road attributes such as road type and road speed limit, and used to spatially represent major roadways, highway ramps, and calculate network-based costs for many situational criteria.

Census geographies such as census metropolitan areas (CMAs), census divisions (CDs), and census dissemination areas (CDAs) were used as spatial units of analysis, served computational purposes, or provided the basis for spatial generalisations or aggregations of features occurring at higher spatial resolutions. In addition, CDA polygons were used to spatially represent demand as the estimated household expenditures on home improvement products. The demand or estimated expenditures were used to calculate the potential and competitive expenditure criteria and were developed with Statistics Canada census data (Balulescu, 2015). Consumer points of origin were used to inform consumer travel behaviours in the parameterisation of network-based criteria such as trade areas and potential and competitive expenditures.

3.4 – Development of Criteria

3.4.1 – Topography and Land Cover

To measure site suitability in terms of the cost of grading a parcel for a retail store development, the maximum slope was calculated at each potential site. A digital elevation model (DEM) with a resolution of 10m was sampled to obtain the topographic statistics of all parcels within the study area. In addition, a high proportion of forest cover within a parcel constrained parcel availability, due to potential issues with environmental assessment regulations. In calculating the land cover proportions of each parcel, a method similar to obtaining topographic statistics was used. Twenty-eight land cover classifications from the Ontario Land Cover Database were re-classified to either water, settlement, forest, agriculture, or unavailable. In accordance with industry expert opinion, parcels containing 50% or more forest cover were constrained from the suitability analysis.

3.4.2 – Proximity to Traffic Volume

Retailers often locate stores along major arterials and roadways with high traffic volumes to increase store visibility and accessibility (Reimers & Clulow, 2004). Annual average daily traffic (AADT) counts along provincial highways were used to quantify the volume of automobile traffic. Traffic along major provincial roadways was assumed to have visibility up to what is known in park management as the middleground of a landscape, which occurs at approximately 805m from a viewing point (USDA 1974, 1995). Parcels within a threshold distance of 805m from a highway were scored based on the distance of the parcel to the highway and the traffic volume. The suitability of a potential site within the distance threshold of a provincial highway with a traffic volume was calculated as follows:

$$S_i = \left(1 - \frac{D_i}{D_{max}}\right) * \frac{T_i}{T_{max}}$$

Equation 2.1

where the suitability S of parcel i is equal to one minus the distance of the parcel to the nearest highway (D_i) divided by the distance threshold (D_{max}). The distance term is multiplied by the traffic volume (T_i) of the highway as a proportion of the highest traffic volume (T_{max}) observed within the census division. Proximity to visible traffic is measured relative to the maximum observed traffic volume within the census division⁴. Conceptually, the proximity to visible traffic is simply inversely proportional to the distance from a provincial highway and proportional to the observed traffic volume at that length of provincial highway. Parcels at a distance greater than the distance threshold are assessed as unsuitable for this criterion, under the assumption that the parcels do not have a line of sight to highway traffic.

⁴ Although traffic volumes were initially taken as a proportion relative to the highest observed traffic volume in the province, the results of the normalized criterion were unusable as most local traffic volumes were significantly lower compared to the provincial maximum.

3.4.3 – Highway Accessibility

The highway accessibility to a potential site was measured using the shortest network-based travel time to a highway ramp. The time required to travel a road length according to speed limits was chosen as a cost attribute since consumers are more likely to patronize a store if they can reach it in less time (Huff, 1966; Suárez-Vega, 2011). The provincial road network identifies 7,017 individual highway ramps, however many ramps serve a single highway intersection or can be found located distant from highways in urban areas where one road merges with another (Figure 2.4). Computing the shortest network route from each potential site to an individual highway ramp would have been computationally prohibitive and yielded spatially inaccurate results.

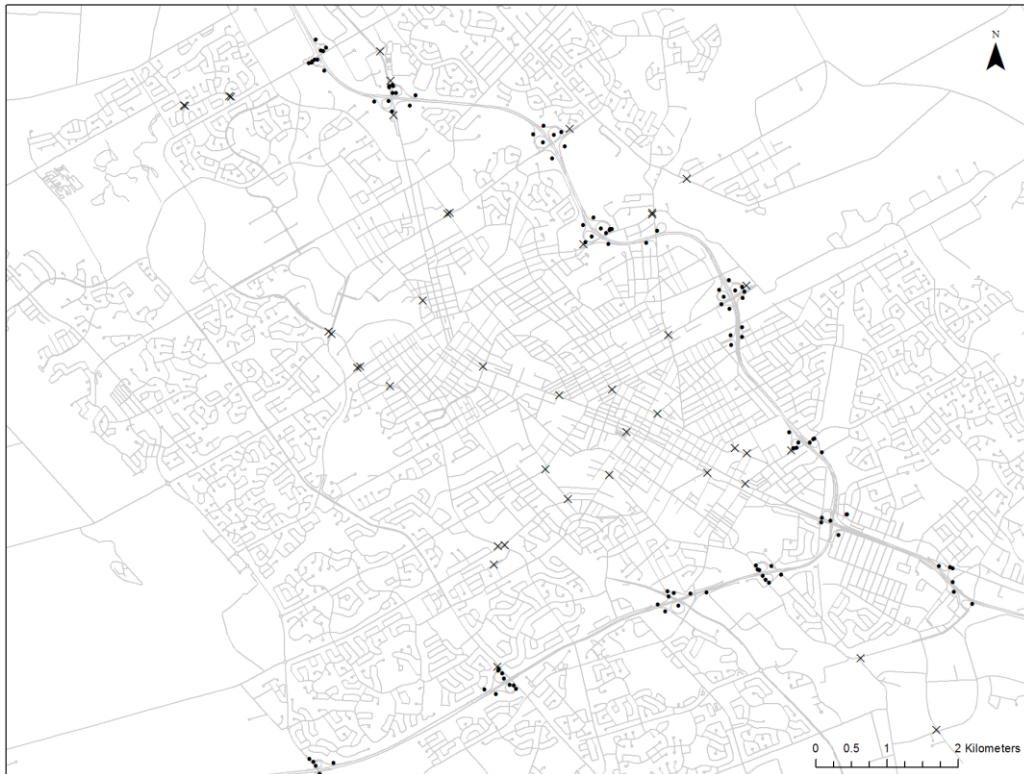


Figure 2.4: Spatial distribution of ramp centroids (black points) along a street network in Kitchener-Waterloo, Ontario. Note the clusters of ramps along highway intersections. Ramps isolated from highways are typically by-pass lanes ('x' markers).

To generalise the spatial representation of highway ramps, highway ramps were clustered to a single point and ramps greater than 200m from highways were removed. Ramp clusters were assumed to be coincident and integrated based on a 200m XY tolerance measured with a GIS, with a generalised point placed at the weighted average distance between the ramp cluster coordinates (ESRI, 2015). Our spatial analysis yielded 1,130 highway access points (HAP), each representing a cluster of highway ramps.

The volume of data used throughout this project was extensive and could be classified as 'big data' in terms of geographic analysis, although the term is recognised to be relative (Kitchin, 2013). For example, to calculate the network distance for each of the 4.7 million potential sites to

the nearest HAP required partitioning parcel data by census division and establishing a 50km buffer zone for street network beyond the census division (Figure 2.5). Applying this approach across all 49 census divisions for Ontario created a moving window approach that allowed for the computation of all 4.7 million potential sites, while avoiding incorrect network routes for potential sites along the edge of the census division (Figure 2.5).

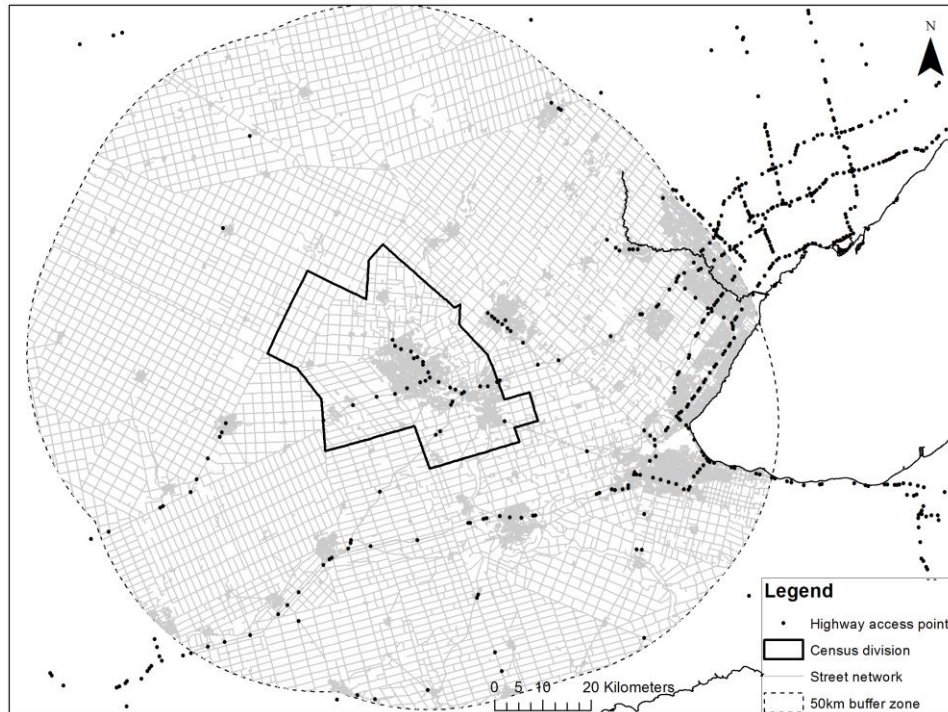


Figure 2.5: The spatial selection and representation of the moving window network analysis for calculating shortest network routes from parcels to HAPs.

3.4.4 – Distance to Distribution Centre

The shortest route of a potential site to a distribution centre provided a measurement of the logistical cost of servicing a potential store location. Using the location of a distribution centre, the shortest street network distance (in kilometers) from every potential site to the distribution centre was calculated. The shortest routes generated using Dijkstra’s algorithm (1959) do not place any preference on major roadways such as highways when traversing dense urban networks. As a result, the spatial representation of a criterion with logistical and operational relevance to site suitability may not be an accurate representation of routes taken for transport services.

3.4.5 – Trade Area Characteristics

In retail, stores draw commerce from a geographic zone known as a service or trade area (Zentes et al. 2012). Retailers often delineate and analyse trade areas based on a number of market and demographic statistics, and describe potential store locations relative to their trade area statistics (Cisneros, 2015; Kumar & Karande, 2000). In particular, site suitability may be

inferred from the trade area using a variety of metrics, such as the market representation of their products, the expenditures that may potentially be allocated to a potential store, as well as the density of competitor and other retail stores within the trade area (Zentes et al. 2012). The trade area characteristics of a potential site therefore have a key role in describing situational criteria influencing potential site suitability.

When representing a trade area through a street network rather than Euclidean space (e.g., Drezner et al. 2002), a key factor in delineating a trade area for a store is the maximum network cost. The maximum network cost represents the highest network-based movement cost that consumers are willing to travel to a potential store location and delineates the spatial extent of the trade area. We used travel time as the unit of network cost and set the maximum travel time to be 19 minutes, which was the mean network travel time calculated from a set of consumer points of origin to 23 big-box home improvement retail stores in Ontario. In developing all trade areas based on a 19 minute travel time, the suitability analysis assumes that the trade areas are representative of all consumer behaviours and structures of urban geography across the study area.

Developing individual trade areas for all potential parcel sites was too computationally intensive across the 4.7 million parcels. Instead, we generalised the approach by generating trade areas from the centroid of each CDA in Ontario (Figure 2.6). Collectively, 19,964 trade areas (one for each CDA) are produced, whereby all locations within a trade area are 19 minutes or less from the CDA centroid. Generalising the trade areas of potential sites by the CDA centroid will produce errors based on the urbanity of the CDA, as CDAs in urbanised and metropolitan areas are smaller in area than CDAs in rural areas or northern regions of Ontario. As a result, it is reasonable to assume that delineating and characterising trade areas in northern Ontario will have significant error, though northern metropolitan CDAs will not be significantly affected.

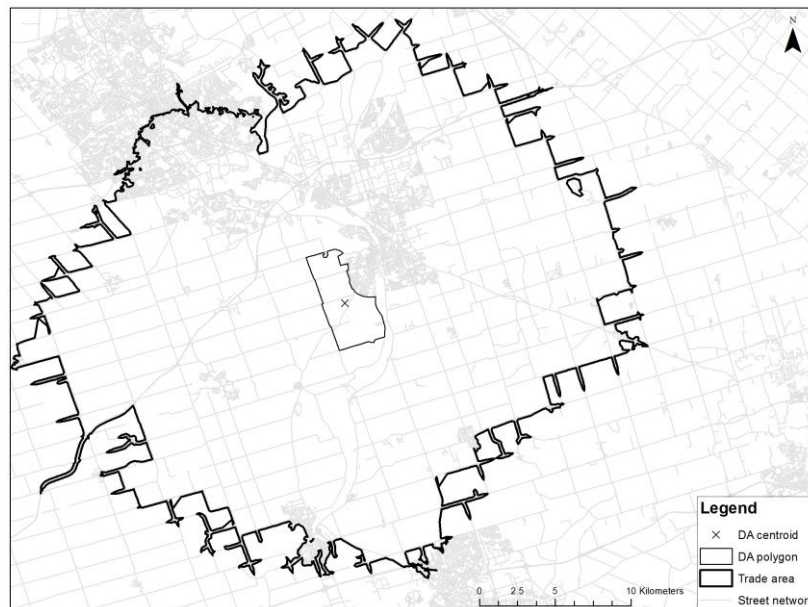


Figure 2.6: Example of a trade area generated from a CDA centroid in Waterloo Region.

Market Representation. In addition to potential expenditures, the market representation of a retailer may be used to identify under- and over-representation of retailers offering specific products in a geographic area (Zentes et al. 2012). Using the ratio of retail chains associated with home improvement products⁵ to all retail stores we implemented a method of market representation within each of the 19,964 trade areas generated throughout the province. To quantify market representation, a location quotient (LQ) was used, expressed in the general form of (Equation 2.2; Strother et al. 2009):

$$LQ = \frac{c/C}{r/R}$$

Equation 2.2

where c is the number of competitors in a geographic sub-region, C is the number of retailers in that sub-region, r is the number of retailers in an industry category, and R is the total number of retailers in the wider region. The number of retailers was calculated from CDA-based attributes based on the proportion of CDA area intersecting the trade area (Figure 2.7). The wider region used provincial values of the LQ obtained from a database of retail chain stores and Canadian Business Patterns (Table 2.3). The location quotient expresses a ratio of proportions between two economic regions of different spatial extents (i.e., trade area representation relative to provincial representation). A LQ value less than 1 represents an under-represented trade area relative to Ontario, and a LQ value greater than 1 indicates a trade area with an over-representation of home improvement retail stores (Strother et al. 2009).

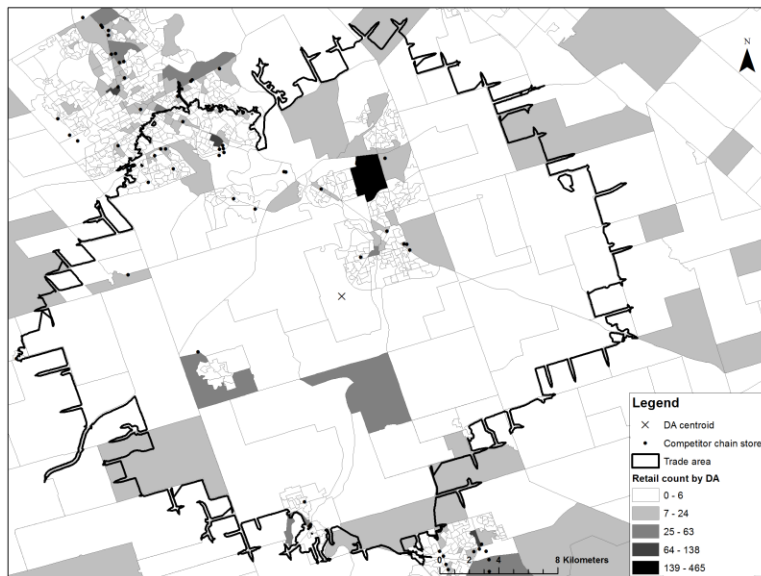


Figure 2.7: Spatial representation of LQ components required from trade area, including competitor chain store locations and retail store counts.

