SMARTer Growth:
A SUITE OF NEIGHBORHOOD DESIGN EVALUATION TOOLS TO HELP SUSTAIN A DESIRED QUALITY OF LIFE:
A Case Study City of Kelowna

by

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Abstract

Auto-dependency has triggered many public health challenges for North American citizens including increases in physical inactivity rates, road collisions, and Greenhouse Gas emissions. As a result, there has been a growing interest in addressing these challenges by promoting more sustainable and livable neighbourhood planning.

In response, researchers from the University of British Columbia and the Canada Mortgage and Housing Corporation have developed the SMARTer Growth (SG) neighbourhood design principles. However, no previous research has evaluated the impact of the full-fledged SMARTer Growth design principles on travel behaviour and community quality of life.

To conduct a comprehensive evaluation of the SG principles, this research developed an agent-based model that evaluates the impact of neighbourhood design on travel pattern by simulating agents' daily trip activities. It employs a framework that integrates Random Utility Maximization-based modelling with reinforcement learning concepts to account for the bounded rationality and knowledge learning process. Moreover, the model utilizes the Diffusions of Innovations Theory to account for the impact of social interactions by simulating how agents share their knowledge and propagate information. It also accounts for the iterative feedback process between agents' actions and the environment. In addition, a suite of tools has been identified to evaluate the impact of neighbourhood design on community quality of life, including: i-THRIVE, air quality, noise pollution, walkability, bikeability, transitability, playability, and social interactions.

The agent-based model and the QoL suite of tools were utilized to evaluate the outcome of three scenarios in three urban centres in Kelowna, BC; the three scenarios are 1) existing, 2) 2040 business as usual, and 2040 SG. The results of the agent-based simulation show promise, as retrofitting the three urban centres using the SG design principles resulted in significant modal shift towards active transportation and reduction in auto use compared to the existing and 2040 business as usual scenarios. Moreover, the QoL evaluation revealed that applying the SG design principles improves walkability, bikeability, playability, and decreases air and noise pollution on local roads.

Lay Summary

Canadians are dealing with several health challenges including increase in physical inactivity rates, road collisions, and Greenhouse Gas emissions. Given the limited impact of existing neighborhood designs in addressing these challenges, researchers have developed SMARTer Growth (SG), a novel neighbourhood design that combines the best characteristics of the traditional grid and culs-de-sac neighbourhood designs. The objective of this research is to evaluate the SG design principles on transportation travel behaviour and community quality of life (QoL). To achieve this objective, this research proposes an agent-based model that appropriately characterize human behaviour and their bounded rationality, accounts for transportation networks and infrastructure, considers land use characteristics and traffic safety, and allows for interactions between different transportation users as well as people-to-built environment interactions. In addition, a suite of tools has been identified to evaluate SG QoL outcomes in terms of health, safety, air quality, noise pollution, walkability, bikeability, transitability, playability and social interactions.

Preface

Some parts of this dissertation have been presented in peer reviewed technical conferences and submitted/published in peer-reviewed technical journals as listed below. For all the listed publications, I was the lead author, responsible for conceptualization, data collection and preparation, formal analysis, results presentation, visualization, and manuscript composition. The work was conducted under the supervision of Dr. Gordon Lovegrove and Dr. Ahmed Idris who contributed to concept formation and provided valuable manuscript revisions.

Portions of section 1.1 and Chapter 5 have been published in the following papers:

- **Masoud, A.**, Idris, A. O., and Lovegrove, G. (2017). Modelling the Influence of Fused Grid Neighborhood Design Principles on Active Transportation Use with emphasis on Street Connectivity. Paper presented at the 96th Transportation Research Board (TRB) Annual Meeting, January 8^{th} – 12^{th}, 2017 Washington D.C.
- **Masoud, A. R.**, Idris, A. O., and Lovegrove, G. (2019). Modelling the impact of fused grid network design on mode choice behaviour. *Journal of Transport & Health, 15*, 100627.

Portions of section 1.1 and a version of Chapter 3 have been presented in the following conference:

- **Masoud, A.,** Idris, A. O., and Lovegrove, G. (2021). Learning-based Model for Evaluating the Impact of Neighbourhood Design on Travel Behaviour. Paper presented at the 100th Transportation Research Board (TRB) Annual Meeting in January 2021, Washington D.C.

and under review in the following journal:

- **Masoud, A. R.**, Idris, A. O., and Lovegrove, G. Learning-based Model for Evaluating the Impact of Neighbourhood Design on Travel Behaviour. *Transportation Research Record*.

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- **Masoud, A.**, Idris, A. O., and Lovegrove, G. (2021). Quality of Life Outcomes of The Smarter Growth Neighborhood Design Principles: Case study City of Kelowna. Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021.

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List of Abbreviations

ABM	Agent-based modelling
AT	Active Transportation
ATIS	Advanced Traveller Information Systems
BDI	Belief–Desired–Intention
BPR	Bureau of Public Roads
CBD	Central Business District
CMHC	Canada Mortgage and Housing Corporation
EF	Emission Factor
FAR	Floor Area Ratio
GA	Genetic Algorithm
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GTFS	General Transit Feed Specification
IID	Independently and Identically Distributed
IPF	Iterative Proportional Fitting
IPU	Iterative Proportional Updating
i-THRIVE	Interactive Sustainable Transport Safety/Healthy Development Index Valuation
ITS	Intelligent Transportation Systems
K-S	Kolmogorov-Simirnov
MDP	Markov Decision Processes
MNL	Multinomial Logit

MOVES	Motor Vehicle Emission Simulator
OCP	Official Community Plan
OSM	Open Street Map
OTS	Okanagan Travel Survey
POM	Pattern-oriented Modelling
QoL	Quality of Life
RDCO	Regional District of Central Okanagan
Repast	Recursive Porous Agent Simulation Toolkit
RL	Reinforcement Learning
ROW	Right of Way
RSS	Road Safety Strategy
RUM	Random Utility Maximization
SAE	Standardized Absolute Error
SCRI	Stop Coverage Ratio Index
SG	SMARTer Growth
TAZ	Traffic Analysis Zone
TDM	Transportation Demand Management
VDF	Volume Delay Function
VKT	Vehicle Kilometer Travelled
WHO	World Health Organization

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To my parents

Mahmoud Masoud

&

Nermin Saleh

Chapter 1 Introduction

1.1 Problem Statement

Historically, urban areas have been shaped by the evolution of the transportation system. For instance, the introduction of horse-drawn streetcars in 1852 enabled cities, for the first time, to slowly expand outwards away from their walking-friendly city centers. Further, the innovation of the electric motor has sparked the "first urban transport revolution" that witnessed the introduction of electric streetcars in 1888; elevated rapid transit lines in 1892; and subway systems in 1898 (Hanson & Giuliano, 2017). Such urban transit technologies have supported further expansion of metropolitan areas in a star-shaped pattern along main transit corridors (Adams, 1970). Meanwhile, a second urban transport evolution was in the making with the introduction of cars in American cities in the 1890s. During this period, cars were primarily owned by the wealthy, but with time, cars started to become affordable to the masses in the 1920s. While cars were initially used for leisure and recreational activities, their influence on urban areas was substantial by making more land accessible for development. This encouraged people to move away from dense "crowded" urban areas located along transit lines to newly developed low-density suburban areas that feature single and multiple dwellings built on larger lots with paved alleys and garages (Adams, 1970). By the late 1930s, people started to rely on cars on every aspect of their daily life activities (e.g. commuting, shopping, and socializing) which led to a significant decrease in public transport ridership and increase in congestion and road collisions. In response, transportation professionals focused mainly on traffic engineering in an effort to improve traffic safety and flow. Note that transportation engineering during that era was called "traffic engineering". This overwhelming acceptance of cars from the public as well as the widespread emphasis on them by professionals and governments (e.g. the 1956 Interstate Highway Act) further accelerated the sprawl of cities and land use segregation.

In addition, land use segregation was supported by urban planners as the main concerns about public health were infectious diseases and poor sanitation (Perdue, Gostin, & Stone, 2003). At that time, it was well established that creating zones to segregate different land uses, such as residential and industrial, would improve public health by limiting emissions and noise in residential areas (Corburn, 2007; Scott, 1969). Scott (1969) affirms that "Zoning was the heaven-sent nostrum for sick cities, the wonder drug of the planners, the balm sought by lending institutions and householders alike". However, the unlimited expansion of cities and excessive land use segregation have contributed to increasing the distances between trip origins and destinations, which also contributed to the creation of the auto-dependency culture that we are facing today.

Auto-dependency has caused many public health challenges for North American citizens including the increase in physical inactivity rates, road collisions, and Greenhouse Gas (GHG) emissions. First, the increasing levels of physical inactivity has become a major challenge for public health. Strain et al. (2020) found that physical activity prevents around 4 million early deaths annually. Unfortunately, only 17.5 percent of Canadian adults (18-79 years) meet the Canadian physical activity guidelines by accumulating at least 150 minutes of moderate-to-vigorous physical activity each week (Centre for Surveillance and Applied Research, Public Health Agency of Canada, 2018). Physical inactivity is associated with increased risk for obesity and many chronic diseases such as type 2 diabetes, stroke, and ischaemic heart disease (Pratt, Norris, Lobelo, Roux, & Wang, 2014; Sallis, Frank, Saelens, & Kraft, 2004; VanBlarcom & Janmaat, 2013; Wang, G. et al., 2005). It is therefore not surprising that physical inactivity imposes a large economic burden on our nation. For instance, the burden of physical inactivity in Canada was estimated at $6.8 billion in direct (i.e. hospitalization, physician, medication) and indirect (i.e. economic output lost due to illness, disability, or premature mortality) costs in 2009 (Janssen, 2012). Similarly, Krueger et al. (2015) estimated the annual economic burden of physical inactivity to be as high as 10.8 billion in direct and indirect costs in 2012.

Second, road collisions are one of the leading causes of death and injury worldwide, responsible for approximately 1.35 million fatalities annually (World Health Organization, 2018). In Canada, almost 2,000 people are killed and 165,000 are injured per year in road collisions (Canadian Council of Motor Transport Administration, 2016). The Canadian economic impact of road collisions is estimated at 37 billion annually or 2.2 percent of Canada's Gross Domestic Product (GDP) (Canadian Council of Motor Transport Administration, 2016). WHO research shows that 95 percent of road collisions are a result of driver errors, which has led to calls for private automobiles use reduction and Active Transportation (AT) use increase. In response, Canada introduced in 2016 its Road Safety Strategy (RSS) 2025, with a long-term vision of Towards Zero collisions, which aims to make Canadian roads and highways the safest in the world.

Finally, the Canadian Government has committed, under the Paris Agreement, to reduce GHG emissions by 30 percent below 2005 levels (Environment and Climate Change Canada, 2016). However, current indicators suggest that Canada will not be able to meet this target, as GHG emissions in 2030 are estimated to be only 21 percent below 2005 levels (Environment and Climate Change Canada, 2018a). Transportation is the second largest contributor to GHG emissions in Canada, accounting for 28 percent of the total emissions nationwide (Environment and Climate Change Canada, 2018b). At the provincial level, 40 percent of British Columbia's GHG emissions are from the transportation sector (BC Ministry of Environment, 2016). Such high levels of transportation-related emissions highlight the critical role of the transportation sector in achieving the 2030 target (Rahman & Idris, 2017).

Consequently, there has been a growing interest in addressing these challenges by promoting more sustainable neighbourhood designs that reduce automobile dependency and encourage people to use more sustainable modes of transportation. The two most employed neighbourhood designs in North America today are 1) the traditional grid pattern and 2) the culs-de-sac or loops and lollypop pattern. The culs-de-sac pattern was employed to address problems associated with the grid street pattern by precluding neighbourhood traffic shortcutting. However, the culs-de-sac pattern has its own disadvantages including being disorienting to navigate within a neighbourhood and increasing distances between origins and destinations (Sun & Lovegrove, 2013).

Neighbourhood design influences individuals' travel pattern in three ways: 1) it shapes potential travel routes and their characteristics, 2) determines public transit accessibility, and 3) defines available activities (e.g. shopping, work, leisure) (Jin, 2010). Beyond travel pattern, which is usually the focus of transportation engineers, neighbourhood design also influences many aspects of human behaviour and our quality of life, including childhood development and human social interactions.

Over one billion children are growing up in urban areas around the world (UNICEF, 2012). In Canada, over 50% of children and youth live in the country's largest urban cities such as Vancouver, Calgary, Toronto, and Montreal (Canadian Institute of Child Health, 2013). While living in cities provides children a greater access to services such as schools and hospitals, it reduces their contact with natural environment, such as parks, forests, and riverbank. In his book, *Last Child in the Woods*, Richard Louv coined the phrase “nature deficit disorder” to describe children’s retrieval to indoors due to urbanism (Louv, 2010). A significant discussion on the benefits of nature contact for children is presented by Chawla (2015). Neighbourhood design has the potential to alleviate this problem as it determines how children engage with public places and their level of access to green spaces. Additionally, parents’ perception of a neighbourhood design determines their children’s level of freedom and independent mobility (Smith et al., 2019). These factors, in turn, affect children’s cognitive, emotional, social, and bodily development (Garau & Annunziata, 2020).

As for adults, social isolation is a major public health concern, especially among older people (Alpass & Neville, 2003; Gerst-Emerson & Jayawardhana, 2015; Luo, Hawkley, Waite, & Cacioppo, 2012; Stessman, Rottenberg, Shimshilashvili, Ein-Mor, & Jacobs, 2014). It is even claimed that social isolation is worse for our physical health than smoking 15 cigarettes a day, which makes it “twice as harmful as obesity and as lethal as alcoholism” (Frame, 2017). It has been well established in the literature that mental health problems (including social isolation) are connected to the built environment (Gehl & ebrary, 2011; Halpern, 1995; Srinivasan, O'Fallon, & Dearry, 2003). In fact, several road design guidelines emphasize the role of roads as public spaces that provide opportunities for social interactions (Meyer, 2016; NACTO, 2013; Transportation Association of Canada, 2017). In addition, one of the main goals of the new urban neighbourhood concepts in urban planning is to increase social interactions (Jin, 2010).

Given the limited impact of neighbourhood designs in promoting more livable and sustainable communities and AT, researchers from the University of British Columbia (UBC) and the Canada Mortgage and Housing Corporation (CMHC) developed the SMARTer growth neighbourhood design principles (formerly known as the fused grid). Figure 1.1 depicts the differences between the traditional grid, culs-de-sac, and SMARTer Growth network patterns. The SMARTer Growth principles combine the best characteristics of both the traditional grid and culs-de-sac street patterns, plus many sustainable community planning principles, including:

1) The tranquility and safety of the culs-de-sac and loop street patterns, but with continuous AT routes connecting between dead ends (Grammenos, Craig, Pollard, & Guerrera, 2008; Sun & Lovegrove, 2013);

2) The high connectivity of the grid pattern, but focused on AT network connectivity within neighborhoods while disrupting and focusing vehicular connectivity onto perimeter arterial/collector roads; and

3) The ubiquity of large and small restorative, socially interactive, and natural play spaces within a one-minute walk of every person living and/or working in the neighborhood.

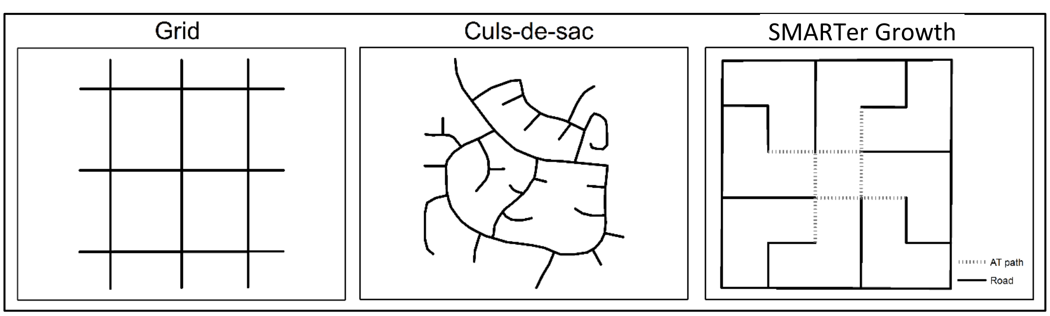

Figure 1.1: Street network patterns

1.2 Motivation

There is a relatively small body of literature relating to the performance of SMARTer Growth neighbourhood design. Most of these studies address individual aspects of the SMARTer Growth's performance such as safety (Sun & Lovegrove, 2013), traffic performance (IBI Group, 2007), and walkability (Frank, L. & Hawkens, 2007). The low number of studies can be attributed to the fact that the SMARTer Growth principles are relatively new, compared to other neighbourhood designs, and have only been implemented partially in Calgary (Saddlestone development). Moreover, the research to date has mainly studied the SMARTer Growth as a street network layout, neglecting the fact that SMARTer Growth is a system-based design that involves many components other than simply a road network layout, including human-scale block sizes, active transport, intersection design, green spaces layout, and land use distribution. Creating a model that can account for the influence of all these factors will provide a more comprehensive evaluation of the SMARTer Growth design.

The research on modelling and evaluation of neighbourhood design in terms of daily travel behaviour has been continuously evolving over the past decades to provide a better understanding of the complexity of neighbourhood design. However, most of the developed models have limited scope as they were aimed to gain further knowledge on a specific aspect of travel behaviour. In addition, many of the proposed models in the literature either only consider walking mode or treat walking and cycling as one mode. Besides, most of the existing work lacks the consideration of psychological factors (e.g. habits), micro-scale built environment characteristics (i.e. current models focus on aggregated zone systems), and the feedback process between people and the built environment. Accordingly, it is necessary to develop a model that appropriately characterize human behaviour and their bounded rationality, accounts for transportation networks and infrastructure, considers land use characteristics and traffic safety, and allows for interactions between different transportation users as well as people-to-built environment interactions.

Additionally, neighbourhood design plays an important role in enhancing (or degrading) our quality of life beyond influencing travel behaviour. For instance, neighbourhood design influences social interactions, residents' sense of community, children's playability, and air and noise pollutions. Thus, there is a need to assemble a suite of tools to evaluate the performance of the SMARTer Growth neighbourhood design for each of these factors.

1.3 Research Goal and Objectives

The over-arching goal of this thesis is to address the challenges of putting the SMARTer Growth neighbourhood design into practices in Canada by providing a better understanding of the influence of neighbourhood design as a system (i.e. not the individual characteristics of neighbourhood design) on travel behaviour and quality of life. This goal will be achieved by pursuing the following main objectives:

1) Develop a state-of-the-art agent-based travel behaviour analysis framework to provide a comprehensive evaluation of the influence of neighbourhood design on travel behaviour;
2) Propose a suite of tools that can be used to evaluate the influence of the SMARTer neighbourhood design on community quality of life; and
3) Demonstrate the developed framework and the suite of evaluation tools via an application to assess the sustainability benefits of the SMARTer Growth design in the city Kelowna.