⁵ Home improvement retailers were identified as those businesses falling within the North American Industry Classification System (NAICS) category 444.

Competitor and Retailer Density. The number of competitors and retailers per square kilometer within a trade area provide measures of competition and agglomeration within the trade area of a potential site (Fotheringham, 1985). Density was chosen rather than absolute quantities of competitors and retailers to account for variations in the size of trade areas throughout Ontario⁶. As a result of our analytical methods, trade areas and associated statistics on market representation, competitor and retailer density were all obtained from CDAs as the aggregate unit of potential sites in the suitability analysis. Due to computationally intensive analyses and limited computational resources, similar spatial generalisations were necessary when calculating the potential and competitive expenditures for potential store locations.

3.4.6 – Potential and Competitive Expenditures

We define potential and competitive expenditures as the allocation of demand (measured by known consumer spending on home improvement products provided by Balulescu (2015)) to a potential store location in the absence and presence of competition. Trade areas are often used to quantify potential expenditures that may be allocated to a store placed at a potential site (e.g., Öner, 2014). In the context of this suitability analysis, one approach involves estimating potential expenditures by calculating the proportion of a CDA polygon within a trade area and allocating that proportion of the CDA expenditure attribute to the trade area. However, the method is conceptually flawed as consumer demand is allocated based on the intersection of areas rather than a distance-based allocation method. While discrete spatial representations of trade areas are useful to inform a number of situational criteria, they are limited in the delineation and allocation of demand in a landscape of competing retail stores. For example, discrete trade areas cannot allocate demand at a single point among multiple store locations. A spatial interaction model (SIM), known as Huff's model, overcomes these limitations by allocating demand to stores based on spatial interaction costs between points of demand and the attractiveness of store locations (Huff, 1966).

Among the many SIMs developed in the fields of operations research and economic geography, Huff's model is particularly appealing for applications in retail. The formulation of Huff's model may be used to divide expenditures at a demand point among multiple stores. The probability of patronage at a particular store is influenced by the spatial interaction cost and the attractiveness of a store, reflecting the preference for consumers to minimise costs and maximise opportunities (i.e., the purchasing desire of a consumer). Embedded in the design of Huff's model is the conceptualisation of a trade area as a continuous field of probability, allowing for the division of demand. Alternative SIMs such as location-allocation utilise the p -median problem to allocate demand by minimising the sum of spatial interaction costs between a set of demand points and a set of stores (Church, 2002). Consequently, location-allocation provides a discrete spatial representation of delineating trade areas and does not divide demand among multiple stores.

In both expenditure criteria, Huff's model was configured to sequentially locate one potential store at a time and re-allocate expenditures to each potential store location. Spatial interaction costs were calculated through the provincial street network and quantified using

⁶ For example, the 3,685 trade areas in Toronto have a standard deviation of 189.5km², while the 755 trade areas in Waterloo have a standard deviation of 81.7km² in area.

travel time as the network cost. The large number of potential sites required the aggregation and representation of parcels by CDA centroid to achieve reasonable computing times. The demand allocated to each potential store location was summed per model iteration to obtain potential and competitive expenditures at each of the 19,964 CDA centroids. The expenditures were then disaggregated back to the parcels based on their location within a respective CDA. In computing competitive expenditures, unpublished location and retail area data on select home improvement retail chain stores were used to inform the attractiveness of competing stores in the SIM. As a result, the competitive expenditures assume that all alternative stores are direct competitors that control for other factors that may influence store attractiveness (e.g., product ranges, product pricing, availability, store hours and staff helpfulness, etc.). Further details on the spatial representation and configuration of Huff's model are found in the description of the network-based implementation of Huff's model in Chapter 3.

3.5 – From Criteria to Suitability Scores

3.5.1 – Normalisation of Criteria Values

Once the criteria values were calculated, criteria values were normalised to criteria scores and weighed to produce suitability scores. The normalisation of criteria values allows for the direct comparison of criteria when calculating suitability and reflects the conceptual relationship between the criteria value and a suitability score (Jiang & Eastman, 2000). The conceptual relationship between a criterion value and suitability may be described using fuzzy functions. For example, a trapezoidal function may reflect that suitability is maximised within a specified range of criteria values (e.g., Dixon, 2005), or a triangular function may reflect an ideal criteria value from which the suitability declines (Figure 2.8; e.g., Jiang & Eastman, 2000, Feizizadeh et al. 2014). Further efforts to model fuzzy membership functions derived from empirical observations have also been noted in the literature (e.g., Ng et al. 2002).

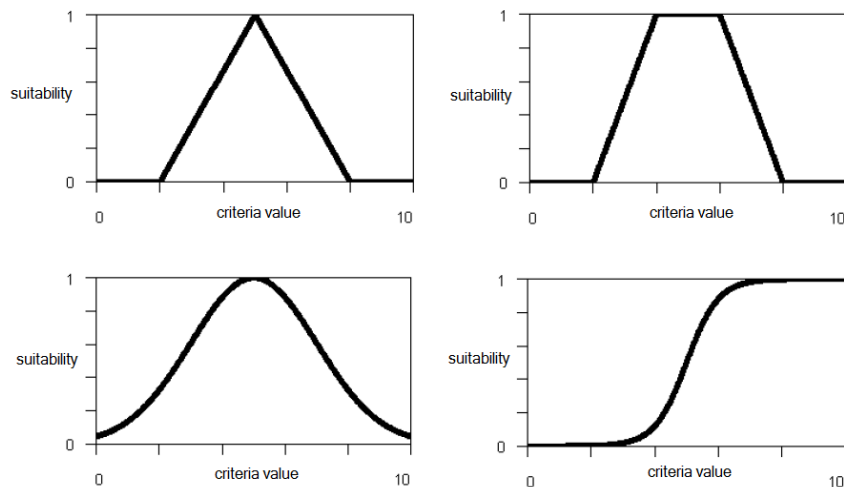


Figure 2.8: fuzzy membership functions (from top left: triangular, trapezoidal, Gaussian, sigmoidal) can be used to describe the relationship between a criterion value and its suitability (Wagner et al. 2011).

In the presented suitability analysis, the relationship between a criterion and suitability was simplified based on either a positive or negative linear relationship (Table 2.4). For example, while a negative relationship exists between maximum slope and suitability, a positive relationship exists between competitive expenditures and suitability (Table 2.4). The selection of a positive or negative relationship between a criterion and suitability was dependent on the relevance of a criteria to the organisational goals of a retail company and based on industry consultations. However, while the direction of the relationship between a criterion and suitability was known, the exact shape of the relationship of suitability as a function of a criterion was unknown and therefore simplified to a linear relationship.

Criteria values were normalised to a common range (between 0 and 1, 0 being least suitable and 1 being most suitable) and calculated to reflect either a positive or negative relationship with suitability (Table 2.4). With the exception of the location quotient, criteria scores were based on the criteria value at a potential site as a proportion of the maximum criteria value observed in the province. This procedure has important implications with respect to the application of constraints within the process of the suitability analysis, as a maximum criteria value may be changed during the application of constraints at the end of the suitability analysis process.

Table 2.4: Relationship between criteria values and scores

Criteria	Relationship Type	Transformation formula
Maximum slope	Negative	$1 - (\text{value} / \text{maximum value})$
Highway accessibility	Negative	$1 - (\text{value} / \text{maximum value})$
Potential expenditures	Positive	$\text{value} / \text{maximum value}$
Competitive expenditures	Positive	$\text{value} / \text{maximum value}$
Trade area retail density	Positive	$\text{value} / \text{maximum value}$
Trade area competitor density	Negative	$1 - (\text{value} / \text{maximum value})$
Distance to distribution centre	Negative	$1 - (\text{value} / \text{maximum value})$
Proximity to traffic volume	Negative	$1 - (\text{value} / \text{maximum value})$
Location quotient	Negative	Values greater than 1 were given a score of 0.

3.5.2 – Development and Application of Weights

The weight of a criterion is critical to the calculation of a suitability score, as weights directly inform the importance of criteria to the suitability of a given potential site. To derive criteria weights, a social survey was completed by industry experts in upper management (e.g., executives of real estate and operations, market research managers and analysts, among others) with experiential knowledge and decision-making influence on store location choices within a dominant home improvement retail company ($n = 11$)⁷. Respondents ranked criteria according to

⁷ A preliminary analysis of statistical approaches to developing weights showed that ordinary least-squares regression (OLS) produced no correlations between existing retail store sales and the suitability criteria at the respective parcels of the stores. A survey-based implementation of AHP was also distributed to a test sample of individuals in management roles at a home improvement retail corporation. Although AHP does ensure a robust pair-wise comparison of all criteria for MCDM, the complexity and number of pair-wise comparisons was difficult to implement as a simple survey. However, AHP has been used by others for retail location decisions (e.g., Roig-Tierno et al., 2013).

their importance (1 being most important, 9 being least important) in affecting the suitability of a location for a home improvement retail store. To invert the low ranks given to the most important criteria and represent them using high suitability values as more suitable, the rankings for each criterion were aggregated by calculating the mean rank for each criterion and applying the rank reciprocal weighting method. This method obtains a criterion weight by dividing a reciprocated criterion ranking by the sum of all reciprocated criteria rankings (Equation 2.3; Table 2.5; Carr & Zwick, 2007).

$$w_j = \frac{(1/r_j)}{\sum(1/r_j)}$$

Equation 2.3

Table 2.5: Mean rank and weight of suitability criteria

Suitability Criteria	Mean rank	Std. Dev.	Reciprocal rank ($1/r_j$)	Weight (w_j)
Maximum slope	7.82	1.78	0.13	0.06
Highway access	6.45	1.69	0.15	0.07
Distribution access	8.00	1.90	0.13	0.06
Traffic volume	5.18	1.94	0.19	0.09
Market representation	3.18	1.47	0.31	0.15
Competitive expenditures	2.64	2.38	0.38	0.18
Potential expenditures	3.09	1.30	0.32	0.15
Competitor density	3.64	1.12	0.28	0.13
Retailer density	4.36	1.91	0.23	0.11
			Sum	1.00

Note: A pairwise Wilcoxon rank-sum test of the normalised criteria distributions showed statistically significant ($p < 0.01$) differences among all pairwise comparisons (Table A1).

The set of criteria weights sum to one such that relative differences between criterion weights are normalised and directly comparable in their importance to suitability (Malczewski, 2006). A weighted linear combination is then applied to the criteria scores and their respective weights from the rank reciprocal weighting method. Thus suitability scores are calculated at every potential site using the following formula:

$$S_i = w_1x_1 + w_2x_2 + \dots + w_jx_j$$

Equation 2.4

where the suitability score of a potential site i is equal to the sum of the products of each criterion score x and its associated weight w . The suitability scores were then transformed to range between a value of 0 and 100, with 0 being the least suitable and 100 being the most suitable potential site for a retail store in Ontario. Using this approach provides an intuitive range

of suitability scores that are relative to the least suitable and most suitable site within the study area.

Despite the impact of weights on the statistical and spatial distribution of suitability scores, sensitivity analyses of GIS-based MCDM are uncommon (Delgado & Sendra, 2004). However, the most frequently used methods of sensitivity analysis in GIS-based MCDM involve the adjustment of criteria values, the relative importance of criteria (e.g., during the application of AHP), and criteria weights (Chen et al. 2010). In this study, a one-at-a-time (OAT) sensitivity analysis was performed on select criteria weights to understand how variations in the input weights affect the statistical distribution of suitability scores. In addition to calculating suitability scores based on equal weights for all criteria, three criteria with the highest standard deviations (i.e., competitive expenditures, traffic visibility, and retailer density) by rank were individually increased and decreased in weight by increments of 5% from the survey weights to a maximum of $\pm 20\%$ (Feick & Hall, 2004). This approach allows for an incremental comparison of how the statistical distribution of suitability is affected by the adjusted criteria rankings relative to the survey weights. Conceptually, the OAT method shows how the suitability outcomes would change under different survey-based results provided by industry experts. However, the OAT approach used in this study does not explore the sensitivity of suitability across all weights, and does not examine the spatial sensitivity of suitable locations. Although examples of spatial sensitivity analysis of multi-criteria weights are found in the literature (e.g., Feick & Hall, 2004), such an analysis is outside the scope of this study.

Overall the suitability scores by weighing scenario showed significant differences⁸, with increases in the criteria weights producing a decrease in the overall distribution of suitability. Summary statistics (i.e., the minimum, median, and mean) decreased steadily with each incremental increase of a criterion weight from the lowest decrease (i.e., -20%) to the highest increase (i.e., 20%) (Table A2). An examination of the adjusted criteria revealed that the normalised competitive expenditures, traffic volumes, and retail density are all distributed with a strong right skew, demonstrating that highly suitable locations with respect to the selected criteria are infrequent relative to a left skewed or normal distribution. As a result, increasing the weights of each of these criteria while decreasing the importance of the other eight criteria would result in distributions of suitability increasingly skewed to the right. Of the three criteria, differences in the mean and median suitability score (i.e., the mean and median have a range of 18.2 and 16.9, respectively) indicate that suitability is the least sensitive to the importance of competitive expenditures relative to the importance of traffic visibility (mean and median range of 22.3 and 24.0) and retail density (mean and median range of 21.8 and 24.4).

The sensitivity analysis demonstrates that statistically, the sensitivity of a suitability result depends only on the magnitude of variation in an input criterion, but also on the nature and distribution of the criterion itself. The distribution of a criterion affects the stability of the suitability analysis and therefore the degree of acceptable uncertainty in the importance of that criteria. The nature of the criterion also appears to play a role as the proximity to traffic volumes produces stable suitability scores despite significant decreases in weight (from -10% to -20%; Figure A1), a consequence of the criterion represented as a fixed-distance metric. In addition, the interquartile range (IQR) of the competitive expenditures criterion increases steadily with each

⁸ A pairwise Wilcoxon rank-sum test among the scores showed statistically significant ($p < 0.01$) differences between all weighing scenarios.

increase in weight (Figure A1). While the overall distribution of competitive expenditures decreases as the criterion weight is increased, the statistical variation of suitability increases as well. However, across all the adjusted criteria, decreases in the weights appear to align the suitability scores more closely with the equal weights scenario. The trend may be due to the OAT method of distributing uniform increases across the other eight criteria with each decrease of weight among the adjusted criteria.

3.5.3 – Application of Constraints

Although suitability scores are calculated across all potential sites using preferential criteria and expert-informed criteria weights, constraints are applied to eliminate sites that are unavailable for development. Parcels unavailable for retail development were defined as containing a land use or land cover (LUC) that is unavailable for retail development (Table 2.6).

Table 2.6: The spatial relationship of constraining LUC to potential sites

Constraint	Spatial relationship	Feature	Data type
Reserves and Parks	Intersect	First Nations reserves	Polygon
	Intersect	Provincial parks	Polygon
	Intersect	National parks	Polygon
Protected areas	Intersect	Niagara Escarpment	Polygon
	Intersect	Wetlands	Polygon
	Intersect	Rivers and lakes	Polygon and line
	> 50%	Forest cover	Raster
Institutions	Intersect	Public schools	Point
	Intersect	Churches and cemeteries	Point
Infrastructure	*	Roads	
	Intersect	Railway stations	Point
	Intersect	Railway lines	Line
	Intersect	Energy pipelines	Line

* In addition to constraining potential sites containing various LUC, parcels that are provincial roads were also constrained based on their perimeter-to-area ratio (PAR). Parcels with a PAR greater than 0.05 were selected and removed after a visual verification with the provincial road network.

To further constrain available parcels, parcels with an area less than 80,000 square feet were also removed. The constraining area is equal to the potential store size used to inform the Huff model in Chapter 3, and is based on the median store area size of big-box competitor chain stores identified across Ontario, including Canadian Tire, Home Depot, Rona, Sears, Target, The Bay, and Wal-Mart. Following the application of constraints, the number of available parcels was reduced from approximately 4.7 million to exactly 153,459 parcels across Ontario.