1.4 Thesis Structure

This dissertation is comprised of seven chapters. Chapter Two summarizes the literature review of the SMARTer Growth neighbourhood design principles, traditional mode choice modelling, agent-based modelling, and reinforcement learning, followed by a discussion on the concept of 'quality of life' and current practices of assessing it. Chapter Three proposes a conceptual framework for an adaptive agent-based model including a discussion on modelling agents' awareness and information learning process, constructing the built environment using GIS data, and generating the synthetic population. Chapter Four outlines the data used in this dissertation and their sources. In addition, the chapter presents a detailed statistical summary of the explanatory variables considered for the agent-based model development and quality of life assessment. Chapter Five discusses the model development and calibration of the various components of the proposed adaptive agent-based model for the city of Kelowna, BC. Chapter Six presents the microsimulation results of travel behaviour and quality of life assessment in Kelowna, BC. Chapter Seven presents the research summary, conclusions, contributions, and embarks on an outlook towards prospective research directions.

Chapter 2 Literature Review

2.1 SMARTer Growth Neighbourhood Design

SMARTer Growth (SG) Neighbourhood Design principles have evolved out of two independent but simultaneous research streams exploring ways to make development patterns and housing forms into more livable and sustainable communities. One stream of research was occurring at UBC (3-way Offset Grid neighborhood design) by Lovegrove et al. (2006), while the second was at the Canada Mortgage and Housing Corporation (Fused Grid neighborhood design) by Grammenos et al. (2008). Their subsequent collaboration resulted in a book on SG design principles (Grammenos & Lovegrove, 2015).

SG begins with a human scale of connecting elements on which green open space, land uses, and transportation systems are superimposed. SG provides the easy orientation and connectivity of a grid road pattern, in combination with the safety and efficiency of an impermeable cul-de-sac development pattern (Grammenos et al., 2008; Sun & Lovegrove, 2013). SMARTer Growth is modular (see Figure 2.1) and at its simplest and most efficient form, consists of four 400-square meter neighbourhood quadrants. Each quadrant consists of a five-by-five grid of walkable, 80 meter blocks. Traffic shortcutting is precluded by a network of ubiquitous corner parks connected by greenways and off-road paths to a larger central community green. These green spaces, which account for approximately 8 percent of the land, render impermeable the local road network, but provide a continuous AT grid network of on-road and off-road routes that allow convenient walking and cycling across the neighborhood in less than five minutes, and, in less time than it takes to drive across (Grammenos & Lovegrove, 2015). Traffic mobility is provided at the periphery of the quadrants using the following spacing: 1) minor collectors at 400 m, 2) major collectors at 800 m, and 3) arterials at 1,600 m; one-way couplets are used for all major perimeter collectors and arterials, which allows for safer 3-way intersections with internal neighborhood roads, as well as safer pedestrian/bike access to perimeter service blocks (e.g. shopping, jobs, health services, etc.), and across to adjacent neighborhoods. All internal local road intersections in the SMARTer Growth module are calmed in favor of low speed, raised pedestrian and bicycle crossings. All other road intersections are controlled with roundabouts. Moreover, approximately 23% of street space that would normally be used in a traditional grid network is reclaimed and used in SG for parks and housing which results in a 30% decrease in total infrastructure cost, including construction, operation, and maintenance costs (IBI Group, 2008).

In summary, SMARTer Growth is composed of several grids built upon the human scale: 1) a continuous pedestrian/bike pathway system of interconnected on/off-road social, green, park, and play spaces; 2) a discontinuous, low-speed local access road grid that serves internal residents, protects pedestrians, and precludes shortcutting; 3) a through mobility grid comprised of major arterial/collector roads for district and regional connectivity arranged in 1-way couplets and controlled by roundabouts; and 4) a service grid overlayed with major, regional services along the perimeter couplets, and with local services (e.g. schools, churches, community centers) along internal local collectors and/or in the central greens. This modular SMARTer Growth Neighborhood design has been demonstrated to support both lower and higher densities, with lower densities (mostly residential) typically in the core, and higher densities (mostly commercial with some residential above) typically along the perimeters, in keeping with conventional urban development planning practices.

Figure 2.1: SMARTer Growth neighbourhood module (Sun and Lovegrove, 2013)

The above SMARTer Growth principles have been investigated in several studies that report on its key features. For instance, Sun and Lovegrove (2013) compared the traffic safety level of five neighbourhood designs (i.e. grid, culs-de-sac, SMARTer Growth, Dutch sustainable road safety patterns, and 3-way offset) using macro-level collision prediction models. The researchers created a total of 45 different neighbourhood test modules to account for different neighbourhood and block sizes. Although the vehicle kilometer travelled (VKT) is arguably an inherited characteristic for each neighbourhood design, the study did control for VKT along with congestion level and socio-demographics to allow for fair and consistent cross-sectional comparisons. By normalizing the impact of density and land use, the study found that the SMARTer Growth neighbourhood design was significantly associated with 30-60 percent fewer road collisions compared to traditional neighbourhood designs (i.e. grid and cul-de-sac).

In addition, CMHC collaborated with UBC researchers to expand on this research and conducted a comparative evaluation of the traffic performance of the Conventional Suburban, Neo-traditional, and SMARTer Growth neighbourhood designs (IBI Group, 2007). The neighbourhood of Barrhaven in Ottawa, ON was selected for this research because it represents a typical suburb in Ottawa with higher than average population density. The street network of the neighbourhood is classified as conventional suburban layout. CMHC developed two design alternatives that represent the Neo-traditional and SMARTer Growth designs. Five land use scenarios were developed to apply for each design of the study area. Traffic volume and modal share for transit and auto modes were first estimated using the city of Ottawa travel demand model developed on EMME/2. Then, Corsim, a microscopic modelling software, was used to estimate delay, level of service and other parameters on each road segment and intersection. The SMARTer Growth neighbourhood design was found to be the most efficient street network in terms of managing traffic flow in/out of the neighbourhood. Moreover, it was found to maintain safer traffic flows on local roads compared to other neighbourhood designs, especially with higher density scenarios.

Jin and White (2012) utilized agent-based modelling to explore the effect of neighbourhood design on local trip patterns such as mode choice, pollution exposure, and social interaction opportunities; the agent-based modelling aspect of this research will be discussed in section 3.3.1. Similar to Sun and Lovegrove (2013), Jin and White developed seven hypothetical neighbourhood designs that represent different layouts. Mode choice models were estimated using multinomial logit formulation based on the random utility maximization framework. In contrast to the study conducted by CHMC, the mode choice models developed in this study accounted for changes in AT trips as well; however, it neglected land use factors. Several parameters were considered in this model related to socio-economic factors (e.g. vehicles per person in a household) and route characteristics (e.g. walking distance within the neighbourhood). The results suggested the SG design promotes the best quality of life in terms of providing high social interaction possibilities, more walking due to shorter distances, and less exposure to harmful air pollution. These benefits were achieved mainly due to the ubiquity and connectivity of the SG design's active transport grid.

Similar to Jin and White (2012), Masoud et al. (2017) utilized multinomial logit mode choice models to explore the influence of fused grid neighborhood design principles on mode choice behaviour in a medium size community for work and non-work trips. This was done by hypothetically retrofitting an existing neighbourhood in the city of Kelowna, BC using the SMARTer Growth design principles. Two design alternatives were developed to show the variability possible in designs that follow SG principles. Although there was small variation in the results, both SG designs showed potential, when compared to the existing neighborhood, to significantly reduce auto use and to significantly increase transit and AT use for work trips.

Together, these studies suggest that the SG neighbourhood design can improve and sustain the quality of life for neighborhood residents, businesses, and visitors in several aspects, including: safer communities, more efficient traffic flow, higher social interaction possibilities, less air and noise pollution, reducing auto use, and increasing the use of transit and AT modes.

However, one significant knowledge gap that remains is the ability to robustly assess SG design impacts on AT mode choice in a reliably empirical manner. Due to computational and methodological limitations, SG research to date has focused on assessing on-road and vehicular traffic impacts. Recent research and computational progress suggest that it is now possible to assess the impacts of non-road components and AT activities related to the system-based approach SG neighborhood design, including SG land use density and mix, green spaces, and off-road pathways.

Therefore, there is an opportunity to provide a more robust assessment of a neighbourhood, including traditional versus SG designs, while accounting for both on and off-road system interactions, and for the feedback process between individuals and the entire built environment within which they live. Moreover, this opportunity would provide the needed additional knowledge to link to quality of life metrics that help define the success of a neighborhood design, and community desirability overall.

2.2 Mode Choice Modelling

Models are used in transportation engineering and other disciplines as one of the most effective ways to simplify complex, real systems; they facilitate increased understanding and analysis. Models also allow us to better predict how a complex system would behave in response to changes, without the need for real life experiments that may be costly, destructive, and/or impractical (Railsback & Grimm, 2012). Discrete mode choice (DMC) models are used to analyze the decision-making behaviour of transportation system users. DMC models predict users' mode choices among discrete alternatives that are collectively exhaustive and mutually exclusive (Koppelman & Bhat, 2006). Mode choice models are conventionally based on the fundamental Random Utility Maximization (RUM) framework. According to the RUM framework, travellers choose a mode that maximizes their utility (benefits) based on their characteristics (e.g. income, sex, etc.) and the attributes of the modes (e.g. travel distance, cost, etc.) (Banister, 1978). In contrast to deterministic utility models, this framework accounts for the analyst's incomplete information on travellers' characteristics, trip attributes, and decision-making circumstances by introducing a random error term to the utility function besides the systematic component as shown in Equation 2-1. The deterministic component is commonly formulated (Equation 2-2), as the additive of three components: 1) characteristics of the individual, 2) attributes of alternative modes, and 3) the interaction between these two components. The random error term in the utility function accounts for the modeller's uncertainty and captures the unmeasured portion of the utility (McFadden, 1986). The assumption about the distribution of the random error term determines the mathematical representation of the model. One of the most common assumptions is that the error term is Independently and Identically Distributed (IID) following the Gumbel (Extreme Value Type I) distribution which eventually lead to the Multinomial Logit (MNL) model formulation as shown in Equation 2-3.

$$U_{im} = V_{im} + \epsilon_{qm}, \qquad 2\text{-}1$$

where:

U_{qm}: utility that individual (q) associates with mode (m),

V_{qm}: deterministic component of the utility of mode (m) for individual (q),

ε_{qm}: random term.

$$V_{qm} = V(X_q) + V(Z_m) + V(X_q, Z_m), \qquad 2\text{-}2$$

where:

$V(X_q)$: characteristics of the individual (q).

$V(Z_m)$: attributes of alternative mode (m),

$V(Z_m, X_q)$: the interaction between the characteristics of individual (q) and the attributes of alternative mode (m).

$$P_{qm} = \frac{e^{(U_{qm})}}{\sum_{m \in C_q} e^{(U_{qm})}}, \qquad 2\text{-}3$$

where:

P_{qm} : Probability of individual (q) selecting mode (m),

U_{qm}: Utility of individual (q) for mode (m),

C_q: Set of alternative modes available for individual (q).

The RUM framework fails to capture the transportation users' lack of information about the attributes of the trip (Banister, 1978; Ben-Akiva, Moshe & Bierlaire, 1999; Koppelman & Bhat, 2006). Consequently, the analyst needs to make some assumptions about the rationality of the travellers. The underlying assumption of the RUM framework is that travellers are overly rational with unlimited knowledge of the available options and make decisions based on extremely complex computations (Ben-Akiva & Bierlaire, 1999). This assumption implies that individuals have consistent and transitive preferences (Ben-Akiva, Moshe E. & Lerman, 1985; Garrow, 2016). Consistent preferences means that decision makers will keep choosing the same mode if faced with the same circumstances, while transitive preferences suggest that if option A is preferred to option B, and option B is preferred to option C, then option A is preferred to option C as well (Ben-Akiva & Lerman, 1985). In addition, the rationality assumption implies that travellers are constantly taking into account all changes that occur to each mode (e.g. price, travel time, wait time) and that they are immediately aware of these changes as they occur (Chorus & Timmermans, 2009).

It can be argued that this overly rational, perfectly predictable behaviour assumption in the RUM framework does not realistically describe a human decision-making process and fails to capture its limitations (Idris, Ahmed Osman, 2013). In other words, the RUM framework describes how travellers would behave in a perfect world, not how they actually do behave (Banister, 1978). Tversky and Kahneman (1974), argue that humans tend to reduce the complexity of decision-making and use simple judgmental operations based on heuristic techniques. These findings suggest that concepts, such as bounded rationality, that do consider cognitive limitations are more appropriate to describe human behaviour. According to the concept of bounded rationality, individuals have limited capacity to access and process information (i.e. limited resources) and rely on simplified thought processes. Hence, they tend to seek a satisfactory decision rather than the optimal one (Acquisti & Grossklags, 2005; Zhang, L., 2006).

Moreover, psychological factors, such as habit, could play a role in influencing the mode choice decision-making process. For example, the Theory of *Repeated* Behaviour proposes that habit is an important factor in determining repeated behaviour (Singleton, 2013). This view is also supported by the Theory of *Interpersonal* Behaviour, which suggests that the intention to do a behaviour is mediated by both contextual situation and habit formation (Galdames, Tudela, & Carrasco, 2011). For instance, a person who always drives to the convenience store would most likely keep doing so, even if the context changes and cycling/walking become as fast as driving. This repeated behaviour occurs because driving to the convenience store for that person is an unconscious, habitual behaviour and will not change without mindful intention. The research question became how to empirically construct a model that included aspects of repeated behaviour and yet allowed for the possibility of mindful intention factors that could influence future changes in behaviour.

All the factors discussed earlier suggest that human decision-making is a complex process that can not be appropriately captured using conventional mode choice modelling. To overcome the aforementioned limitations, researchers developed several extensions to traditional discrete choice models such as the nested logit model (relaxes the independence of irrelevant alternatives, IIA, property) (Berkovec & Rust, 1985), mixed logit model (allows for random taste variation) (Bhat, Chandra R. & Castelar, 2002), and integrated choice and latent variable models (allows for the inclusion of users' attitudes and perceptions) (Ashok, Dillon, & Yuan, 2002). However, no evidence was found in the literature that a statistical mode choice model overcame the limiting awareness problem related to all individuals being immediately and fully aware of changes to the transportation and land use systems as they occur.

Recognizing this complex nature of the transportation mode choice decision making process has led researchers to explore alternative techniques to model it without being limited by mathematical intractability. Over the years, a considerable literature has been developed around utilizing computational techniques in mode choice modelling (Auld et al., 2016; Chen, Peng, Zhang, & Li, 2016; Klugl & Rindsfuser, 2011; Mao, Zou, Xue, Li, & Liu, 2015; McDonnell & Zellner, 2011; Zou et al., 2016); of which Agent-based Modelling has received a lot of attention. Agent-based Modelling research to date has shown the capability to account for human bounded rationality, awareness, and psychological factors that influence mode choice behaviour by using simple rules that can be represented in various forms. A literature review of agent-based modelling is presented in the following section.

2.3 Agent-based Modelling

Agent-based modelling (ABM) is a simulation of the interaction of a collection of entities (agents) with each other and their environment, with these micro-level interactions resulting in an emergence of a macro-level phenomena (Epstein, Joshua M. & Axtell, 1996). Agents are defined as unique and autonomous entities (e.g. travellers) that interact locally with each other and make adaptive decisions affected by their status and the status of other agents and their environment (Railsback & Grimm, 2012). Agents are unique because each agent has its own characteristics such as location, attributes, rules of behaviour, and interaction history (Boero, 2015; Epstein & Axtell, 1996; Railsback & Grimm, 2012). Being autonomous means that agents make independent decisions to pursue their own objectives based on rules that govern their behaviour (Railsback & Grimm, 2012). It is also argued that agents must have the capability to adapt new behaviour based on their own experience. In addition, agents usually do not have global information (i.e. they have imperfect knowledge) (Boero, 2015; Epstein & Axtell, 1996; Macal & North, 2017). A set of topologies or connectedness traits define how and with whom agents can interact, which could be static or dynamic (Macal & North, 2017). Agent-based modelling is considered a multi-level model because it is used to understand the behaviour of the system in response to agents' actions, and at the same time, the behaviour of the agents in response to change(s) in their environment (Railsback & Grimm, 2012).

Agent-based modelling has been utilized in a broad spectrum of applications including the social sciences (Billari, Prskawetz, Diaz, & Fent, 2007; Epstein, J. M., 2002), biology (Folcik, An, & Orosz, 2007; Gorochowski, 2016), and economics (Ma & Leung, 2007). In transportation engineering, Agent-based modelling has been used to study numerous transportation-related phenomena such as hurricane evacuation (Yin, W. H., Murray-Tuite, Ukkusuri, & Gladwin, 2014), traffic congestion simulation (Anantsuksomsri & Tontisirin, 2016), car-sharing (Balac, Ciari, & Axhausen, 2017; Ciari, Balac, & Axhausen, 2016), and driver decision-making processes (Kim, S., Son, Chiu, Jeffers, & Yang, 2016).

2.3.1 Agent-based Mode Choice Models

A number of studies have begun to explore the integration of mode choice modelling with agent-based modelling. Mode choice models are incorporated into the behavioural rules component of agent-based models. These rules can be formalized in numerous ways such as logical statements (i.e. if-then statements) or mathematical functions (Parunak, Savit, & Riolo, 1998), which provide researchers with the flexibility to incorporate various mode choice modelling techniques. For example, McDonnell and Zellner (2011) represented the mode choice behaviour in their agent-based model as a decision to switch between two transportation modes (bus and car) if the increase in travel time exceeds the agents' tolerance. Although this research was useful to evaluate new transportation systems with limited data, it oversimplified the mode choice decision making process and failed to consider factors other than the effect of increasing travel time.

A number of studies have explored incorporating more realistic decision-making processes into their agent-based models. Most of these studies used logical statements that were derived based on machine learning algorithms or fuzzy set theory. For instance, Zou et al. (2016) developed an agent-based model for travel mode choice and departure time that considered bounded rationality to evaluate the impact of various traffic management strategies and policies. Agents in the model gain spatial and temporal knowledge based on their own accumulated travel experience through a Bayesian learning model, then decide whether to search for alternative travel modes and departure times if their perceived search gain exceeds search cost. This search process was modelled using if-then statements that were derived from socioeconomic and demographic variables as well as trip-related information (e.g. travel distance). Subsequently, agents decided whether to switch to the travel mode and departure time identified earlier in the search process, or to make no changes based on another set of decision rules. These rules were also represented as if-then statements that were derived using the JRip machine learning algorithm (Cohen, 1995).