3.6 – Analysing the Suitability Scores

Our analytical approach is guided by the research question of describing the distribution of suitability for retail development. Given that the 153,459 potential sites occur at a high spatial resolution (as small as 7,432m²) relative to the extent of the study area, visualising and analysing

the results presented a challenge. In locating highly suitable areas, we aggregated the suitability scores of parcels by census metropolitan area and census dissemination area for visualisation and analysis. The CMAs and CDAs were selected as the geographic unit of a spatial analysis based on the concentrated populations in the metropolitan areas of southern Ontario.

With 43 CMAs and 11,469 CDAs containing potential sites distributed throughout Ontario, standard deviational ellipses were used to establish that a majority of CDAs fall within southern Ontario. In identifying the underlying spatial trend of site suitability, the analysis divides Ontario into north and southern regions of the province. Based on the mean center of the CDA centroids, the standard distance of CDA centroids weighted by maximum suitability along an x- and y-direction from the mean center were calculated. The resulting x- and y-axis delineate an ellipsis of a shape, area, and orientation that describes the spatial distribution of CDAs within a standard deviation of the mean centre (Mitchell, 2005). By calculating a standard deviational ellipse for multiple standard deviations, 95% of the CDAs were located within the extent of the spatial visualisation. The directional distribution of CDAs weighted by maximum suitability provides a reference point to further visualise site suitability across the province (Figure 2.9). Given the relatively normal spatial distribution of maximum suitability scores, approximately 95% of the 11,469 CDAs across the province are found within two standard deviations of the mean centre of all CDAs (Figure 2.9).

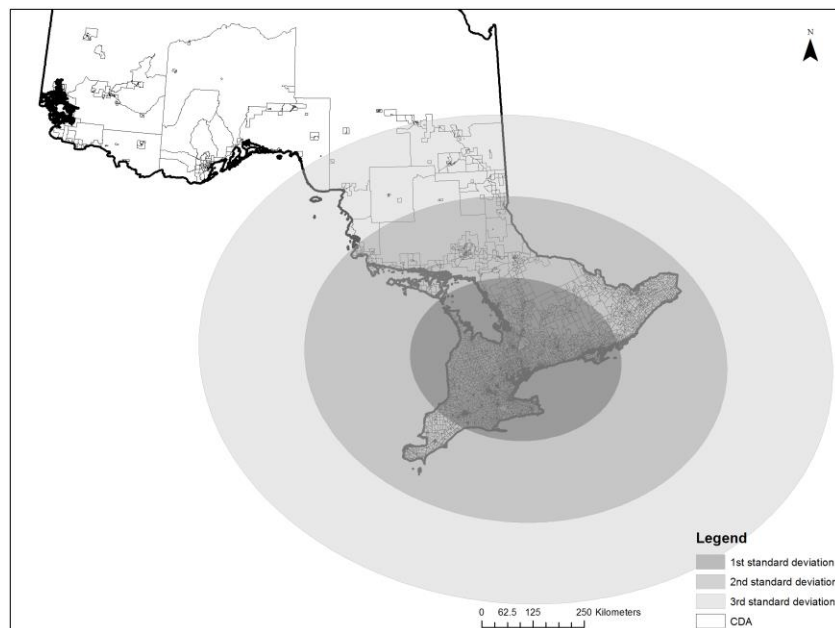


Figure 2.9: Standard deviational ellipses based on DA centroids within three standard deviations of the mean centre show that the second standard deviation includes all of southern Ontario.

While the northern CMAs are quantified and described, our analysis thus focuses primarily on census geographies in southern Ontario. Although the second standard deviation contains metropolitan areas in northern Ontario (defined as all areas north of Ottawa-Gatineau) such as Sault Ste. Marie and Sudbury, the analytical emphasis on site suitability found in southern Ontario describes the majority of CDAs with available parcels. Within the prescribed geographic units of southern Ontario, the maximum suitability and density of parcels is

visualised across the study area, allowing for the comparison of the highest suitability score relative to the density of potential sites within a region. The statistical distribution of the potential site suitability scores is also analysed by CMA to provide the reader with a general overview of the suitability scores and significant metropolitan areas. To compare the mean suitability of all CMAs, a pairwise Wilcoxon rank-sum test was also performed.

4 – Results

4.1 – Statistical Distribution of Site Suitability

The statistical distribution of suitability scores varies widely across the province, with statistically significant differences among all the mean suitability scores of the province and the northern and southern CMAs (Table A3). A pairwise Wilcoxon rank-sum test among the means of the 43 CMAs showed that 8.6% of the 903 pairs of CMAs were statistically similar, with the remainder showing significant differences.

Relative to the province as a whole, the CMAs of northern Ontario offer only a small proportion of sites that are also of low suitability. The northern CMAs ordered by increasing suitability to include Elliot Lake, Kenora, Hawkesbury, Timmins, Sault Ste. Marie, Petawawa, Pembroke, Temiskaming Shores, Thunder Bay, Sudbury, and North Bay collectively make up 7.6% of the potential sites in all CMAs and 4.5% of all potential sites in the province (Table 2.7). Among these northern metropolitan areas, the mean and maximum suitability is 29.7 and 52.7 compared to the higher provincial mean and maximum of 38.6 and 100 (Table 2.7). In comparison to northern CMAs, southern Ontario CMAs contain 54% of all potential sites across the province and 92% of potential sites found in metropolitan areas (Table 2.7). The southern CMAs produce a higher minimum suitability and a wider range of maximum suitability of 78.4 than the northern areas (49.4), partly due to the highest observed suitability located in Toronto (Table 2.7).

Table 2.7: Summary statistics and count of potential sites by province and region

Statistic	Ontario	Northern CMAs	Southern CMAs
Minimum	0	3.3	21.5
1st Quartile	32.9	26.5	36.3
Median	36.9	30.0	40.2
Mean	38.6	29.7	42.9
3rd Quartile	41.7	33.1	45.8
Maximum	100.0	52.8	100.0
Count	153,459	6,906	83,382

Note: Ontario count contains all potential sites in the province.

Among the northern CMAs, the maximum suitability value of 52.8 is located in North Bay, although only 625 potential sites are found within the CMA (Figure 2.10). The top five most suitable northern CMAs share a small range of maximum suitability of 5.1 relative to the range of maximum suitability of 39.4 in the top five CMAs of southern Ontario (Figure 2.10). With the exception of Sudbury and Thunder Bay, all northern CMAs are in the bottom half of CMAs by parcel count. However, the low variation in maximum suitability suggests that CMAs

with higher parcel counts such as Sudbury and Thunder Bay are more likely to contain available real estate for retail development (Figure 2.10). Upon closer inspection, Sudbury has approximately as many potential sites as Thunder Bay while also containing a greater frequency of more suitable parcels (Figure 2.10).

In southern Ontario, Toronto dominates the landscape of retail location suitability with both the highest suitability scores observed provincially and the largest number of potential sites in any CMA (Figure 2.10). Given that the Greater Toronto Area is the most populous region in Ontario (Wolfson & Frisken, 2000), the CMA contains 27% of all CMA-based parcels and 15% of all parcels within the province (Figure 2.10). Of suitability scores at or above the 75th percentile of suitability scores across the province, only seven of 3,593 potential sites are located outside the Toronto CMA (one in Ottawa – Gatineau and six in Guelph). In examining suitability scores at or above the 90th percentile of suitability within the CMAs, all are located within Toronto. Clearly, Toronto is a major driving force of the more frequent, higher, and therefore wider range of suitability in southern Ontario and the province as a whole. Among the selected criteria, the large population and economy of Toronto (Statistics Canada, 2012) drive the demand underlying the potential and competitive expenditures, while the proximity to the major provincial highways increases the potential site visibility of potential sites to traffic and increases highway accessibility. However, Toronto's noteworthy suitability does not comprehensively describe the cost or availability of real estate within the metropolitan area.

Other notable CMAs include Ottawa – Gatineau (Ottawa), Guelph, Hamilton, and Kitchener – Cambridge – Waterloo (KCW; Figure 2.10). Although Guelph and Ottawa share a nearly equal maximum suitability, Guelph has only 51 potential sites at or above the 90th percentile of its highest site suitability while Ottawa contains 103 similar potential sites (Figure 2.10). Ottawa contains the second largest number of potential sites among all CMAs, with approximately as many potential sites (7.7% or 7,011) as all the northern CMAs combined. However, the mean suitability in Ottawa is 41.2 while the mean suitability in Guelph is 47.3. The lower overall suitability of Ottawa relative to Guelph is observed in the higher right skew (1.01 in Ottawa versus 1.18 in Guelph) of potential site suitability in the capital. We speculate that Guelph has a higher maximum suitability and lower right skew than Ottawa due to the proximity of the Guelph to Toronto and the associated impacts on the situational criteria observed in the smaller CMA. Hamilton and KCW also share a higher mean site suitability than Ottawa of 43.3 and 42.7 respectively, however the most suitable sites found within either CMA are 62.9 and 60.5, well within the top 10% of parcels by suitability (suitability of 56.9). Hamilton and KCW have similar overall statistical distributions of site suitability, though Hamilton has a higher maximum site suitability and a larger number of potential sites (3,343 parcels in Hamilton versus 3,089 in KCW).

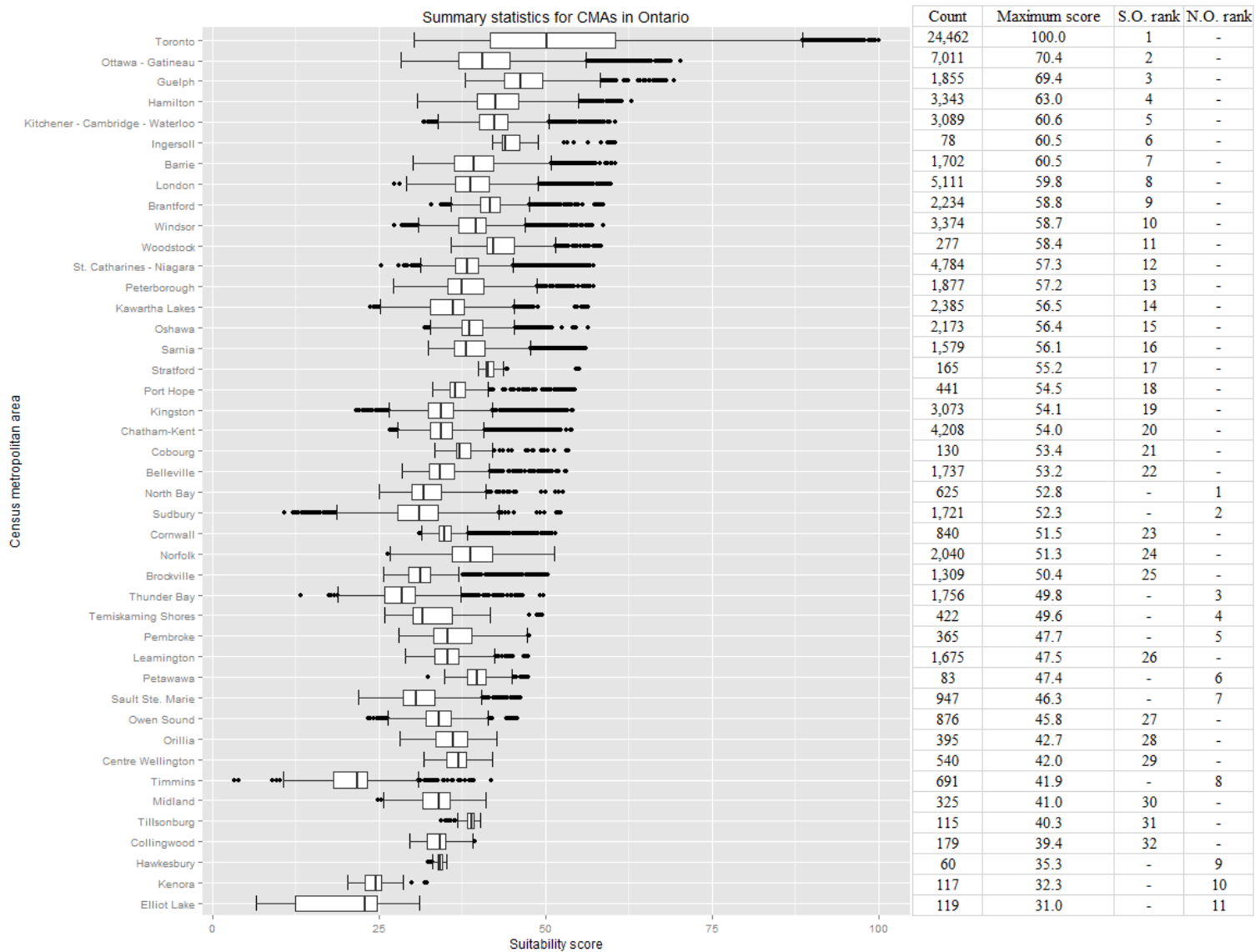


Figure 2.10: Summary statistics of CMA-based suitability scores, ordered by descending maximum suitability. CMAs are also ranked by their maximum suitability in southern Ontario (S.O. rank) or northern Ontario (N.O. rank).

4.2 – Spatial Distribution of Site Suitability

Based on the maximum site suitability and parcel density of CMAs in southern Ontario, CMAs proximate to the southwest and northwest of Toronto are among the most suitable (Figure 2.10). While the top five CMAs in the province are present, Brantford to the southwest and Barrie to the northwest have a maximum suitability of 58.7 and 60.4, respectively (Figure 2.10; Figure 2.11). Other populous CMAs such as Windsor, London, St. Catherines, and Kingston are noted as being only moderately suitable. Among the top CMAs, Toronto contains between 4.6-6.0 parcels per square kilometer while Guelph and KW and Cambridge contain 2.5-4.5 parcels/km² and Hamilton has a lower density 1.9-2.4 parcels/km². Brantford has approximately the same density of suitable sites as Hamilton, while Barrie contains fewer potential sites (1,702) and a greater maximum suitability (60.4) than Sudbury (52.3) (Figure 2.10; Figure 2.11).

By increasing the spatial resolution of visualising the maximum site suitability and parcel density based on the 11,469 CDAs in the study area, the proximity of suitable areas to major highways becomes evident (Figure 2.12). Census dissemination areas with a maximum suitability score approximately at or above the 90th percentile of all suitability scores are observed along the provincial highways in Windsor, Chatham-Kent, and Sarnia before joining in London and entering Brantford, KCW, and Guelph. A similar pattern of suitable CDAs along the highway east of Toronto and following the shore of Lake Ontario to Kingston and Cornwall is also observed. It is unclear whether these suitable areas are correlated to a conceptual emphasis of suitability on highways or if the most densely populated (i.e., correlating with demand or expenditures) areas of Ontario are located along highways. Nevertheless, the maximum suitability of CDAs appears to approximately coincident with highways throughout southern Ontario. The distribution of high potential site density appears coincident among CMA-based CDAs, though in constrained CMAs such as Toronto the parcel availability is low in the downtown core.

Spatial clustering of the maximum suitability scores by CDA was verified using a global measurement of spatial autocorrelation (Table 2.8). Moran's I statistic confirmed a strong clustering tendency of high statistical significance when compared to a random spatial distribution of values.

Table 2.8: Global spatial autocorrelation of all CDAs by maximum suitability

Statistic	Ontario
Moran's I	0.904827
Expected I	-0.000088
Variance	0.000023
z-score	189.20
p-value	0.000000

At the local scale, the results of the cluster analysis show that either high or low suitability CDAs occur throughout the province in homogenous clusters. Of the 11,469 CDAs included in the statistic, 21.3% are classified as high-high clusters while 11.7% are classified as low-low clusters. The remaining 66.8% of CDAs were classified as not exhibiting significant local spatial autocorrelation, while only 3 CDAs (in the Thunder Bay, Belleville, and Kingston CMAs) were classified as high suitability values surrounded by low values.

All high-high clusters are found within four of the top five southern CMAs by maximum suitability, with Toronto again dominating the landscape with 94.4% of all high-high clusters in the province. By contrast, Ottawa is the second largest in terms of containing highly autocorrelated CDAs of high suitability, with 5.3% of all high-high clusters. High-high clusters extend southwest from the Toronto CMA and into the northwest of Hamilton along the 403 highway, producing two high-high clusters. Another two high-high clusters are also located in the Guelph CMA, within the township of Puslinch.