However, their research was limited to study the mode choice behaviour of drivers who switch to public transit only (i.e. metro or bus).

Similarly, in their proposed public traffic demand forecast framework, Chen et al. (2016) represented the human decision-making process as logical statements based on the Belief–Desired–Intention (BDI) model. In BDI, the belief set contained all available mode choices for different scenarios. The desired set contained all available mode choices for the current scenario, where the intention set showed the preferable mode choice for a certain agent. In contrast to Zou et al. (2016), Chen et al.'s framework did not account for human lack of information.

Although the aforementioned studies discussed how their models addressed some of the limitations of conventional mode choice modelling, most of them did not provide an evaluation on how their models performed compared to the conventional techniques. Mao et al. (2015) conducted a study to compare agent-based modelling with equation-based modelling by developing an agent-based model that utilized the same framework used by Zou et al. (2016) and a comparison Multinomial Logit (MNL) model using the same dataset. Three main findings were reported based on this comparison. First, the forecasting performance of the agent-based model slightly outperformed the traditional MNL model. However, the forecasting performance for both models became similar when the dataset was categorized into two sub-groups and separate MNL models were developed for each sub-group. Second, the forecasting precision of the agent-based model increased with sample size while the traditional MNL model precision appeared to be less sensitive to changes in sample size. Finally, the agent-based model was less influenced by 'noisy' (i.e. high variance) data compared to the MNL model.

A case could be made that these three factors (i.e. precision, dataset size, and data noise) are not inherent to agent-based models. Rather, they depend on the algorithm used to generate agent's behavioural rules. For instance, Mao et al. (2015) utilized the JRip, which implements a rule induction learner algorithm called the RIPPER, based on Cohen (1995). RIPPER is known for avoiding overfitting and providing high forecasting accuracy compared to other machine learning algorithms. Thus, different model behaviour is expected if the researchers were to use the same dataset with a different algorithm (e.g. neural network, random forest, etc.) to generate the decision-making rules.

That being said, analysts need to be careful when choosing which algorithm to use to generate the decision-making rules. For example, in contrast to regression modelling that focus on the statistical validity of models, the main focus in rule induction learner algorithms (e.g. RIPPER) is to search for patterns that generalize the data to be able to make accurate future predictions (Johannes Furnkranz & Tomas Kliegr, 2015; Weiss & Indurkhya, 1998). Moreover, being an induction approach implies that these patterns are non-deterministic since infinite sets of patterns could be induced for the same dataset. For further discussion on this topic, see Freitas (2000). Thus, analysts need to be cautious when utilizing such algorithms in mode choice modelling applications where the focus is usually on the policy implications of the models (i.e. model inference and interpretability).

In addition to logical statements, a few researchers attempted to incorporate mathematical functions in agents' behavioural rules. For instance, Jin and White (2012) developed a mode choice agent-based model that represented the human decision-making process as mathematical functions based on the RUM framework. Agents were populated with unique socio-economic characteristics and trip plans according to data obtained from the 2001 household travel survey in Ottawa, ON. In addition, agents were randomly allocated on the map since address information was not available in the dataset. During the first iteration, agents traveled according to their trip plans (i.e. travel destination and mode choice) recorded in the household travel survey. Agents choose travel route based on a customized Dijkstra's shortest path algorithm that accounts for automobile and pedestrian traffic, sidewalks and AT corridors availability, and road user's imperfect knowledge. Agents' mode choice for the following iterations were estimated using an MNL model, where the utility for each mode was expected to change according to an agents' accumulated experience. The utility measure considered in this study were related to the trip (e.g. travel time), socio-economic status (e.g. income), and route characteristics (e.g. traffic volume). For the last measure, the authors used neighbourhood average values based on their assumption that people choose travel modes according to their perceived evaluation of the entire neighbourhood transportation network, not the specific route they choose. While this model accounted for novel characteristics related to travel behaviour such as pedestrian-automobile interactions, it still lacked consideration for human bounded rationality (i.e. awareness, learning) and land use factors (e.g. population and employment densities).

Overall, it would appear that most of the previous studies have focused primarily on using supervised learning techniques to model agents' behavioural rules and overlooked incorporating simple traditional statistical techniques (i.e. MNL), that have been well established in mode choice modelling. In fact, it can be argued that incorporating both, agent-based modelling and traditional statistical techniques can address most limitations of the latter, and thus, maintain the simplicity and interpretability of mode choice models for transportation planners and engineers. However, there are other factors that need to be addressed in this agent-based mode choice modelling research in order to also address its limitations. First, most of the agent-based mode choice models lack the consideration for psychological factors such as habit formation. Second, most of the developed models treat walking and cycling as one mode, instead of studying each one individually. Research on these and other factors are discussed below in more detail.

2.4 Factors Influencing Mode Choice

Other factors that influence individuals' transportation decision making process can be grouped into four sections for discussion, including: socio-economic characteristics (e.g. age, income), built environment (e.g. land use, density, parks), trip specific route characteristics (e.g. number of pedestrian crossings), and social interactions (e.g. pedestrian/car encounters).

2.4.1 **Built Environment**

A considerable amount of literature has been published on the relationship between the built environment and transportation mode choice including automobile, transit, and AT (Frank, Lawrence et al., 2006; Gebel et al., 2005; Khan, M. Kockelman, & Xiong, 2014; Kim, D., Ahn, Choi, & Kim, 2016; Munshi, 2016; Newman & Kenworthy, 1999). While most of these studies provided evidence that the built environment indeed influences mode choice behaviour, there is still a debate regarding the magnitude and statistical significance of different built environment factors (Ding, Wang, Liu, Zhang, & Yang, 2017). For instance, Frank et al. (2006) studied the relationship between built environment, measured by a walkability index, and physical activity. After controlling for sociodemographic variables, the results revealed a significant correlation between higher AT use and living in a "walkable" neighbourhood, characterized by high density, mixed land use, more AT accessible retail, and connected road network. Cervero (2002) explored the effect of the three core dimensions of built environment, known as the "3 Ds" (density, diversity, and design) on mode choice behaviour in Montgomery County, Maryland. The results indicated that the 3 Ds, especially at a trip destination, have low to moderate impact on driving mode choice for work trips. Specifically, the design dimension revealed the most significant negative relationship with driving. Zhang (2004) used the MNL model to evaluate the impact of built environment on Mode choice behaviour in Boston and Hong Kong. The results revealed that built environment variables have a variable degree of influence on mode choice behaviour depending on trip purpose (i.e. work or non-work) and the trip end at which the variable was measured (i.e. origin or destination). Lee (2006) used the directed acyclic graphs method to investigate the relationship between built environment and travel behaviour. The results indicated that low land use mix contributes to captive-driving for work trips. In addition, the results showed that higher job density and regional accessibility are statistically correlated and causally connected to less driving.

The majority of the previous studies that investigated the impact of built environment on mode choice behaviour have used aggregate built environment data at a predefined administrative boundary, such as TAZ (Cervero, 2002; Khan et al., 2014; Lee, 2006; Zhang, 2004). However, using such aggregate data leads to a spatial analytical problem, known in the geographic literature as the modifiable areal unit problem (Páez & Scott, 2004; Zhang, M. & Kukadia, 2005). This problem makes it inappropriate to make statistical inferences and draw conclusions about human behaviour using such data (Ewing & Cervero, 2010). Few studies have investigated capturing built environment variables using different geographic scales. Krizek (2003) divided the Central Puget Sound metropolitan area into 150-m grid cells and then averaged their values over one-quarter mile buffer (walking distance) for each household. Lee et al. (2014) explored the impact of the built environment on mode choice behaviour using two geographic scales: at the TAZ level and over one quarter-mile buffer. The results revealed that the buffer-based built environment measures were more significant and explained more variance than the TAZ-based measures.

2.4.2 **Social Interactions & Personal Security**

While the built environment does not have a direct effect on the content and quality of social interactions, it does increase possibilities of passive contacts — "possibilities that both take on a quality of their own and become important as background and starting point for other forms of" restorative, stress-reducing interactions (Gehl & ebrary, 2011). Appleyard and Lintell (1972) conducted one of the first comprehensive studies to examine the social impact of built environment design in 1972. The study found that there was a link between people-friendly transportation designs and an increase in social interactions among residents. Similarly, Leyden (2003) studied the effect of the built environment on people's social capital (i.e. social networks and interactions). The results indicated that people living in a walkable and mixed-use neighbourhood are more likely to have higher levels of social capital than those living in a car-dependent suburb.

Similarly, social interactions in turn influence transportation travel behaviour. In fact, the concept of "people-attract-people" has been discussed in the urban planning literature for over three decades (Yin, L., 2013). However, the concept and methodology to assess it has only recently become more common in transportation modelling (Dugundji et al., 2011; Páez, 2009). The concept of 'people-attract-people' implies that a higher number of people walking/cycling in a spatial or social network will encourage others to walk/cycle in that network, and vice versa. For instance, Lund (2003) found that the frequency of social interactions is positively and significantly correlated with the frequency of walking trips. In addition, a study conducted by the Mineta Transportation Institute reported that almost two-thirds of the participants (60%) agree or strongly agree that the presence of other pedestrians influences their route choices (Weinstein Agrawal, Schlossberg, & Irvin, 2008).

While the studies presented thus far provide considerable theoretical evidence that social interactions influence travel behaviour, few studies have tested this claim objectively, with robust empirical accuracy, due to data and/or computational limitations. Instead, researchers have been making subjective assumptions about the mechanism and the weight of which social interactions influence travel behaviour. For instance, Jin and White (2012) utilized perceived distance to model the influence of social interactions on route choice, such as people perceive the road to be longer with high car traffic, and shorter with high pedestrian traffic. In addition, they assumed that the neighbourhood average values of encountering other pedestrians or cars influence walking mode choice.

The concept of people-attract-people has also been predicted in other transportation research: safety in numbers and crime prevention through environmental design. Safety in numbers describes the phenomenon that the pedestrian or cyclists' collision rate with motorized vehicles (per-pedestrian/per-cyclist) declines as the number of pedestrians or cyclists increases (Jacobsen, Peter Lyndon, Ragland, & Komanoff, 2015). Many researchers attribute this counterintuitive phenomenon to the change in drivers' behaviour as they encounter more non-motorized users (Elvik & Goel, 2019; Jacobsen, P. L., 2003; Robinson, 2005). For instance, Fyhri et al. (2017) utilized the seasonal variation in cycling frequency in Oslo, Norway to understand the factors contributing to the safety in numbers concept. They found that cyclists' volume is negatively correlated with near-misses and occasions of being overlooked by cars.

Crime prevention through environmental design is based on the idea that "the proper design and effective use of the built environment can lead to a reduction in the fear and incidence of crime, and an improvement in the quality of life" (Crowe, 2000). In particular, a neighbourhood design that facilitates walkability increases natural surveillance "extra eyes on the street" which leads to increased level of safety and security (Foster, Giles-Corti, & Knuiman, 2010). In addition, Wood et al. (2008) found that a higher level of social interactions in a neighbourhood is associated with an increased perception of safety and personal security.

2.4.3 **Traffic Safety**

Numerous studies in the literature have identified traffic safety as a significant factor that influences transportation mode choice behaviour, especially for walking and cycling modes. For instance, Winters et al. (2011) conducted a study to assess the main motivators and deterrents of cycling in Metro Vancouver, BC by surveying 1,402 potential and current cyclists. The results revealed that safety was the most frequently cited factor that influences the likelihood of cycling. Similarly, Handy et al. (2006) found that traffic safety increases the likelihood of walking even if self-selection is controlled. In addition, Aziz et al. (2018a) explored the influence of traffic safety on mode choice behaviour for AT commuting trips using a mixed logit model. They found that improving traffic safety for pedestrians and cyclists (i.e. reducing the number of walk and bike crashes) was correlated with an increase in the likelihood of walking and cycling. While the estimated impact of improving traffic safety on the likelihood of walking and cycling was statistically significant, its magnitude was limited. In addition, Lee (2020) developed an empirical model to predict cyclists' perception of comfort and safety. He found a strong significant correlation between cyclists' perceived level of safety and infrastructure type (i.e. bike lane width and level of separation). In addition, he found that infrastructure type had a predictive effect on perceived level of safety, even more so than adjacent traffic volume and speed.

The chapter that follows presents a learning-based travel behaviour model which utilizes an adaptive learning-based mode choice model that integrates the RUM Theory with reinforcement learning concepts (Idris, A. O., Shalaby, & Habib, 2012) . Therefore, the following section provides a brief summary of the literature review relating to reinforcement learning.

2.5 Reinforcement Learning (RL)

Reinforcement learning is a computational approach to learning through interactions in which a learner aims to maximize its rewards by learning from experience (i.e. learn by trial and error), while having no prior information about the environment (Sutton, Richard S. & Barto, 1998). The roots of reinforcement learning go back to the work of Edward Thorndike on learning by trial and error and his law of effect which states that "actions that lead immediately to pleasure are remembered and repeated, eventually fossilizing into habits, whereas actions leading to pain are suppressed or avoided" (Thorndike, 1911). At each stage, the learner observes the environment, takes an action, and then receives immediate evaluation of its action as negative or positive rewards, see Figure 2.2. The learner in a reinforcement learning system is usually referred to as an agent which is an entity (e.g. a traveller) that perceives the environment and then acts to achieve a goal, while the environment is the space in which the agent operates and interacts (e.g. built environment, pathways) (Schwartz, 2014). This previous research confirms a good fit between reinforcement learning models and observed human behaviour, subject to an acceptable modeling framework.

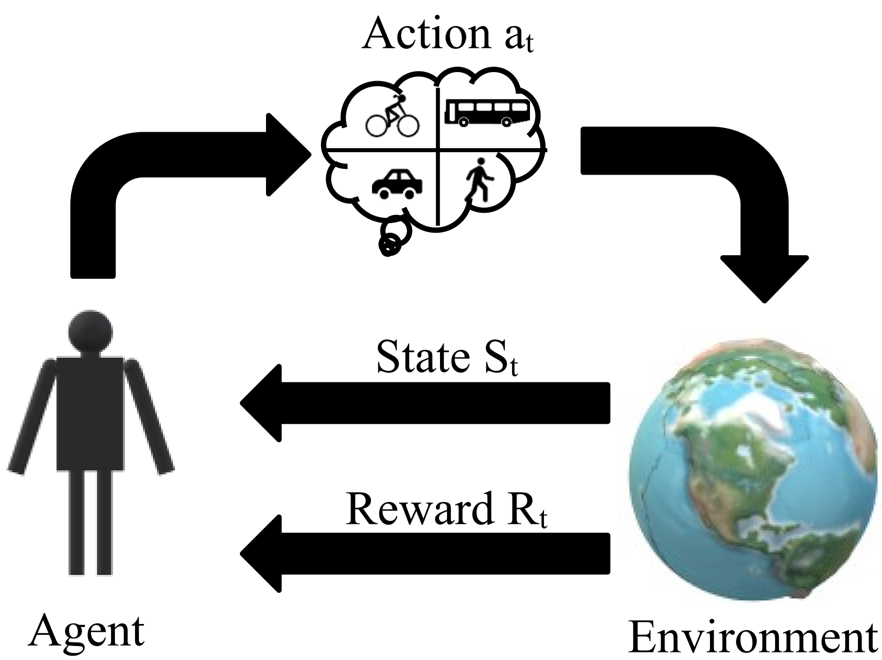

Figure 2.2: Reinforcement learning framework

2.5.1 Markov Decision Process

Reinforcement learning systems are usually modelled under the framework of Markov Decision Processes (MDPs) which defines a transition model for states, actions, and rewards in an uncertain environment (Russell & Norvig, 2010; Schwartz, 2014; Sutton & Barto, 1998). In an MDP, the interaction between an agent and the environment occur sequentially over discrete time steps (i.e. t=0, 1, 2, 3, ...). At each time step, the agent perceives the environment as state ($s_t \in S$) and based on this state, the agent selects an action ($a_t \in A$). In the following time step (t+1), the agent receives a numerical reward ($r_{t+1} \in R$) and the environment makes a transition to state (s_{t+1}). The sequence of the agent selecting an action, receiving a reward, and transitioning to a new state creates a trajectory that can be represented as $(s_0, a_0, r_1, s_1, a_1, r_2, s_2, a_2, r_3, \ldots)$. Since sets S, A, and R have finite discrete elements, the random variables $r_t$and s_t have a discrete probability distribution that only depends on the state and action at time step (t). Thus, the probability of transitioning to a new state (s') and receiving reward (r) after making action (a) in state (s) can be expressed as (Sutton & Barto, 1998):

$$p(s', r \mid s, a) = Pr\{S_t = s', R_t = r \mid S_{t-1} = s, A_{t-1} = a\}. \tag{2-4}$$

In summary, a reinforcement learning is said to satisfy the Markov assumption if the "future is independent of the past, given the present" (Russell & Norvig, 2010).

2.5.2 **Reinforcement Learning Elements**

In addition to the agent and the environment, reinforcement learning consists of three sub-elements: 1) policy, 2) reward signal, and 3) value function (Sutton & Barto, 1998). First, policy defines the actions an agent takes at each state of the environment (i.e. the sequence of actions that an agent will take at each state of the system). A policy can be either deterministic or stochastic. A deterministic policy specifies uniquely which action to take at each state. For instance, if an agent follows deterministic policy π, then $A_t = \pi(s)$ where (A_t) is action at time (t) and $\pi(s)$ is a mapping function from states to actions for all s ∈ S and $\pi(s) \in A$. On the other hand, if an agent follows stochastic policy (π), then the action to be taken in state (s) is probabilistically determined as a conditional probability $\pi(a|s)$ of $A_t = a$ in state (s) (Sugiyama, 2015).

The second sub-element of a reinforcement learning system is the reward signal which implicitly defines the goal of the system. A reward signal is a negative or positive value that an agent receives after taking an action in a given state to indicate what is good or bad now (i.e. just for the current state). For example, if the system goal is to assess walkability, then the reward signal would be a positive value for the act of walking in the current state.