In comparing Anselin local Moran's I to the global spatial autocorrelation, there are several notable observations. The high concentration of highly suitable sites in the Toronto CMA may contribute to a very high global spatial autocorrelation, producing a bimodal frequency distribution among the significant cluster types. While Toronto is certainly a statistically significant result in the suitability analysis, Anselin local Moran's I does identify CDAs within the Puslinch (Guelph) township as high-high values outside of the other large CMAs such as Ottawa and Hamilton. This observation is confirmed by the presence of Guelph among the top ranked CMAs by maximum suitability and its distribution of parcel scores. More specifically, potential sites in the southeast region of Puslinch are observed to have trade areas extending to include several key metropolitan areas and regions, namely Guelph (to the northwest), Cambridge (west), Milton (east), and Hamilton (south).

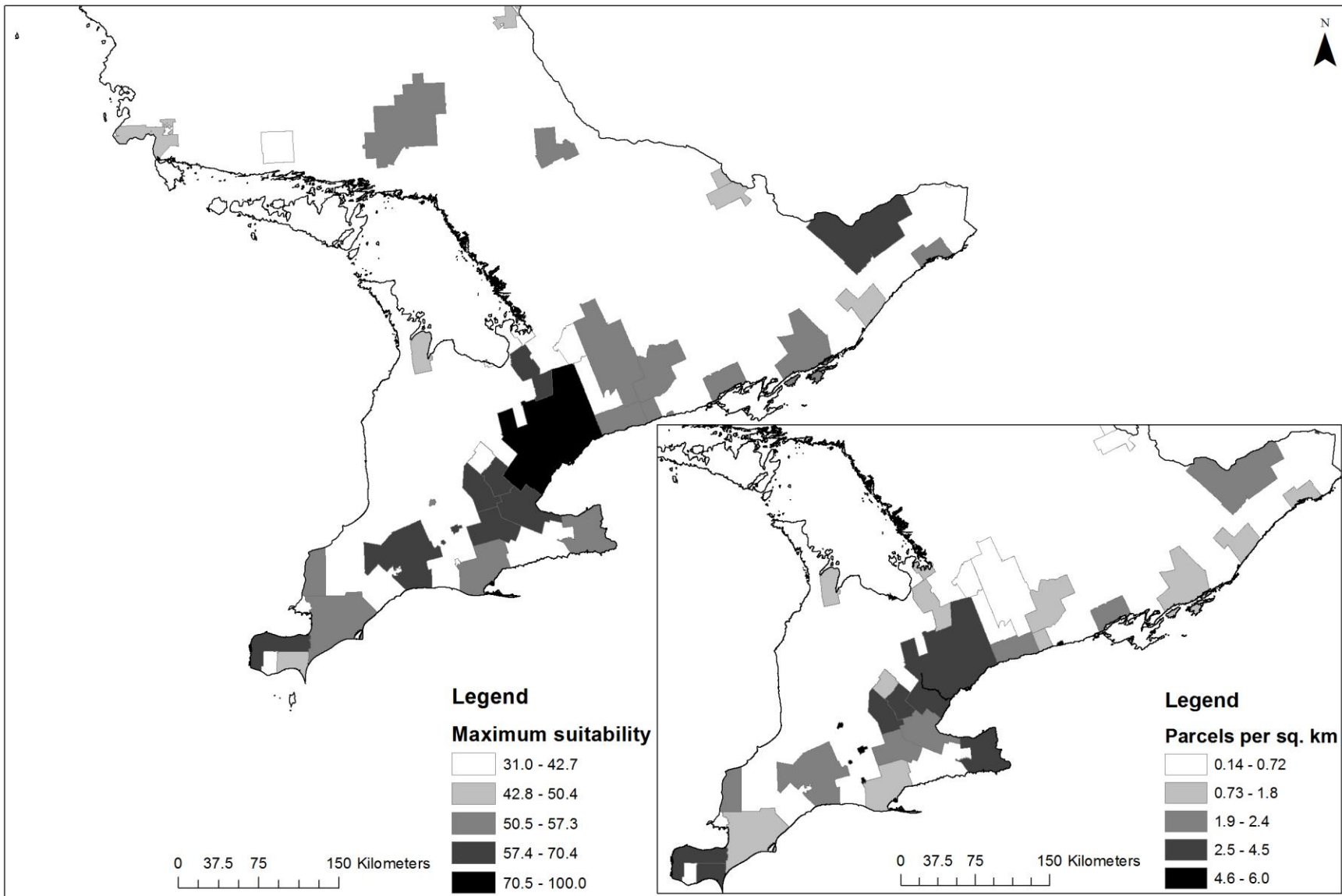


Figure 2.11: Maximum parcel suitability and parcel count per square kilometer (inset) by CMA in southern Ontario.

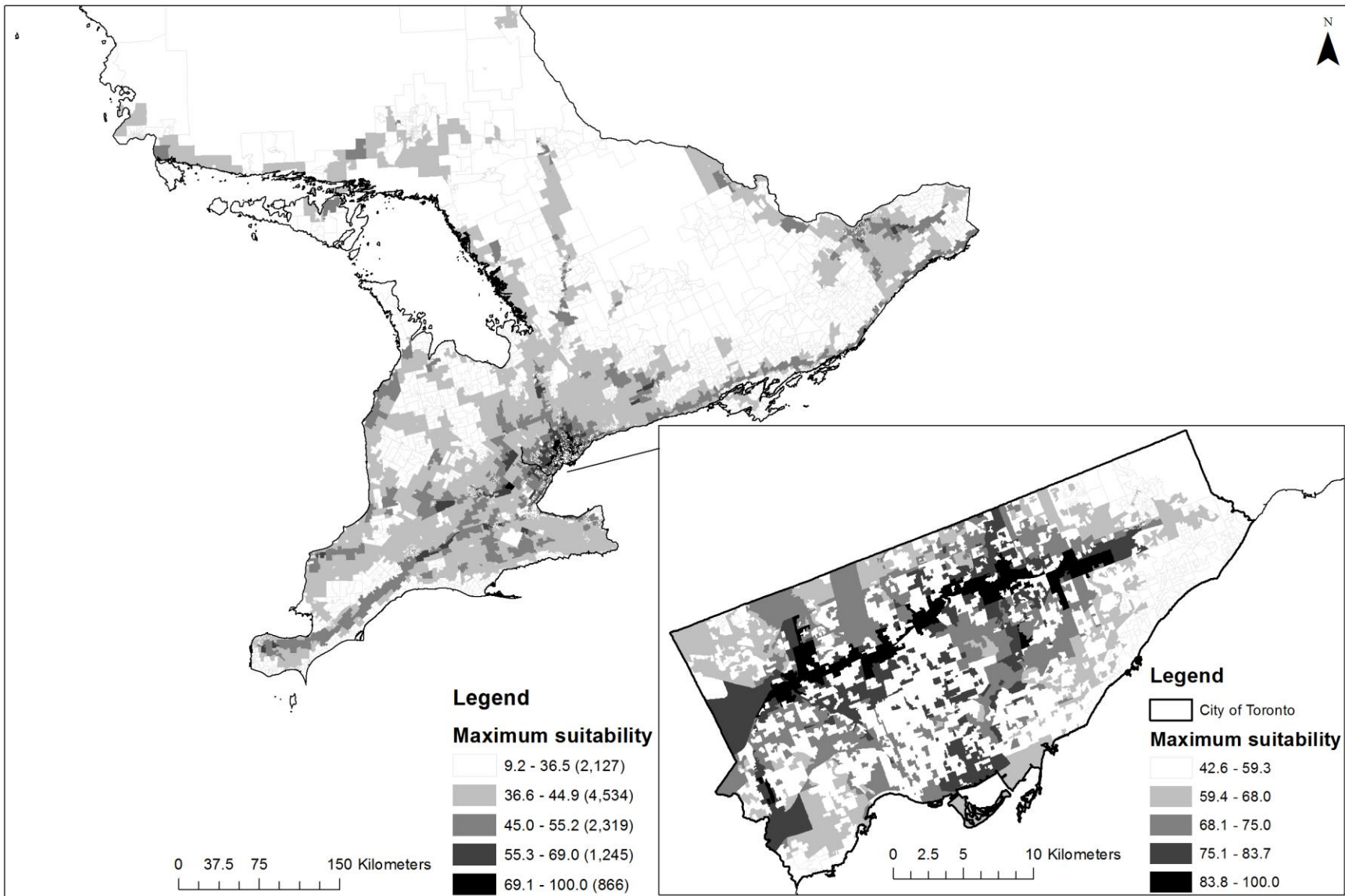


Figure 2.12: Maximum parcel suitability by CDA in southern Ontario, with emphasis on the City of Toronto (inset).

5 – Discussion

Defining and describing suitability

The suitability analysis of this study demonstrates that spatial representations of multiple criteria across a large number (4.7 million parcels) of potential sites and a large extent may be filtered and aggregated for a more focused visualisation and analysis of key locations by decision-makers and managers in retail companies. While the presented results do not specify exact parcels of high suitability, key areas in the province are identified for further decision analysis. Furthermore, our study has described the distribution of suitability for retail development across the province and yielded significant findings for further investigation, such as the township of Puslinch and Kitchener-Waterloo and Cambridge metropolitan areas. The GIS-based MADA presented here demonstrates a potential for key decision support roles to different organisational components within a company seeking to locate and open new retail stores. For example, the suitability analysis provides real estate teams with specific areas for further planning and portfolio analysis, while marketing teams are provided with trade areas for demographic analysis (Hernandez & Thrall, 2007). Relative to existing research, the suitability analysis is performed over a large spatial extent and incorporates criteria of varying complexity (i.e., from parcel slope to competitive expenditures), including estimated consumer expenditures at potential site locations based on spatial interaction model outcomes. To the author's knowledge, no examples exist in the literature of spatial interaction modelling performed at such a large scale, particularly with the use of empirically-informed model components such as the estimated market expenditures (i.e., demand) and competitor store locations and attributes (i.e., retail area).

However, the methodology and results of this study have also highlighted limitations and areas of improvement in utilising GIS-based MADA for retail location decisions, beginning with the area of measuring uncertainty and validation. The results of this study identify the challenge and importance of comprehensively defining land use suitability using a minimal set of criteria. In considering and selecting different criteria, the conceptual independence of the criteria reduces the risk of over-estimating the importance of geographic features or spatial relationships common to criteria, producing a limited set of potential site criteria that comprehensively describe suitability for retail development and location. For example, trade area statistics of a potential site that incorporate the network cost to or size of nearby competitor stores were considered. However, these characteristics are implicitly included when measuring competitive expenditures at a potential site with Huff's model, as the model measures competitive expenditures based on the shortest network cost to and attractiveness of nearby alternative stores. Selecting and defining criteria that are independent conceptually and in terms of spatial representation produces ensures a clear definition of suitability. By quantity of criteria and weight, situational criteria such as trade area characteristics, potential and competitive expenditures define the suitability of a potential site.

It is possible that retail experts could weigh the importance of suitability criteria without fully understanding the representation or interactions within a set of criteria. As the conceptualisation and computation of a given criterion influence one another, the final spatial representation of the criterion may differ from the expert understanding of it. In this analysis, the results of the maximum suitability by CDA show that high suitability and major highways appear coincident, suggesting that multiple criteria (i.e., highway access, proximity to traffic volumes,

distribution access) place an emphasis on roadway proximity for different concepts of suitability. Whether this result is due to a conceptual emphasis of criteria selection, the criterion weights, or the interaction of criteria such as the presence of demand along highways is a source of uncertainty in this study. Reducing the conceptual duplication of criteria is nevertheless important due to the computational resources required to calculate the suitability criteria over the spatial extent of Ontario. Each criterion required specifically designed computational methods and approaches for reasonable calculation times, and considerable computer resources were required for developing the potential and competitive expenditures in particular.⁹

Aggregation, analysis, and site selection

The small size of the potential sites relative to the extent over which the sites are observed requires a different analytical approach. The uncertainty associated with the conceptual definition of suitability criteria is more clearly understood when the appropriate spatial scale of analysis is selected (i.e., at the CDA level). Aggregating potential sites by different geographic areas allows the study to increase the spatial extent of analysis and visualisation for a retail location decision, increasing the number of potential sites for consideration. Simultaneously, the suitability results may be misunderstood by wide variations of the spatial distribution and frequency of highly suitable sites across the urban geographies of Ontario. For example, the high number of highly suitable potential sites in the Toronto CMA is not apparent based on the spatial visualisation and analysis of the results. Moreover, the scale of analysis for the Anselin local Moran's I statistic did not provide a meaningful identification of low or high clusters among northern CMAs due to the varied spatial dispersion of potential sites along the latitude of the study area. Performing separate spatial analyses for the northern and southern regions of Ontario may identify highly suitable areas within their regional context, though this approach would make it difficult to compare results between regions.

Although the results of this study appear to uphold the ideal commercial “main and main” location of emphasising potential sites along major highway intersections (Hernández & Simmons, 2006), we believe that several interesting locations are observed in southern Ontario. First, the intuitive retail location of a site within a major metropolitan area may be the absolute “best” potential site without being the optimal site, as competition for real estate (i.e., in Toronto) reduces parcel availability and increases acquisition costs. Provided that such a site is successfully acquired, the failure of a retail store through disappointing or unexpectedly poor sales is proportionately larger and more costly (Zentes et al. 2012).

Cost effective locations that are successful may be sites that draw trade from multiple metropolitan areas rather than from within a single metropolitan area. This location strategy is illustrated in Reilly's Law of retail gravitation, where two cities competing for trade from a town located between them would attract trade in direct proportion to the city populations and in inverse proportion to the distance of each city to the town (Reilly, 1931). Rather than selecting a retail location site within one of the cities, the highly suitable areas observed in the region of

⁹ A method of distributed computing was developed to process 39,928 iterations of Huff's model on up to 60 machines with Core i7 processors and 8GB of RAM. Each computer contributed to a common collection of text-based solutions to determine the next available model iteration for computation.

Puslinch suggest that an optimally located site relative to multiple cities will draw significant trade from the high-growth suburban regions (e.g., Milton) surrounding the metropolitan areas. This retail location strategy is consistent with the larger population growth rate in suburban areas surrounding downtown areas across Canada's metropolitan areas (Hernandez & Jones, 2005). Although there is empirical evidence that household and appliance sales remains a stable minority of total retail sales in downtown Toronto (Hernandez & Jones, 2005), there is also evidence that the spatial distribution of big-box retailing has moved from the metropolitan area to the surrounding suburban regions (Jones & Doucet, 2000).

Uncertainty and validation of suitability

One source of uncertainty in the methodology of the suitability analysis (rather than the concept of suitability) is in the criteria weights given by the retail experts to measure the importance of a criterion to the suitability of a potential site. The criteria weights provided are imprecise estimates of suitability, and are not associated with any measurement of error or confidence by the expert (Benke & Pelizaro, 2010). Modifying the criteria weights to examine the changes in the distribution of suitability could be used to develop more robust weights and determine the spatial stability of highly suitable areas under conditions of uncertainty (Chen et al. 2010; Feick & Hall, 2004). For retailers, understanding how different prioritisations of decision criteria affect suitability outcomes across a potential market produces a flexible analysis that better represents the expert consensus on what criteria are relevant to a successful store location.

Another source of uncertainty in the suitability analysis is the lack of information on the availability of parcels for real estate acquisition (i.e., purchasing a parcel) and store development. While our analysis certainly incorporates many important constraints, the ownership status and land use zoning permitting a retail development within a parcel are not considered when focusing on potential sites. Examining suitability by various census geographies (i.e., CMA and CDA) may therefore provide retailers with a generalised overview of suitability (rather than a precise location decision) for further investigation or “ground-truthing” by real estate teams (Hernández & Thrall, 2007).

The measuring and reduction of uncertainty would also be coupled with a method for validating the suitability analysis, with one potential approach to validation correlating the distribution of new stores opened after the completion suitability analysis with highly suitable areas or sites (Estoque & Murayama, 2010). Ideally, store sales of new competitor store locations would provide a measure of store success, though in practice the proprietary nature of the data would require methods of estimating competitor store sales (Balulescu & Robinson, 2015).