In contrast to a reward signal, a value function determines what is good or bad in the long-term based on an agent's actions and resulting reward signals over many states; an agent's objective is to optimize their value function (i.e. maximize cumulative rewards) across all assumed states (Sutton & Barto, 1998). In other words, the value function is the mechanism used by an agent to update its knowledge. A value function is usually expressed in terms of the expected return when following policy (π) starting from state (s). In the simplest form, expected return can be calculated as the sum of future rewards $G_t = R_{t+1} + R_{t+2} + \cdots + R_T$ along trajectory $h = [s_1, a_1, \dots, s_T, a_T, s_{T+1}, a_{T+1}]$. This approach is most appropriate in applications where there is a terminal state followed by a new episode that starts independently of the previous one. However, in applications with continuing tasks (i.e. $T = \infty$), expected return is calculated as cumulative discounted reward $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$, where (γ) is a discount rate for future rewards (i.e. the immediate reward is preferred over future rewards), $0 < \gamma \leq 1$. Under this assumption, the state-value function of state (s) when following policy (π) can be mathematically expressed as the following:

$$v_\pi(s) = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,|S_t = s\right], \qquad \text{2-5}$$

where $\mathbb{E}_\pi$ is the expected value of a random variable given that the agent follows policy (π). Similarly, the action-value function of taking action (a) in state (s) and following policy (π) afterward can be expressed as (Sutton & Barto, 1998).

$$q_\pi(s,a) = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}\,|S_t = s, A_t = a\right]. \qquad 2\text{-}6$$

2.5.3 The Exploration-Exploitation Dilemma

One of the challenges in RL is the trade-off between exploitation and exploration, which is usually illustrated in the RL literature through the multi-armed bandit (MAB) problem. MAB was introduced by Robbins (1952) where a gambler facing multiple slot machines must decide which arms to pull to maximize their total rewards given their limited resources. To maximize expected rewards, one might tend to exploit the actions (i.e. bandits) that have accumulated the most rewards based on their experience. However, this habitual approach risks missing opportunities to explore emerging and/or higher value actions that will result in accumulating even higher rewards. On the other hand, too much exploration may not be of practical benefit as it will not enable agents to apply what they have learned from their experience (Sugiyama, 2015; Sutton, R. S., 1999; Sutton & Barto, 1998).

There are various methods to resolve this exploitation-exploration dilemma; two common methods are the 'ϵ-greedy' selection and 'soft-max' selection. For the ϵ-greedy selection, an agent selects the best actions most of the time, but occasionally picks another action at random without taking into account the expected reward for each action (i.e. all actions have identical probabilities). The soft-max selection method tweaks the ϵ-greedy method by assigning greater probabilities for actions with higher expected reward (Poole & Mackworth, 2010). The probability of each action can be estimated using the Boltzmann distribution as shown in Equation 2-7 (Abdulhai & Kattan, 2003):

$$P_a = \frac{e^{\frac{Q_t(a)}{\tau}}}{\sum_{b=1}^{n} e^{\frac{Q_t(b)}{\tau}}}, \tag{2-7}$$

where:

P_a: probability of selecting action a,

Q_t: the value of action a,

τ: temperature parameter.

The temperature parameter is a positive parameter that determines the extent to which actions with different expected rewards vary in their selection probability. It is usually determined via the calibration process. As the temperature parameter, τ, approaches zero, the soft-max selection policy becomes greedy (i.e. always selects the highest reward action).

2.6 Quality of Life – Objective/Subjective Measures

No standard published definition for 'quality of life' (QoL) was found in the literature, due in large part to its historically abstract references. However, many researchers argue that it is a multidimensional construct of interacting objective and subjective dimensions (Bowling et al., 2003; Lawton, 1991; Lee, Richard J. & Sener, 2016), with Lee and Sener (2016) arguing QoL can be classified into four categories: 1) objective, 2) subjective, 3) combination of objective and subjective, and 4) domain specific. QoL in its simplest form can be defined as "how well we are doing, and how well things are going for us" (Ferkany, 2012). At the opposite extreme, the WHO (World Health Organization, 1997) has defined QoL as "individuals' perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards and concerns. It is a broad ranging concept affected in a complex way by the person's physical health, psychological state, level of independence, social relationships, personal beliefs and their relationship to salient features of their environment". The question then becomes how to assess QoL, and thus the success of a neighborhood's design (e.g. SG).

Given that QoL covers a wide array of life domains, several indicators and indices have been proposed to measure it. For instance, Poortinga et al. (2004) proposed a list of 22 indicators based on an extensive literature review of human values and wellbeing in regard to sustainable development, as shown in Table 2.1. The list includes indicators related to, but not limited to, social aspects (e.g. partner and family, social relationships, and social justice), health, safety, security, privacy, freedom, environmental quality, spirituality, materialism (e.g. money/income and Material beauty), access to nature, education, and leisure. The indicators can be used to estimate the change in people's quality of life by constructing a multi-attribute evaluation matrix given predefined weights for each indicator.

Table 2.1 Quality of life Indicators as proposed by Poortinga et al. (2004)

Indicator	Description
Aesthetic beauty	Being capable of enjoying culture and nature beauty.
Challenge/excitement	Facing challenges and experiencing exciting things.
Change/variation	Having various experiences in life.
Comfort	Having an easy and convenient life.
Education	Having access to good training and education.
Environmental quality	Having access to clean water, air, and soil.
Freedom	Having the right to act and speak freely.
Health	Having a good health and being able to access adequate health services.
Identity/self-respect	Being able to develop a unique identity.
Leisure time	Having a good work/life balance.
Material beauty	Owning nice possessions.
Money/income	Having sufficient income to make ends meet and live a pleasant life.
Nature/biodiversity	Having access to natural landscapes and parks.
Partner and family	Having an intimate partner and stable family relationships.
Privacy	Being able to seclude from others.
Safety	Being protected from accidents and criminality.
Security	Feeling cared for by others.
Social justice	Having the same rights, responsibilities, and possibilities as others in the society.
Social relations	Being able to make social interactions and connect with family, friends, and colleagues.
Spirituality/religion	Being able to freely practice spirituality and/or religion.
Status/recognition	Being valued by others.
Work	Being able to find employment equitable opportunities with adequate working conditions/

Similar to Poortinga et al. (2004), Felce and Perry (1995) proposed a QoL model that incorporates objective and subjective dimensions, as well as a new dimension that captures personal autonomy of individuals' values and preferences across domains, In particular, their model accounts for 1) physical wellbeing, 2) material wellbeing, 3) social wellbeing, 4) development and activity, and 5) emotional wellbeing, as shown in Table 2.2.

Table 2.2 Quality of life Indicators as proposed by Felce and Perry (1995)

Domain	Indicator
Physical wellbeing	Health, fitness, mobility, and personal safety.
Material Wellbeing	Finance income, stability/tenure, housing quality, neighbourhood, security, transport, possessions, and meals/food.
Social Wellbeing	Interpersonal relationships, acceptance and support, activities and events, relatives, friends and social life, family/household life, and community involvement.
Development and Activity	Competence/independence, job, homelife/housework, leisure/hobbies, education, choice/control, and productivity/contribution.
Emotional Wellbeing	Positive affect, status respect, satisfaction, fulfillment, self-esteem, faith/belief

These previous measures come from the sociology literature, as do most quality of life measures, which is not surprising since the concept 'quality of life' evolved from research on social indicators (Ferriss, 2004). Few researchers have explored developing urban and/or transportation quality of life measures.

For urban-specific measures, the Dutch government have identified six sustainability principles related to improving quality of life: 1) health, climate resistance, mobility, circularity (i.e. recycling and reusing), energy, and social economy. Serag El Din et al. (2013) identified seven domains of quality of life: 1) environmental, 2) physical, 3) mobility, 4) social, 5) psychological, 6) economical, and 7) political. In addition, Bonaiuto et al. (2006) presented more compact urban quality of life measures with four domains: 1) architectural and town-planning (i.e. peoples' perception of space and green areas), 2) socio relationship (i.e. social interactions), 3) functionality (i.e. welfare, recreational, commercial, and transportation services), and 4) Contextual (i.e.

psychological wellbeing). Table 2.3 presents a summary of the three aforementioned QoL models (a complete list of each Urban QoL model is presented in Appendix A). Together these studies provide important insights into some of the critical/universal QoL indicators including: 1) sustainable transportation 2) multi-modal connectivity, 3) green public areas, 4) compact, mixed land use neighbourhood with close proximity to services, 5) healthy urban living, 6) social interactions, and 7) job accessibility.

Table 2.3 A Summary of the Urban QoL Indicators

Indicator	Dutch	Serag El Din et al. (2013)	Bonaiuto et al. (2006)
Compact, mixed land use neighbourhood with close proximity to services	✓	✓	✓
Affordable housing	✓	✓	
Mix housing types	✓	✓	
Healthy Urban Living	✓	✓	✓
Long-term community plan	✓	✓	✓
Green public spaces	✓	✓	✓
Job accessibility	✓	✓	✓
Sense of Community	✓		✓
Sustainable transportation	✓	✓	✓
Multi-modal connectivity	✓	✓	✓
Traffic safety	✓	✓	
Shared mobility	✓		
Well-defined street hierarchy	✓	✓	
Preserving heritage and historic sites	✓	✓	
Social interactions	✓	✓	✓
Maintenance management		✓	✓
Security and tolerance	✓	✓	✓
Gender Equity and social justice	✓	✓	
Privacy	✓	✓	✓
Integrated urban governance	✓	✓	

Indicator	Dutch	Serag El Din et al. (2013)	Bonaiuto et al. (2006)
Public consultation	✓	✓	
School services	✓		✓
Social-care services	✓		✓
Sport services	✓		✓
Waste Management	✓	✓	
Energy saving	✓	✓	
Biodiversity	✓	✓	

As for transportation-related QoL, Jamal (2019) identified seven QoL indicators based on an extensive literature review including 1) energy saving, 2) air quality, 3) health, 4) road safety, 5) congestion and travel time, 6) noise, and 7) equity. In addition, Lee and Sener (2016) proposed a framework for the interactions of transportation planning and quality of life. In particular, their framework linked three components of the transportation system (vehicular traffic, mobility/accessibility, and the built environment) to four domains of quality of life (physical, mental, economic, and social well-being). Likewise, Wey and Huang (2018) identified 18 indicators to be related with three dimensions of quality of life as follows:

1. *Environment:* GHG emissions, land consumption in transportation, energy use, air and noise pollution, active transportation use, and land use density.
2. *Economy:* infrastructure, government investment on transportation, congestion level, household expenses on transportation, mix land use, and intelligent transportation systems (ITS).
3. *Society:* diversity of the transportation system, quality of the transportation for disadvantaged groups (e.g. elderly citizens and people with disabilities), safety, health impact, satisfaction.