Further improvement to the existing methods of the suitability analysis would involve calibrating the maximum travel time parameter that is critical in informing trade area characteristics, as well as the potential and competitive expenditures. Early research in determining the size of trade areas has traditionally used consumer surveys as a method of determining consumer travel behaviors, and remains an effective tool for retailers today (Applebaum, 1966; Huff, 2003). Although empirical data was provided in the form of consumer points of origin, the mean travel time of 19 minutes consistently produced larger trade areas than

expected, particularly in dense urban and metropolitan areas. Developing dynamic travel times based on local market conditions, urbanity, or street network structure would also provide a regionally calibrated parameter as opposed to a global maximum travel time parameter (Fotheringham, 1981; Goodchild, 1984; Tiefelsdorf, 2003). Recent efforts have identified that modelling spatial autocorrelation among spatial interactions may be used to create local distance decay functions through a street network (Griffith, 2009), though the application to such a large suitability analysis may be computationally prohibitive.

Future directions for retail site selection

Retailers often question how changes to an existing store or market conditions will impact store sales over time (O’Kelly, 2008). However, the suitability analysis described in this study is a static, spatial model of retail location suitability and lacks a temporal dimension. Relatively recent modelling approaches and improvements to spatial interaction models such as Huff’s model present an opportunity to address this limitation. Incorporating the multiplicative competitive market interaction (MCI) model (Nakanishi and Cooper, 1974) as a multi-dimensional representation of store attractiveness in Huff’s model would allow retail analysts to pose hypothetical scenarios involving the effects of store modifications on sales (Jain & Mahajan, 1979). Moreover, the suitability analysis may be extended into a spatio-temporal model by implementing the analysis as a decision-making method in an empirically informed agent-based model. Agent-based models represent the decisions and interactions of virtual objects known as agents over time in a virtual environment (Macal & North, 2010). By instantiating competitor chains as agents in a spatially represented retail market (i.e., similar to that of Huff’s model described in Chapter 3), the suitability analysis would feed different retail store location strategies for the store location decisions of a competitor chain. However, few examples of tightly integrated GIS-based ABMs exist (Brown, 2005; Robinson & Brown, 2009). One particularly notable barrier to nesting spatial interaction models (i.e., location-allocation, Huff’s model) within a GIS-based ABM would be the computational cost of scaling. We argue that reducing the time required to compute SIMs is necessary for retailers to fully realise the benefits of anticipating emerging market trends with advanced modelling tools (Hernández & Thrall, 2007).

6 – Conclusion

The suitability analysis performed in this study demonstrates an applied case study in retail store location, evaluating all 4.7 million parcels in Ontario based on nine criteria of varied spatial complexity and relevance to retail location. The results of this chapter show that although Toronto dominates the landscape of suitable locations for a retail store, a closer analysis reveals that a key region within Guelph also merits further analysis and ground investigation by a prospective retailer. However, the author also cautions that the suitability analysis produces a distribution of favourable outcomes based on the selection of criteria, as well as the conceptualisation, spatial representation, and impact of each criterion on potential site suitability. Communicating the conceptualisation and spatial representation of each criterion to a panel of retail experts would provide an opportunity for improvement of criteria in these areas before the suitability scores are calculated. Further improvements to the suitability analysis would include a study on how the aggregation of spatial features affects the outcome of a particular criterion.

Chapter 3 – Effects of spatial representation in Huff’s model on retail locations in Waterloo, Ontario.

1 – Introduction

In economic geography and operations research, the study of retail location theory has attempted to describe the economic environment in which retail stores are located. To describe retail commerce relative to store location, different conceptual approaches to represent the boundaries of geographical retail zones known as trade or service areas have been used (Applebaum, 1966; Christaller & Baskin, 1966). Retailers have applied trade areas to identify target demographics and quantify consumer expenditures or demand that may patronise a given store location. To describe the effect of competing retail stores on the boundaries of trade areas, basic models were first proposed by Hotelling and Reilly (Hotelling, 1929; Reilly, 1931). Widely held as the first to describe trade areas, Hotelling posed the scenario of two identical ice-cream vendors competing for customers along a straight length of beach. The model assumes that customers patronise the nearest vendor, and questions what locations of the vendors would create a stable competitive state.

Reilly’s model went further to propose that two cities competing for trade from a town located between them would attract trade in direct proportion to the city populations and in inverse proportion to the distance of each city to the town. Subsequently known as Reilly’s Law of retail gravitation, the model extended Hotelling’s scenario to also include the attractiveness of a destination when allocating trade (Anderson et al. 2010). Further development of Reilly’s Law recognised that there is a breaking point location for the town where all customers on one side of the town would trade in one of the two cities while all customers on the other side of the town trade with the other city (Converse, 1949). The central limit theorem (Rosenblatt, 1956) would place this breaking point at halfway between the two cities, though Reilly’s Law adjusts the location of the breaking point relative to the size (i.e., attractiveness) of the two cities.

Since the conception of Reilly’s Law, more advanced models of trade areas have become necessary for allocating demand amongst competitor stores of varying attractiveness. To meet this challenge, spatial interaction models (SIMs) have been developed to measure the cost of movement and attraction between consumers and stores (Fotheringham, 1983; Huff, 1963; Yrigoyen & Otero, 1998). In operations research, the problem of locating facilities relative to points of supply is described as location-allocation, and makes use of computational geometry and algorithms to minimise the sum of spatial interaction costs between points of supply and facilities (Cooper, 1963; Teitz & Bart, 1968). While examples exist of location-allocation being used in retail location and trade area analysis (Goodchild, 1984; O’Kelly, 2009), location-allocation represents discrete trade areas by allocating demand at a point fully to one store at a time. Location-allocation therefore assumes that consumers predominantly patronise stores based on proximity and regardless of store attractiveness. These assumptions arguably limit the application of location-allocation for spatial interaction modelling of consumer choices.

In contrast to discrete SIMs such as location-allocation, the most widely applied SIM in retail location and market analysis has been Huff’s model (Huff, 1966; Huff, 2003). Huff’s model formulates and conceptualises trade areas as continuous demand surfaces (Huff, 1964; Yrigoyen & Otero, 1998). Continuous trade areas represent the probability of consumers patronising a given store based on the utility of an interaction between a consumer and a store.

The utility of a store is the product of the attractiveness of a store (often measured with store sales or retail area) and a spatial interaction variable (often a measure of cost such as distance or travel time) that reduces the probability of store selection as the spatial interaction variable increases (Yrigoyen & Otero, 1998). While Huff's model represents consumer movements based on empirically informed model components (i.e., consumer expenditures, retail stores), the model does not represent consumer decisions based on the spatial relationships between stores.

To address the lack of spatial relationships between stores in Huff's model, the competing destinations model (CDM) models the effects of spatial competition and agglomeration between retail stores on the movement of consumers (and by extension, expected revenues) (Fotheringham, 1985). The theory underlying the assumption of spatial competition and agglomeration is that consumers prefer clusters of retail stores that accommodate multi-purpose shopping opportunities relative to retail stores dispersed within the same area (Leszczyc et al. 2004; Reimers & Clulow, 2004; Southworth, 1985). As a result, consumers provide mutually beneficial increases in revenues among agglomerations of retail stores, whereas higher spatial interaction costs between retail stores results in a depressive, destructive effect on retail store revenues (Fotheringham, 1985).

In addition to advances in the theory of consumer choices in space, the representation of consumer movements in SIMs has also seen improvement. Although Huff's model initially represented spatial interactions over a Euclidean plane, the approach has been extended to measure distances along street networks (Okabe & Okunuki, 2001; Okunuki & Okabe, 2002). The added complexity of the spatial representation of SIM components and the accurate measurement of spatial interactions allows geographic information systems (GIS or GISystems) to serve as ideal environments for modelling trade area demand based on retail location (Murray, 2010; Suárez-Vega, 2011). Moreover, the capacity for GIS-based SIM to consider large numbers of scenarios is under-utilised by retailers (Hernández & Bennison, 2000).

When retail companies consider locating stores in new markets, executive decision-makers are faced with an overwhelming number of factors driving sales and store success, including a seemingly infinite number of potential store locations (Hernández & Bennison, 2000). By automating a SIM such as Huff's model within a GIS, difficult store location decisions may be evaluated and supported at high spatial resolutions and across large spatial extents. However, examples of spatial interaction models applied in this manner are not found in the literature. In this study, we pose the problem of a retailer faced with a store location decision in a market with a large number of potential locations. To solve this research problem, we ask how Huff's model may be implemented in a GIS and automated for subsequent analysis. We further question how different spatial representations of model components (namely the spatial interaction costs) affect the distribution of Huff's model outcomes, and how these results are relevant for retailers interested in applying GIS-based SIM for store location decisions. How do GISystems facilitate and impose limitations on the application and analysis of Huff's model and its outcomes? Based on the implications of applying Huff's model in a GIS, what are the future research directions for GIS-based spatial interaction models?

To address these questions, we describe two automated scenarios of Huff's model each different spatial representations of the model components. Each scenario presents a different approach to measuring spatial interaction costs with Huff's model, beginning with spatial interactions based on Euclidean distances and a second scenario incorporating street network

measurements. The automated approach sequentially locates a potential store and recalculates the potential store expenditures, allowing for the iterative modelling of 755 potential store locations within a study area in Ontario. We then compare the scenario outcomes by analysing the statistical and spatial distribution of consumer expenditures. Statistics for global and local spatial autocorrelation statistics are used to identify spatial clustering of consumer expenditures at different spatial scales. The following discussion explores how the implementation of Huff's model may be improved based on existing research.

2 – Study Area

Located in southern Ontario, the Region of Waterloo (43°28'00" N, 80°30'59" W) is a medium-sized regional municipality consisting of three cities and seven townships, with a total area of 1,389km² (Figure 3.1). The Region had a total population of 507,096 in 2011, with the Cities of Kitchener, Cambridge, and Waterloo comprising the largest population centres at 219,153, 126,748, and 98,780 respectively (Statistics Canada, 2012a). The townships of Wilmot (19,223), Woolwich (23,145), and Wellesley (10,713) are geographically larger and more sparsely populated, with populations of 19,223, 23,145, and 10,713 (Statistics Canada, 2012a). Though the provincial economy and housing market have shown slow growth since the 2008 economic crisis, the Region of Waterloo has been an exception. The population and economy of Waterloo Region are growing at rates well above the provincial average, with population growth at 6.1% between 2006 and 2011, exceeding the provincial and national growth rates of 5.7% and 5.9% respectively (Statistics Canada, 2012b; Waterloo Region, 2011). Population growth forecasts over 5 years and 10 years also predict a 6.1% and 15.6% growth rate, suggesting that the rate of growth is set to increase (Statistics Canada, 2012b; Waterloo Region, 2011). To accommodate this growth, new housing and upgrades to existing housing will expand the housing market, particularly in Woolwich and Wilmot (Waterloo Region, 2011).

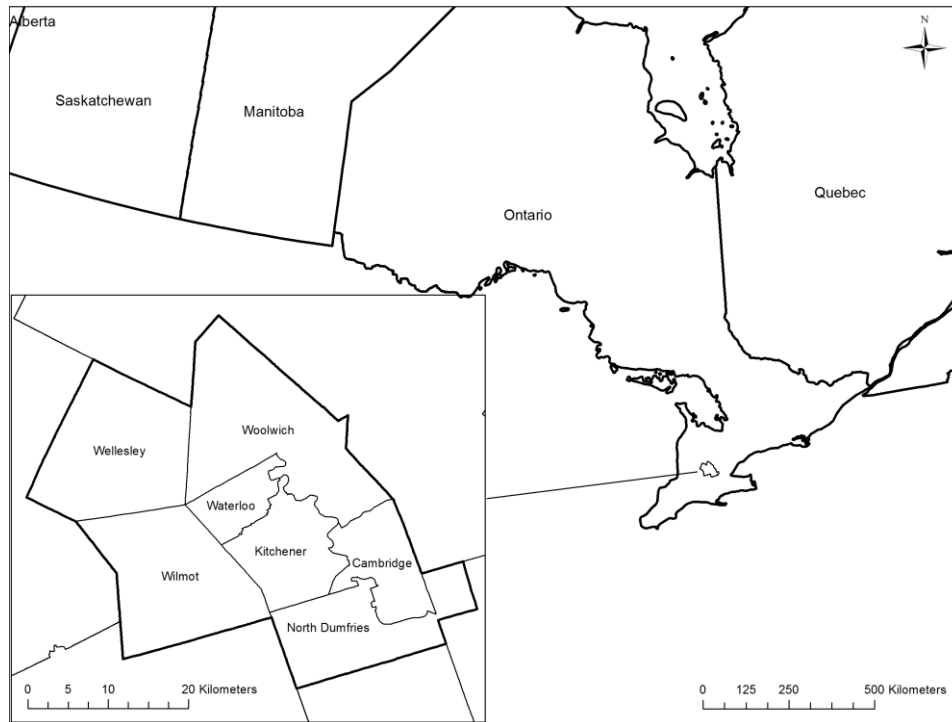


Figure 3.1: Regional Municipality of Waterloo in Ontario, Canada, is composed of three cities (Kitchener, Waterloo, and Cambridge) and four townships (Wilmot, Woolwich, Wellesley, and North Dumfries).

Intertwined with population growth is the expanding economy, with Waterloo Region named as Canada's "Technology Triangle" (Nelles et al. 2005). The top economic sectors of Waterloo Region are technology and manufacturing, with 18% of the labour force employed in manufacturing as of 2014 (Canada's Technology Triangle Inc., 2014; Nelles et al. 2005). The location of three major post-secondary schools and other research institutions within the Region bolster a well-established and diverse technology sector. The leading population and economic growth of Waterloo Region indicate a growing market for specific retail sectors such as home improvement products. Although prospective retailers may consider larger geographical extents for locating new stores, the expanding and heterogeneous economic geography of Waterloo Region make the study area suitable for the application of spatial interaction models.

3 – Methods

3.1 – Conceptual Model

Huff's model calculates the probability of patronage at a given store as the ratio of the utility of that store to the sum of utility among alternative stores (Equation 3.1, Huff 1966).

$$P(p_{ij}) = \frac{U_{ij}}{\sum_{k=1}^J U_{ik}} = \frac{S_j^a D_{ij}^b}{\sum_{k=1}^J S_k^a D_{ik}^b}$$

Equation 3.1

The probability P of customer p travelling from demand point i to store j from a set of stores J is given by the ratio between the utility U of store j and all competing stores in J . The set of stores J may include all stores in the study area, though in practice J is limited to stores within a maximum network cost. Utility is defined as the product of store attractiveness S and the shortest network path D from the origin to the store. Both utility terms are parameterised by a and b , where a and b may respectively represent a non-linear effect of store attractiveness and distance decay on store utility.

A distance decay function is used to specify the rate at which an increase in some spatial interaction cost between two points (e.g., distance, travel time, monetary travel cost) decreases the probability of an interaction (Fotheringham, 1981). Considerable literature suggests that the specification of the distance decay parameter is critical to measuring accessibility in spatial interaction models (Fotheringham, 1981; Fotheringham, 1985; Tiefelsdorf, 2003). Accordingly, there is a wide variation in the complexity and application of distance decay functions (Taylor, 1971). However, Huff's original model specified the power of an inverse exponential function.

Accordingly, the probability of a consumer patronising a store is directly related to the size of the store, inversely related to the distance between the store and consumer, and inversely related to the utility of competing shopping areas. In addition, the probability of patronising a store is significantly influenced by the time, effort, and expense involved in travelling to alternative store locations. The assumption that consumers prefer to minimise the cost of travel to a store reflects the rational economic choice of minimising opportunity costs (Huff, 1966).

To illustrate the allocation of demand using Huff's model, consider the simple scenario of nodes with an arbitrary unit of demand along an artificial network. Two Stores A and B with differing arbitrary units of attractiveness are approximately equidistant from a demand point (i.e., Node 2) with a demand of 50 units (Figure 3.2). The probability of node 2 patronising Store A is calculated as approximately 33% (Equation 3.1). Accordingly, one-third (i.e., approximately 16.6 units) of the demand at node 2 is allocated to Store A, while the remainder is allocated to Store B (i.e., approximately 33.3 units). Thus potential store expenditures may be obtained as the product of the probability of a point of demand patronising a store and the demand weight.

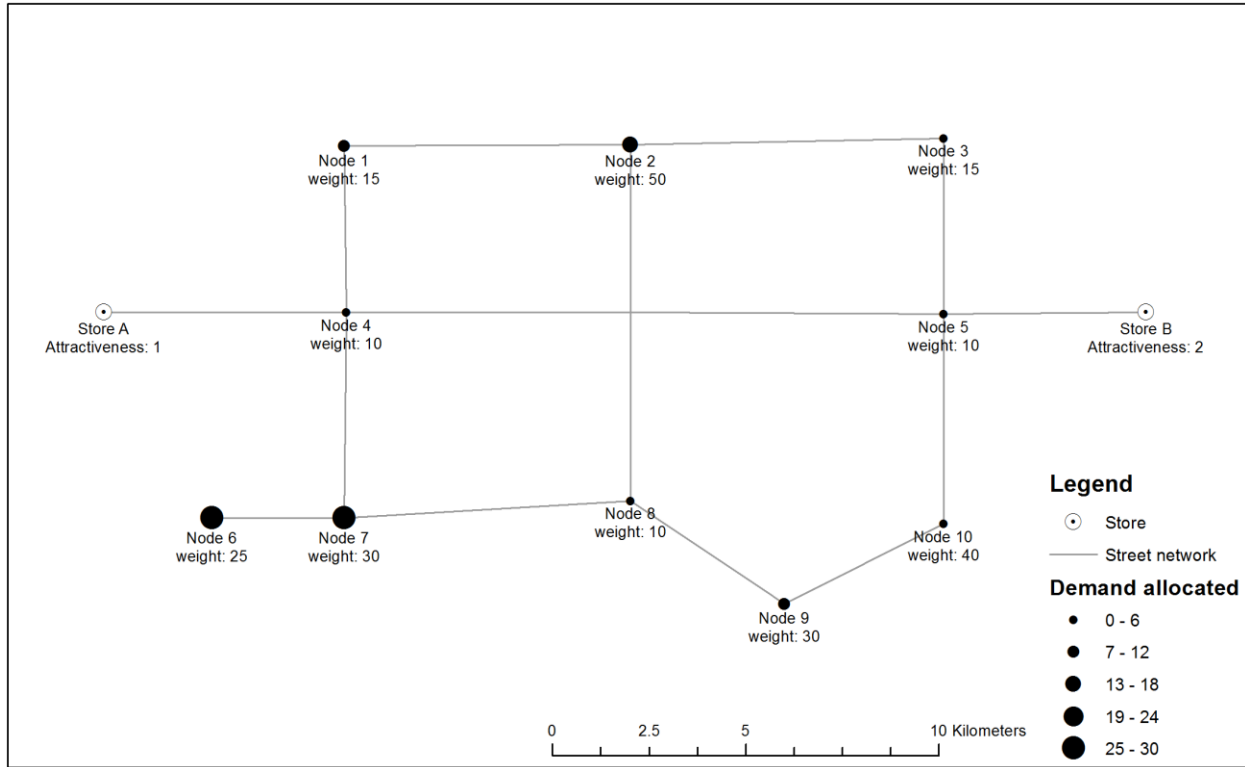


Figure 3.2: Constructed Huff's model scenario showing the demand allocated to Store A.

3.2 – Model Configuration

Although Huff's model conceptually represents trade areas as continuous probability surfaces, we operate the model by sequentially locating a potential store relative to demand and competing stores. The probability of a set of demand points being allocated to a potential store is multiplied by the estimated demand to obtain the consumer expenditures at a potential store location. The spatial components common to both model scenarios are the stores and demand interacting within the study area. Stores are represented as points, with empirical data on retail areas of competing stores informing the store attractiveness of all stores (Table 3.1). Although store sales provide a direct measure of store attractiveness, sales data are often proprietary and confidential information. We use the retail area within a retail store parcel as a measure of attractiveness relative to alternative stores, as larger retail areas imply a wider product selection for the consumer (Huff, 1966; Grewal et al. 2012; Thang & Tan, 2003).

Demand is spatially represented using the centroids of the census dissemination areas (CDAs) polygons (Table 3.1), with the weight of each point informed by an expenditure estimate derived from census attributes obtained by Statistics Canada. The demand weights were estimated as the sum of annual household spending on select home improvement retail products across counts of different household income brackets within a CDA (Table 3.1; Balulescu, 2015).

The spatial interactions between the stores and demand points were measured using an origin-destination cost matrix based on either Euclidean distances (ED) or the shortest-path

network (NW) costs through a network data set derived from the provincial road network (Table 3.1; Dijkstra, 1959).¹⁰ The speed limits and road lengths measure time as the friction variable between each possible spatial interaction of a store and demand point (Table 3.1). Time was chosen as the cost attribute for all network interactions as consumers are more likely to patronise a store if they can reach it in less time (Huff, 1966; Suárez-Vega, 2011). Analysis of consumer points of origin and destination stores (unpublished data) across the province resulted in an average travel time of 19 minutes, which was used as a maximum travel time in both spatial interaction (SI) models (Table 3.1). While contemporary implementations of Huff’s model often rely on consumer surveys at store locations to calibrate distance decay (Huff, 2003), we simplified b to a value of -1 to represent a linear inverse relationship between the distance of a spatial interaction and the impact on the probability of consumer patronage.

The Euclidean distance- and network-based representations of spatial interaction produce an ED and NW scenario each consisting of 755 CDA-based consumer expenditure values, with a DA centroid selected as a potential store for each corresponding expenditure value. The attractiveness of each potential store was fixed at 80,000 square feet of retail area, based on the median retail area of a set of big box retail chain stores in Ontario (i.e., Canadian Tire, Home Depot, Rona, Sears, Target, The Bay, and Walmart locations) (Table 3.2). At the same time, the authors recognize that the term “big box” is difficult to define as a precise category of retailers (Buliung et al. 2008; Jones & Doucet, 2000; Hernández, 2003; Lichtenstein, 2005).

Table 3.1: Input data sets required for implementing the spatial interaction models

Description	Data Type	Size	Source
Census Division (CD)	Vector polygon	1 polygon	Statistics Canada, 2013
Census Dissemination Areas (CDAs)	Vector polygon and point	755 polygons	Statistics Canada, 2013
Ontario Road Network (ORN)	Vector line	93,692 lines	Ontario Ministry of Transportation, 2013
Road Speed Limits (speed limit in km/h)	Text	-	Ontario Ministry of Transportation, 2013
Competing stores	Vector point	90 points	Unpublished data

Note: All spatial data sets were projected to Ontario MNR Lambert Conformal Conic.

Retail chain stores were included on the basis of competing in the retail space of home improvement consumer products in Ontario (Table 3.2). To develop the stores included in each model scenario, competing retail chains were selected and located from store addresses and coordinates that were geo-coded using a GIS¹¹ and other tools (e.g., Google Maps API). The point locations of stores were manually verified using Google Street View and other online sources. Where street-view imagery was unavailable, secondary sources such as parcel information, Google Image, and business directory websites were used.

¹⁰ Both scenarios were processed using ESRI’s ArcGIS software and Python 2.7. The ED scenario was processed using Flater’s (2013) implementation of Huff’s model in ArcGIS.

¹¹ ESRI’s North American Address Locator

Table 3.2: Competing retail chain stores included in the spatial interaction models

Competing retail chains		
Akzo Nobel	Home Depot	Target
Bargain Shop	Home Hardware	The Bay
Best Buy	Lowe's	TruServ
Canadian Tire	Rona	TSC Store
Castle Building Group	Sears	Turkstra
Future Shop	Sheridan Nurseries	Walmart

Retail areas of competing chain stores (Table 3.1) were manually digitized within the bounds of each competing store parcel using aerial photograph interpretation of imagery from 2007 to 2011 acquired from the Ontario Ministry of Natural Resources (OMNR)¹². On-screen digitizing of the retail store area was performed at a scale 1:500 with a linear minimum mapping unit (MMU) of 2.5m. In some cases, limited data or unusual retail developments would require a different approach. For example, where aerial imagery was unavailable in certain regions of the study area, ESRI imagery was used if suitable. Google Street View was used to identify land uses that were obstructed or unclear based on aerial imagery. Where Google Street View imagery was unavailable or obstructed, our research team collaborated to make a best judgment decision for land use and land cover classification.

Potential stores and demand were spatially represented in both models by CDA centroids rather than individual parcels, reducing the number and complexity of model computations. Although individual parcels were initially considered as potential stores for each model scenario, the large number of parcels (161,552) and limited computational resources required an alternative approach. The representation of demand as CDA centroids connects demand points to a road network in a GIS, though CDAs with larger areas remove the travel time from the polygon centroid to the nearest network edge.

The area and number of parcels per CDA provide an indication of the homogenisation of potential store and demand expenditures at larger spatial scales. Dependent upon the area of a CDA, an increase in the spatial resolution of either model would provide more specific retail location expenditure results. Parcel-based model results would be expected to be more accurate for large DAs, though the increased spatial resolution would yield less variation in expenditure results for parcels within small CDAs. Within Waterloo Region, 91.7% of CDA polygons are equal to or less than 1km², while the largest CDAs may be up to 35.6km². Although 72.7% of parcels fall within these smaller CDAs, there is evidence that the aggregation of demand affects SIM outcomes (Goodchild, 1979; Murray & Gottsegen, 1997, Nordbeck & Rystedt, 1971).

SIM outcomes are affected by study area boundaries in that potential stores located near the edge of the study area may have less demand allocated. The edge effects were minimised by including competitors and demand within a 10km buffer zone around the study area (Figure 3.3). The 10km distance was chosen such that the 10km buffer approximates the total market demand of the study area while still mitigating edge effects (Table 3.3).

¹² Southwestern Ontario Orthoimagery Project (SWOOP) 2011

Table 3.3: Total market expenditures based on buffer size.

Buffer distance (km)	Total market expenditures (millions \$ CDN)
0 (no buffer)	537
10	705
20	981
30	1,419
40	2,106
50	3,101

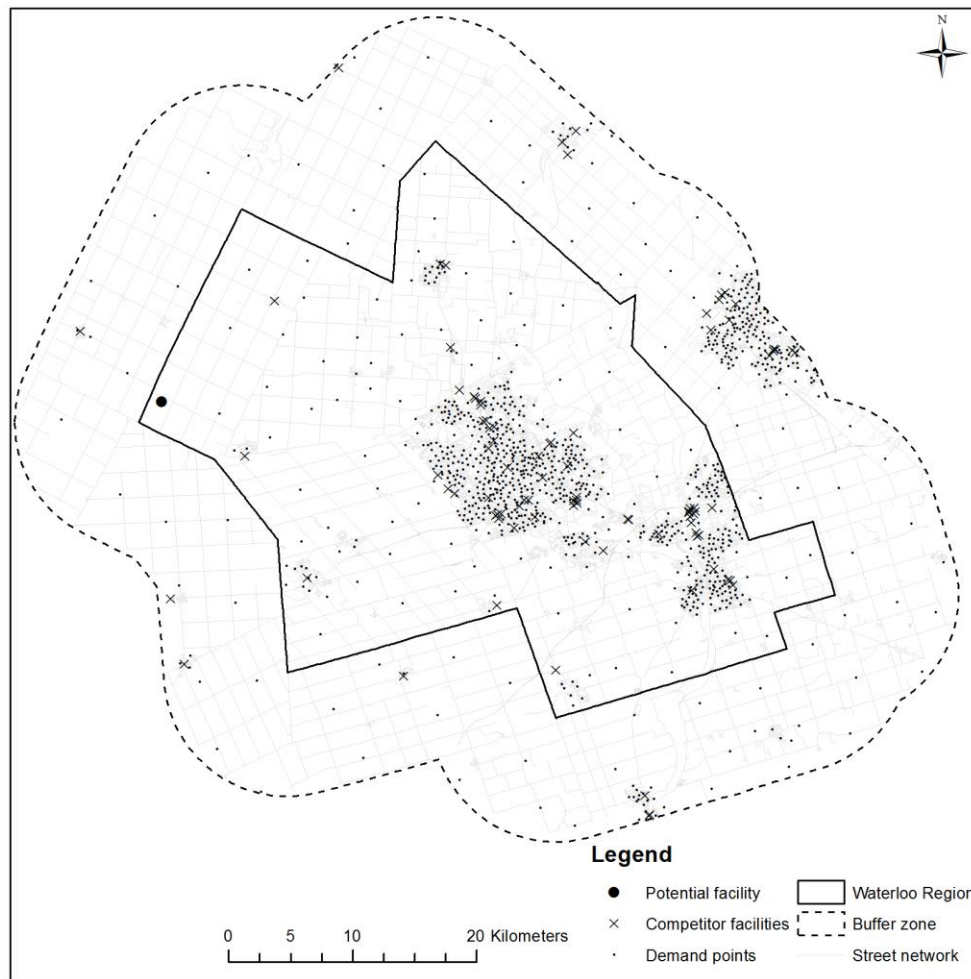


Figure 3.3: An example of a Huff's model NW scenario, including the spatial representation of demand, the street network, and competitor stores selected within the 10km buffer zone. Potential stores (e.g., in the northwest) are always located within the boundary of the study area.

3.3 – Analytical Approach

To explore how the spatial representations of interactions influence the model outcomes, a comparative analysis of the statistical and spatial distribution of consumer expenditures was performed. Descriptive statistics and kernel density estimations are used to describe and probabilistically compare the distributions of each representation of spatial interaction costs. A spatial analysis of the results includes a spatial visualisation of the model scenarios as well as the application of spatial statistics to identify statistically significant clusters of consumer expenditures. The model scenarios are spatially visualised using choropleth maps, with consumer expenditures classified using Jenks (1967) natural breaks for both scenarios.

To understand and compare the spatial distributions of the model scenarios, we analyse the spatial association of consumer expenditures based on the distances between observations with Moran's I statistic as a measure of spatial autocorrelation (Moran, 1950). However, measuring spatial autocorrelation at the extent of the study area does not provide an exploration of local associations amongst potential store expenditures. Local associations may produce more variation in spatial autocorrelation due to the outcomes of different conceptual models of spatial interaction costs, in addition to the structural heterogeneity that street networks introduce in comparison to Euclidean distances. The spatial variations in spatial interaction costs may produce significant clusters of low- or high-expenditures CDAs, identifying significant spatial differences between the Huff's model scenarios based on the localised spatial association of consumer expenditures at a potential store location.

To identify local clusters of consumer expenditures, we perform a spatial analysis with the Anselin local Moran's I statistic (Anselin, 1995). While the Moran's I statistic is preferred to measure the association of a variable within the distance of a single point in the study area, Moran's I is applied globally to the study area (Getis & Ord, 1992; Moran, 1950). Anselin's local Moran's I statistic is a similar interpretation and extension of the G family of statistics in that both focus on patterns of local spatial association (Lloyd, 2010). Anselin defines a body of local indicators of spatial association (LISA) as any statistic that meets two requirements. First, the LISA for each observation indicates the extent of significant spatial clustering around the observation. Second, the sum of LISAs for all observations is proportional to the global Moran's I statistic (Anselin, 1995). The second requirement allows us to compare average patterns of local spatial autocorrelation to the global statistic, identifying statistically significant observations of high- or low-value clusters.

An incremental spatial autocorrelation allows us to identify the spatial scale at which interaction costs have the greatest effects on model outcomes, thereby informing the scale of the cluster analysis. To determine an appropriate bandwidth for measuring Anselin's local Moran's I, the minimum distance (510m) of the eight nearest observations was used as the initial bandwidth for an incremental spatial autocorrelation analysis performed at 150m increments. The first statistically significant distance of global spatial autocorrelation (2,160m) was selected as a fixed bandwidth for measuring local spatial autocorrelation.

4 – Results

4.1 – Statistical Distribution of Expenditures

The ED scenario of Huff’s model produces a highly centred distribution of consumer spending with a mean and median of \$13M and \$13.32M, respectively (Table 3.4). The inter-quartile range (IQR) of \$2.94M and range of \$11.81M show a wide distribution, with a standard deviation of \$2.49M and a variation of \$6.21M. The overall distribution of consumer expenditures is skewed to the left, with a Fisher-Pearson coefficient of -0.91.

The NW scenario produces also produces a highly centred distribution, with a mean and median of \$12.31M and \$12.29M. The IQR of \$2.85M indicates a similarly centred distribution with a wide range of \$13.35M. The standard deviation of the NW scenario is \$1.94M, with a variation of \$3.76M. The overall distribution of consumer expenditures shows a less significant skew to the left, with a Fisher-Pearson coefficient of -0.44 (Table 3.4).

Table 3.4: Descriptive statistics of consumer expenditures (in millions CDN) in Huff’s model

Summary Statistic	ED Scenario	NW Scenario
Minimum	4.87	2.92
1st Quartile	11.98	10.98
Median	13.32	12.29
Mean	13	12.31
3rd Quartile	14.92	13.83
Maximum	16.68	16.27
IQR	2.94	2.85
Range	11.81	13.35
<hr/>		
Distribution Statistic		
Standard deviation	2.49	1.94
Variation	6.21	3.76
Skew	-0.91	-0.44
Kurtosis	0.43	0.35

Both model scenarios produce a peaked kurtosis value above the normal distribution, though the peak of the ED scenario is more pronounced than that of NW. The scenarios share a similarly narrow centre, producing approximately equal IQRs (Table 3.4, Figure 3.4) in addition to the approximately equal mean and median values within each scenario. However, the mean and median of the NW scenario occur approximately \$1M lower than that of the ED scenario (Table 3.4). The more pronounced peak and higher centre of the ED scenario produces a further left skew than the NW scenario. Although the NW scenario has a wider range, the lower standard deviation and variation show that the NW-based consumer expenditures have a narrower spread. The spread of the ED scenario is higher due to more frequent outliers along the left tail of the distribution.

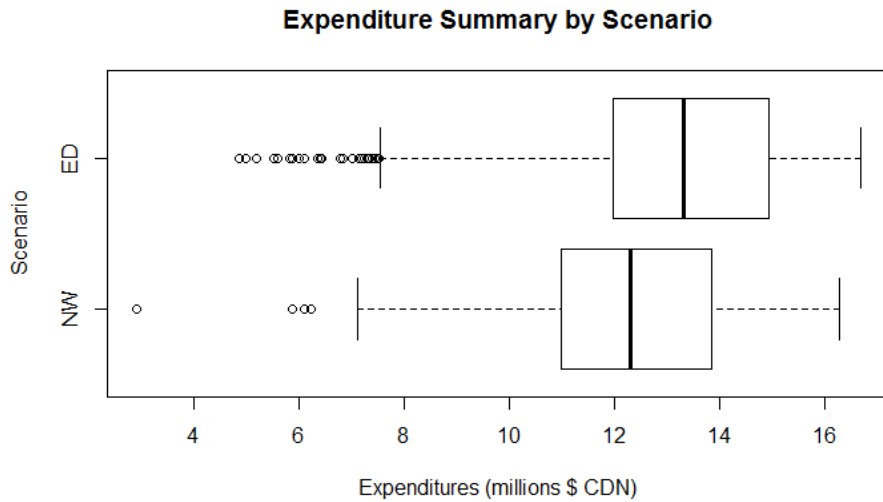


Figure 3.4: Box plot of Huff's model consumer expenditures by scenario.

The kernel density estimation shows further differences in the frequency of consumer expenditures between the model scenarios (Figure 3.5). The NW scenario falls mostly within the density curve of the ED scenario, with the exception of values between \$8M and \$12M that have a higher probability of occurrence. However the ED scenario produces a pronounced peak of expenditures approximately at the \$8M value, a result that may be explained by the spatial distribution of the ED consumer expenditures.

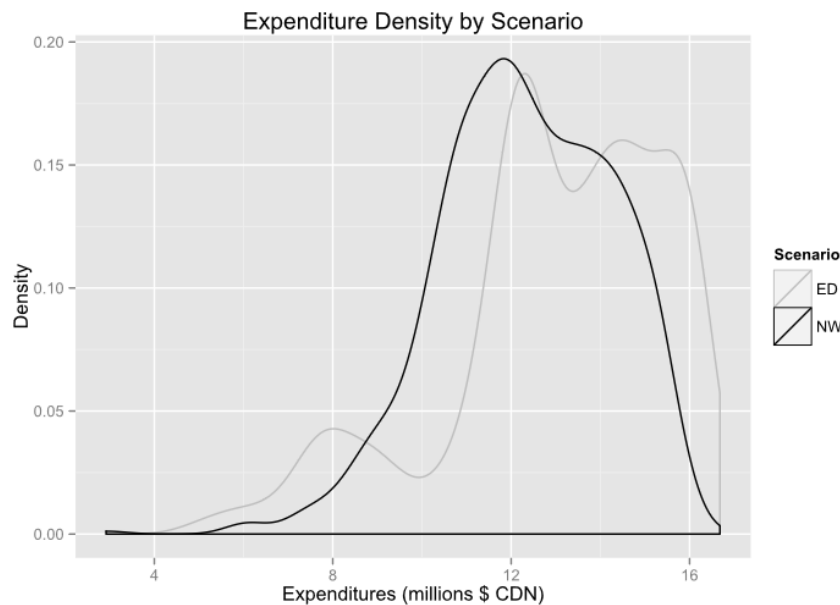


Figure 3.5: The probability distribution of a consumer expenditure value or less occurring is given by the density (for e.g., $P(x < 8M) = 0.2$), with the area under the curve equal to one.¹³

¹³ ED bandwidth = 0.526, NW bandwidth = 0.464

4.2 – Spatial Distribution of Expenditures

Both model scenarios exhibit highly significant spatial clustering based on the global Moran’s I statistic for measuring spatial autocorrelation (Table 3.5). However, the higher z-score of the ED scenario indicates a more clustered spatial distribution of consumer expenditures, as observed in the higher consumer expenditures in Kitchener-Waterloo (Figure 3.5). By comparison, the lower z-score of the NW scenario indicates that consumer expenditures are more dispersed across the study area.

Table 3.5: Moran's I for spatial autocorrelation of Huff's model scenarios

Statistic	ED Scenario	NW Scenario
Moran’s I	0.715715	0.634774
Expected I	-0.001326	-0.001326
Variance	0.000145	0.000145
z-score	59.6397	52.9044
p-value	0.000000	0.000000

The mapped consumer expenditures show that the global Moran’s I accurately describes the spatial distribution of model scenarios (Figure 3.6). In the ED scenario, the local peak of CDAs valued at approximately \$8M (Figure 3.5) is explained by the spatially clustered distribution of consumer expenditures. The ED scenario produces a spatially homogenous gradient of consumer expenditures that decreases from the centre of the study area (Figure 3.6). As a result, the number of CDAs with consumer expenditures of between \$6M and \$10M comprise 88 of the 755 potential store locations, with many of these locations comprising the lowest consumer expenditures found outside the cities of Kitchener, Waterloo, and Cambridge. In the NW scenario, the highest class of expenditures are also found within the cities of Kitchener and Waterloo (Figure 3.6). However, a higher observed frequency of consumer expenditures between approximately \$9M and \$12M (Figure 3.5) are dispersed throughout the southern half of the study area, particularly in the townships of Wilmot and North Dumfries (Figure 3.6).

The Anselin local Moran’s I statistic identifies a spatial pattern of local clusters common to both scenarios, consisting of either insignificant, high-high or low-low clusters (Figure 3.7). In the NW scenario, the occurrence of low-low clusters is more frequently observed and spatially varied within the urban geography of Waterloo Region. High-high clusters are concentrated in the city cores of Kitchener and Waterloo, with the ED scenario producing a cluster of 270 high-high CDAs and the NW scenario a cluster of 237 CDAs. This observation is consistent with the Moran’s I result and a visual comparison of spatial clustering of consumer expenditures. Low-low clusters in the ED scenario occur exclusively across all the townships of the study area, with a total of 64 CDAs classified as low-low. Of these 64 CDAs, only eight occur in a city (Cambridge). The NW scenario identifies 126 CDAs as low-low clusters, with 94 of these clusters found in the cities of Kitchener, Waterloo, and Cambridge. The remaining 32 low-low clusters are located in the townships, with the majority found in Woolwich and North Dumfries. Overall, the frequency and distribution of high and low clusters in the ED scenario is consistent with the higher spatial clustering and lower spatial heterogeneity of consumer expenditures across the study area.



Figure 3.6: Huff's model expenditures for Euclidean distance- (left) and network-based (right) spatial interaction costs.



Figure 3.7: Anselin local Moran's I statistic of Huff model expenditures for Euclidean distance (left) and network-based (right) spatial interaction costs.

5 – Discussion

Although Huff's model has been implemented along networks (Okunuki & Okabe, 2002), examples in the research literature of automating the model have not been found by the author. In automating a widely used model of retail commerce to address a research question, this study demonstrates how the expected consumer expenditures at a large number of potential store locations may be produced. By assuming that the probability of patronage is equal to the proportion of demand spent at a potential store, the distribution of consumer choices and expenditures based on spatial interactions may be visualised and communicated to retail decision-makers in an intuitive way. As a result, retailers may use Huff's model to evaluate the suitability of many potential store locations based on consumer choice, among other criteria in retail location. By changing the representation of spatial interactions within Huff's model, this study explores how network-based interactions produce statistically and spatially distinct outcomes relative to simplified Euclidean-based interactions. In the context of a larger suitability analysis, the spatial representation of a criterion has a significant impact on the outcomes and scalability of the criterion across large extents. Consequently, retailers may be interested in solving the problem of model scalability in order to model the consumer expenditures at large numbers of potential store locations.

Spatial representation and structure

The formulation of Huff's model tends to produce spatial clusters of high-expenditure retail store locations. With all other variables being equal, the probability of consumer expenditures aggregating at a potential location increases as the sum of distances to alternative stores is decreased. This formulation of Huff's model increases the spatial autocorrelation of consumer expenditures. Despite modifications to the representation of measuring spatial interactions, this conceptual tendency of Huff's model is reflected in the consumer expenditures produced in both the Euclidean and network-based scenarios. The original Huff's model uses Euclidean distances to calculate spatial interaction costs, producing a centralised and homogenous distribution of consumer spending. Based on the results of this study, there is a basis to argue that Euclidean distances provide an accurate reflection of the conceptual approach of Huff's model, while exaggerating the spatial autocorrelation of consumer expenditures. However, the results clearly show that the spatial distribution of suitable potential stores in Huff's model varies greatly based on the representation of spatial interaction costs. The incorporation of shortest path network costs reduces the statistical and spatial centralisation of consumer expenditures in comparison to ED-based interaction costs.

Further analysis of the results shows that spatial heterogeneity largely reflects the distribution of the spatial structure of interaction costs across space (Roy & Thill, 2004). For instance, the heterogeneous spatial structure of the street network will influence the NW scenario results, with higher consumer expenditures occurring at locations with minimum cumulative impedance through the network to the set of given demand points. The spatial structure of the network costs is therefore observed in differences of consumer expenditures relative to the ED scenario, particularly in the townships of Wilmot and North Dumfries. Anselin's local Moran's I statistic shows that the differences in consumer expenditures of townships between the Huff's model scenarios are not statistically significant. This indicates that the differences between the

scenarios are due to the effects of heterogeneity arising from spatial structure and not local spatial autocorrelation (Anselin, 2010).

GIS-based spatial interaction models in retail

For retailers, the comparison of the ED and NW scenario demonstrate that Euclidean distances are a poor substitute for adequately modelling the urban structure of spatial interaction costs, particularly outside urban cores. Potential store expenditures are overestimated within urban cores and underestimated in peripheral locations. Network-based interaction costs provide more accurate, empirical representations of consumer behaviour and movement, presenting an empirically informed spatial interaction model for delineating and quantifying trade areas. Rather than modelling and visualising delineated trade areas around a limited number of potential stores, we quantify and visualise potential store expenditures at hundreds of sites (755 to be exact). The operation of SIMs within a GIS allows us to sequentially model potential store expenditures at every possible location point within a study area, increasing the spatial extent and resolution of the models. For decision-makers in retail, traditional approaches of retail store location based on experience and intuition may be supported with thematic maps that integrate hundreds of Huff's model results. On the other hand, the implementation of this study has demonstrated three challenges in the further application of GIS-based SIM in retail location.

First, our study simplifies the distance decay function used to transform spatial interaction costs into probabilities of patronage. Others have argued and empirically demonstrated that distance decay functions vary over heterogeneous spatial structures such as street networks and competing stores (Fotheringham, 1981; Tiefelsdorf, 2003). Fotheringham (1981) suggests that the variation in distance decay may be a function of the spatial scale used when examining spatial heterogeneity. Other studies in location analysis have adopted an empirical approach to calibrating distance decay through the use of consumer surveys (Brown, 1978; Iacono et al. 2008). Given that our implementation of Huff's model assumes a constant distance decay to describe spatial consumer behaviour, empirical studies of consumer behaviour in local markets may be used to configure SIMs according to local conditions (Goodchild, 1984). Alternatively, the spatial autocorrelation of an interaction may be measured to model a distance decay function (Griffith, 2009). Moreover, the determination of what retail chains constitute a competitor or a complimentary business must be incorporated in Huff's model. Further developments in SIMs have incorporated positive and negative distance decay parameters according to the complementary or competitive nature of retail categories or formats near a store location (Fotheringham, 1981; Fotheringham, 1985; Fox et al. 2004).

The development of the maximum travel time also presents a limited assumption of consumer behaviour. Our study makes use of empirical data to develop a fixed maximum travel time, assuming that consumers only drive to stores. However, our efforts to model travel time in urban networks do not include delays at network vertices based on traffic conditions and the time or availability needed for parking (Salonen & Toivonen, 2013). Moreover, studies indicate that the relationship between spatial decision-making and travel time is much more complex and non-linear. In a heterogeneous retail landscape, empirical research has demonstrated that product availability and the certainty of a retail store holding a desired purchase item in stock will increase the willingness of consumers to drive further (Dijst & Vidakovic, 2000; Grewal et al.

2012). To improve the modelling of consumer behaviour and spatial interaction, maximum travel time and distance decay could vary based on the spatial structure of the surrounding street network and retail landscape.

Second, the representations of model components such as store attractiveness simplify both spatial representation and consumer behaviour. Although Huff (1966) specifies retail area as a store attractiveness variable, consumer spatial choice is influenced by the availability of complementary shopping opportunities (Fotheringham, 1985), the shopping experience, pricing, and product selection and availability (Fox et al. 2004; Grewal et al. 2012). A major improvement to Huff's model was made by Nakanishi and Cooper (1974), incorporating a multiplicative competitive interaction (MCI) model to describe store attractiveness in terms of multiple components. Further research has applied the MCI model to specific attributes of attraction in food retailing (Jain & Mahajan). In this study, we assume that retail area implies a wider inventory of merchandise and is the sole determinant of store attractiveness. The assumption that retail store attractiveness is determined by product selection has some empirical support (Fox et al. 2004).

Third, the spatial representation of model components as aggregated data may have a significant impact on model error. For example, the representation of potential stores and demand as the aggregation of parcels by CDA sacrifices spatial resolution and accuracy to reduce spatial complexity and extend the model. Several studies have been conducted to examine the effects of spatial resolution on the scaling and error of SIMs such as location-allocation (Gould et al. 1971; Casillas, 1983; Goodchild, 1979). Analytical study using location-allocation has shown that spatial aggregation produces acceptable model error (Murray & Gottsegen, 1997), while similar efforts have produced large deviations in error (Fotheringham et al. 1995). Further research has also suggested that data aggregation results in under-estimated sales (Tóth et al. 2009). However, no similar studies have been undertaken to examine the stability of Huff's model.

In our study, demand is represented by census geography centroids and thus cannot be further disaggregated, though research has been undertaken to disaggregate census data based on LUC (Cisneros, 2015). However, the aggregation of potential store locations by CDA rather than by parcel will vary the network distance from a demand point to the potential store, introducing a source of error. A study of the effect of spatial aggregation on margins of error in Huff's model would potentially involve running the model with different measures of disaggregation and comparing how consumer expenditures change across the groups of aggregated stores (Casillas, 1983). Understanding the stability of Huff's model to varying spatial scales of aggregation among model components would assist researchers in validating model results. For retailers, understanding the inverse relationship between model scaling and model error would provide potential methods to compensate or compromise for error in potential store sales. Research into how scaling affects the error in Huff's model would also advise future research directions with SIMs.

Future directions for spatial interaction modelling

For spatial interaction modelling to remain relevant to retailers, future research efforts should focus on two challenges. First, many retailers traditionally use executive experience, intuition, and common sense to make retail store location decisions (Hernández & Bennison, 2000). However, retailers increasingly face store location decisions with overwhelming numbers of alternatives across large spatial extents. Decisions made across such large extents include spatially heterogeneous urban geographies, markets, and landscapes of real estate. While traditional approaches of retail store location are likely to continue, new methods in spatial interaction modelling must be developed to support retail store location decisions across such large and varied markets. Although this study is a modest step in addressing the first challenge, more research is needed to develop SIMs in two key conceptual and operational areas, namely regional parameterisation and scaling.

To extend the objectives and methods of our study using network-based spatial interactions across the province of Ontario would require 19,964 scenarios, equal to the number of CDAs within the province. The limitations of a fixed-parameter, automated method of spatial interaction modeling become evident in relation to the extent and varied distribution of model components across such a large study area. To address this limitation, regional parameterisation would vary the travel time constraint, distance decay function, and potential store location and attractiveness based on local geographic conditions. For example, the maximum travel time may conceptually represent the aversion of consumers to travel costs, and would be spatially represented based on the density of the local street network. The network density or a consumer survey may then inform the distance decay function. A potential store could be located and sized using a multi-criteria decision analysis of parcel characteristics, where the potential store attractiveness would be informed by the parcel area. Huff's model would then be parameterised according to the regional context, while automated to scale across a large spatial extent.

Scaling the model to a provincial extent would require a simplified computational process to reduce the resources required for model automation. For example, the GIS-based Huff model must measure all possible spatial interaction costs by computing an origin-destination (OD) matrix of least-cost network paths between all demand points and store locations in a region. If we consider a generalised Huff model scenario of n nodes representing both origins and destinations along a street network, the cost matrix would be $n \times n$ elements in size (Table 3.6). If Huff's model is calculated once for a potential store location at each node (a , b , c , d), the cost matrix is re-calculated rather than simply retrieving the spatial interactions of the node that corresponds to the new potential store location (Table 3.6).

Table 3.6: Symmetric matrix with arbitrary unit costs for nodes along a network representing origins and destinations.

	a	b	c	d
a	-	4	3	10
b	-	-	2	5
c	-	-	-	1
d	-	-	-	-

For example, automating Huff's model to sequentially locate potential stores in the regions of Waterloo and St. Catherines, the model would require 755 and 740 iterations (i.e, one calculation of Huff's model with each new cost matrix) in Waterloo and St. Catherines, respectively. Consequently, 755 and 740 cost matrices would be constructed, rather than constructing one cost matrix per region and querying the matrix as needed with each new potential store location. Combining research efforts in the areas of regional parameterisation and scaling may thus provide a synergistic improvement to Huff's model as retailers consider large spatial markets. By dividing a decision space into geographic regions, cost matrices of reasonable dimensions could be constructed and subsequently used for each new potential store in a region. The computational performance of SIMs across large spatial extents would be lowered as a result. SIM performance would be greatly improved and computational resources could be freed for localised parameterisation and increasing the spatial resolution of representing model components.

6 – Conclusion

This study began by posing empirically informed Huff's model scenarios with differing representations of spatial interaction costs. The process of automating each scenario to iteratively compute Huff's model for a re-located potential store provides a method of producing maps of sales expenditures at potential store locations. A spatial analysis of consumer expenditures based on a Euclidean representation of spatial interaction costs revealed a strong spatial autocorrelation of retail trade, while the network-based scenario increased the spatial heterogeneity of consumer expenditures. Our GIS-based implementation of Huff's model demonstrates that improved parameterisation and spatial representation is critical to applying the model across large spatial extents. For retailers, this study highlights the importance of model parameterisation and the potential for model automation in considering the suitability of large numbers of potential store location alternatives. For researchers in retail location, we outline future research directions to develop a regional parameterisation of Huff's model, as well as modifications to the technical operation of the model for improved scaling efficiency over large spatial extents. This has implications for developing models of retail gravitation that consider large numbers of potential locations for both decision-makers in retail and economic geographers.

Chapter 4 – Conclusion

The second chapter of this thesis implemented and examined the results of a suitability analysis of potential retail store locations in Ontario, Canada. To evaluate the 4.7 million potential parcels based on nine criteria, the site and situational characteristics of potential parcels were incorporated into a GIS-based MADA. The spatial representation of each criterion varied widely in complexity, from measuring the development cost of a potential site with topographic statistics to modelling the sales of a potential store location based on spatial interactions with empirically informed demand and competitors. Drawing on expert opinion, the ranked importance of each criterion to the suitability of a potential site was used to answer the research question of understanding the main drivers of retail suitability among the selected criteria and to develop suitability scores. Finally, area and LUC constraints were applied to remove parcels considered unavailable for retail development, leaving 152,910 parcels across Ontario. To address the research question of describing and analysing the statistical and spatial distribution of suitability, potential sites were aggregated and summarised according to census geographies such as metropolitan areas. Notable results showed that while Toronto contains a significant proportion of the most suitable locations (particularly along the provincial highways), Ottawa – Gatineau emerged as the second most suitable metropolitan area ahead of Guelph. Although Toronto contains the most suitable potential sites by far, the prominent suitability of the region of Puslinch within the Guelph CMA suggests a viable alternative location for field investigation by retail real estate teams.

The third chapter addressed the research question of analysing how a commonly used model of retail commerce may be automated within a GIS to estimate consumer expenditures at a large number of potential store locations. The chapter also included a statistical and spatial comparison of how the complexity of representing spatial interactions within Huff's model affects the estimated consumer expenditures at potential store locations. In the context of the suitability analysis, the chapter demonstrates by example how the outcomes of a criterion are affected by the spatial representation of that criterion. By comparing the distribution of potential store sales based on Euclidean and network-based spatial interactions, the study revealed that while both methods of measuring spatial interactions produce centralised results (a consequence of the concept of Huff's model), network-based interactions produced more spatially heterogeneous outcomes. The study also identified existing limitations in the methods used to configure Huff's model, while providing suggestions to further improve the implementation and scaling of spatial interaction models for future research.

Situated within the body of retail location theory, the thesis has demonstrated and applied a GIS-based suitability analysis across a large spatial extent, incorporating many different criteria. The careful definition of suitability and the inclusion of expert opinion informed of the concept and representation of criteria has been emphasised. Certainly in the author's opinion, more questions have been revealed than answered throughout the course of this study. Further research is needed to measure how the aggregation of spatial data affects the distribution of various criteria, while improvements to the parameterisation of Huff's model are needed. The over-simplification of distance decay and the size of trade areas must be replaced with empirically informed models of consumer behaviour. Alternative methods would involve the calibration of distance decay and trade area size based on local environmental conditions, with the assumption that consumer behaviour is largely based on the surrounding urban environment.

Renewed efforts to improve the analysis of big datasets across large spatial extents would also be welcome.

The benefits, challenges, and limitations associated with what we consider to be “big data” have been raised many times throughout the study. Although this thesis asserts that the suitability analysis addresses the needs of retailers that are increasingly faced with difficult location decisions and many potential options, the benefits of “big data” must be realised with caution. Despite contrary beliefs, voluminous datasets and intensive computations do not necessarily yield useful information or representative models of spatial phenomena. Big data merely allows for the scaling of sound models across large spatial extents, while suffering from many of the same weaknesses found in smaller datasets.

To ensure that the methods developed in this thesis are reliable for applications in business location decisions, further collaboration with retail experts is needed to ensure that decision-makers in retail are aware of the limitations of this study. Future developments would benefit greatly in revisiting the inclusion and spatial representation of criteria, while directing further efforts into improving the scaling and regional parameterisation of Huff’s model. Reducing the computational and technical cost of implementing the suitability analysis as a whole would free resources for retailers to consider suitability analyses under hypothetical market scenarios. Reducing the overall costs of a suitability analysis could also allow retailers to use GIS-based suitability analyses to anticipate emerging market trends and make more timely decisions. In addressing the importance of “location, location, location”, the understanding that “time is of the essence” must also become part of the supporting role of a GIS-based suitability analysis.

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Appendix A1

Table A1: Pairwise Wilcoxon rank-sum test of the nine normalised criteria

Criteria	1	2	3	4	5	6	7	8	9
2	<2e-16	-	-	-	-	-	-	-	-
3	<2e-16	<2e-16	-	-	-	-	-	-	-
4	<2e-16	<2e-16	<2e-16	-	-	-	-	-	-
5	<2e-16	<2e-16	<2e-16	<2e-16	-	-	-	-	-
6	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	-	-	-	-
7	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	-	-	-
8	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	-	-
9	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	-

Note: Criteria are numbered according to order of Table 2.5. The results of the Wilcoxon rank-sum test show statistically significant differences ($p < 0.01$) across all pairwise comparisons.

Parcel slope (1), highway access (2), competitive expenditures (3), potential expenditures (4), competitor density (5), retailer density (6), traffic volumes (7), distribution access (8), and location quotient (9).

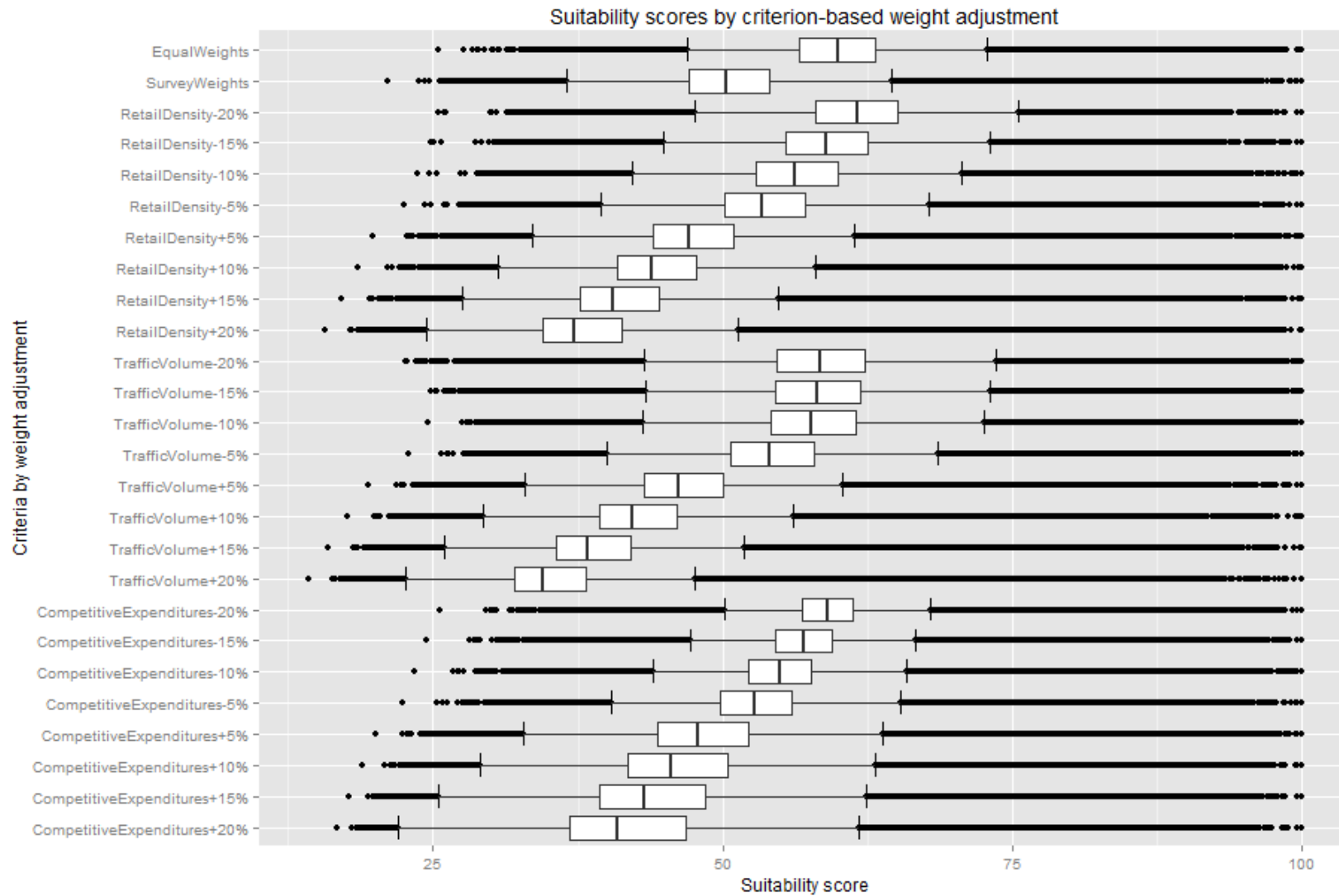


Figure A1: box plot distributions of suitability based on a one-at-a-time sensitivity analysis of weights for three select criteria, with suitability distributions of the equal weights and survey weights included (top) for comparison.

Table A2: Summary statistics for OTA sensitivity analysis of suitability analysis

Scenario	Minimum	Median	Mean	Maximum	Std. dev.	Range	Skew	Kurtosis
Equal Weights	25.5	59.9	60.5	100.0	6.9	74.5	0.8	2.5
Survey Weights	21.1	50.3	51.6	100.0	7.7	78.9	1.5	4.0
RetailDensity-20%	25.5	61.6	61.8	100.0	6.3	74.5	0.3	2.0
RetailDensity-15%	24.8	59.0	59.4	100.0	6.5	75.2	0.5	2.1
RetailDensity-10%	23.6	56.2	57.0	100.0	6.9	76.4	0.8	2.4
RetailDensity-5%	22.5	53.4	54.5	100.0	7.3	77.5	1.2	3.1
RetailDensity+5%	19.8	47.0	48.8	100.0	8.3	80.2	1.9	5.0
RetailDensity+10%	18.5	43.8	45.9	100.0	8.9	81.5	2.2	6.1
RetailDensity+15%	17.1	40.5	42.9	100.0	9.5	82.9	2.4	7.1
RetailDensity+20%	15.7	37.2	40.0	100.0	10.3	84.3	2.6	8.1
TrafficVolume-20%	22.7	58.4	59.2	100.0	8.3	77.3	1.1	3.3
TrafficVolume-15%	24.8	58.1	59.1	100.0	8.2	75.2	1.3	3.6
TrafficVolume-10%	24.5	57.7	58.8	100.0	8.2	75.5	1.4	3.8
TrafficVolume-5%	22.9	54.1	55.3	100.0	7.9	77.1	1.5	3.9
TrafficVolume+5%	19.4	46.2	47.8	100.0	7.7	80.6	1.6	4.1
TrafficVolume+10%	17.6	42.2	44.1	100.0	7.9	82.4	1.8	4.5
TrafficVolume+15%	15.9	38.3	40.5	100.0	8.2	84.1	2.0	5.4
TrafficVolume+20%	14.3	34.5	36.9	100.0	8.6	85.7	2.2	6.5
CompetitiveExpenditures-20%	25.5	59.1	59.9	100.0	6.1	74.5	1.3	4.0
CompetitiveExpenditures-15%	24.5	57.0	57.9	100.0	6.4	75.5	1.4	4.1
CompetitiveExpenditures-10%	23.4	54.9	55.9	100.0	6.8	76.6	1.5	4.2
CompetitiveExpenditures-5%	22.3	52.7	53.9	100.0	7.3	77.7	1.5	4.1
CompetitiveExpenditures+5%	20.0	47.9	49.4	100.0	8.2	80.0	1.5	3.8
CompetitiveExpenditures+10%	18.9	45.5	47.2	100.0	8.8	81.1	1.5	3.7
CompetitiveExpenditures+15%	17.8	43.2	45.1	100.0	9.3	82.2	1.5	3.5
CompetitiveExpenditures+20%	16.7	40.9	43.0	100.0	9.9	83.3	1.5	3.4

Table A3: Pairwise Wilcoxon rank-sum test of CMA-based suitability scores by regions of Ontario

	Ontario	Northern CMAs	Southern CMAs
Northern CMAs	< 2.2e-16	-	-
Southern CMAs	< 2.2e-16	< 2.2e-16	-
n	152,910	6,789	83,382

Note: The results of the Wilcoxon rank-sum test show statistically significant differences ($p < 0.01$) across all pairwise comparisons.