Table 2.4 presents a summary of these transportation QoL indicators. Five indicators were common in the previous studies including: 1) air quality, noise pollution, transit and non-motorized modes, road safety, and congestion and travel time.

Table 2.4 A Summary of the Transportation QoL Indicators

Indicator	Jamal (2019)	Lee and Sener (2016)	Wey and Huang (2018)
Air quality	✓	✓	✓
Noise pollution	✓	✓	✓
Transit and non-motorized modes	✓	✓	✓
Energy use	✓		✓
Road Safety	✓	✓	✓
Density and mixed land use		✓	✓
Congestion and travel time	✓	✓	✓
Transit accessibility		✓	✓
Transportation cost			✓
Government funding			✓
Equity	✓		✓
Satisfaction			✓

QoL evaluation tools have also been previously identified and/or developed by researchers at the Sustainable Transport Safety lab at the University of British Columbia Okanagan (Jamal, 2019; Ovi, 2020). In particular, eight tools and indicators are considered and discussed below, including: 1) i-THRIVE , 2) air quality, 3) noise pollution, 4) walkability, 5) bikeability, 6) transitability, 7) playability, and 8) social interactions. Table 2.5 presents a summary of the QoL evaluation tools.

Table 2.5 STS Identified QoL Evaluation Tools

Tool	Reference	Methodology
i-THRIVE	(Masoud, 2015)	An excel based tool that was developed based on the theoretical foundations of the Peel Healthy Development Index and the Sustainable Transport Safety Principles. The i-THRIVE score is calculated by summing the points achieved for each of the i-THRIVE metrics.
Air Quality	(Rahman & Idris, 2017)	Emissions are estimated by multiplying emissions factors by vehicle kilometres travelled (VKT) on each road segment.
Noise Pollution	(Khalil, 2015)	Noise population is estimated using the Ontario Ministry of Transportation traffic noise model which is a function of traffic composition, volume, and speed.
Walkability	(Frank et al., 2009)	The sum of the z-score of four variables at the block group level: 1) intersection density, 2) residential density, 3) retail FAR, and 4) land use entropy.
Bikeability	(Winter et al., 2013)	Bikeability is computed by first creating 10m grid-cell raster surfaces for 1) cycling route density, 2) cycling route separation level, 3) connectivity of cycling friendly, 4) topography, and 5) destination density. Then, each surface was reclassified to deciles with a scale from 1 to 10. Finally, the bikeability index for each grid-cell is computed by summing the score of the five components.

Tool	Reference	Methodology
Transitability (i.e. access to transit service)	(Foda and Osman, 2010)	Transitability is calculated using the Stop Coverage Ratio Index (SCRI) which equals to the 400 m pedestrian network buffer divided by the 400 m circular buffer around the stop.
Playability	(Kurka et al., 2015; Lambert, Vlaar, Herrington, & Brussoni, 2019; Page, Cooper, Griew, & Jago, 2010; Waygood, Friman, Olsson, & Mitra, 2020)	Subjectively evaluated based on key elements of the built environment that have been identified to be associated with children playability, including: 1) destinations, walkability, traffic safety, green space, and residential density.
Social Interactions	(Appleyard & Lintell, 1972; Jin, 2010)	Number of potential encounters of pedestrians and cyclists.

2.6.1 **I-THRIVE (Health & Safety)**

The Interactive Sustainable Transport Safety/Healthy Development Index Valuation (i-THRIVE) is an MS Excel-based tool that has been developed to help community planners and engineers in assessing the sustainability benefits of developing/retrofitting transportation and land use designs of a neighbourhood (Masoud, 2015). The theoretical foundations of the tool have been relied on heavily, but modified slightly from the Peel Healthy Development Index (Dunn, Creatore, Peterson, Weyman, & Glazier, 2009) and the Sustainable Road Safety principles (Wegman, Aarts, & Bax, 2008). The tool is accordingly divided into two components: healthy development and sustainable transport safety.

The healthy development component consists of seven elements including density, 2) service proximity, 3) land-use mix, 4) street connectivity, 5) road network and sidewalk characteristics, 6) parking, 7) aesthetics and Human Scale. Each element is further broken down into quantifiable measures, as shown in Table 2.6.

The STS component consists of five elements including: 1) functionality, 2) predictability, 3) homogeneity, 4) forgivingness, and 5) state awareness. The STS principles were proposed in 1992 by the Dutch Road Safety Research Institute with two goals to prevent road collisions by decreasing the risk of human errors and, 2) to reduce the severity of road collisions, if any, to a level that the human body can tolerate (Wegman et al., 2008). Similar to the healthy development component, each element of the STS principles is further broken down into quantifiable measures and scores, as shown in Table 2.6. The first element of the STS principles is functionality, which aims to create clear road classifications according to their traffic functions. Thus, street layout should be designed to serve one function only, such as providing access for local roads and providing high mobility for arterial roads.

The second element, predictability, aims to develop recognizable road environment by including distinguishable characteristics (e.g. road surface and edge marking) for each road category; thus, the road user will be able to predict the speed, acceptable maneuvers, and type of road users.

The third element, homogeneity, aims to separate road users that have high variance in speed, mass, and direction. For example, cyclists should be separated from high-speed vehicles and heavy traffic volume streets. If separating cyclists and motorists is not possible (i.e. limited right of way), then the speed need to be reduced to minimize the VRUs injury risk.

The fourth element is forgivingness which aims to provide a road environment that minimizes the negative consequences of driver errors. Forgiving road design measures include, but are not limited to, rumble strips, medians, and wide shoulders.

The last element is state awareness which aims to encourage the inclusion of intersection design that reduces drivers' task demand, such as 3-way intersections, and roundabouts. The bulk of research evidence suggests that roundabouts and 3-way intersections provide safer environment for all road users (Elvik, 2003; Lovegrove & Sayed, 2006; Tanner, 1953).

Table 2.6 The i-THRIVE Metrics and Scores

Element	Metric
Density	Residential density
	Floor-area ratio
Service proximity	Proximity to services
	Proximity to transit
	Proximity to employment
Land-use mix	Heterogeneity of land use mix
	Heterogeneity of building mix
	Mixed housing types
Street Connectivity	Intersection density
Road network and sidewalk characteristics	Traffic Calming
	Speed Control / Pedestrian Priority
	Sidewalks and buffer strips
	Cycle friendly design
	Lighting
Parking	Unbundled & Shared parking
	Parking price and restrictions
	Parking location and alleys

Element	Metric
Aesthetics and human scale	Building height to street width ratio
	Setbacks and street walls
	Tree placement and characteristics
Functionality	Functional classification
	Access Management on collector roads
Predictability	Distinguishable design characteristics
Homogeneity	Road users homogeneity
Forgivingness	Forgiving road design measures
State Awareness	Reducing motorists task demand
	Reducing cyclists task demand

2.6.2 **Air Quality (GHG & Particulates)**

In addition to GHG emissions, the transportation sector is a major contributor of other air pollutants such as particulate matter, carbon monoxide, nitrogen oxide, and volatile organic compounds (Xia et al., 2015). Passenger vehicles account for a large sum of the total transportation related emissions in Canada including 4% of particulate matter, 21% of nitrogen oxide, and 51% of volatile organic compound emissions (Environment and Climate Change Canada, 2017). A number of epidemiologic investigations have provided strong evidence that traffic-related air pollution exposure is associated with human health effects including increased risk of coronary heart disease, chronic bronchitis, and asthma attacks (Gan et al., 2011; Han & Naeher, 2006; Künzli et al., 2000). In addition, Tsai et al. (2010) found that traffic-related air pollution exposure is associated with cardiovascular mortality. In fact, a Coroner's court in London, UK just recently, in an unprecedented decision, ruled that air pollution (specifically, nitrogen dioxide and particulate matter) contributed to the death of a nine-year girl, Ella Kissi-Debrah, who passed away in 2013[1].

Numerous studies have been conducted to assess the impact of the built environment on transportation-related emissions (Derrible, Saneinejad, Sugar, & Kennedy, 2010; Duncan, Nadella, Giroux, Bowers, & Graham, 2017; Mahendra, Bowen, Simons, & Adler, 2012; Rahman, 2016; Tiwari, Cervero, & Schipper, 2011; VandeWeghe & Kennedy, 2007). There is a great Dutch case study for the Central Business District (CBD) of The Hague, which has been totally closed to private auto traffic and rebuilt as a pedestrian/transit/bike-only, car-free zone due to higher than permitted air pollution indicators (Reurings, 2010). A common approach for estimating transportation-related emissions is utilizing emission factors (EF) to calculate total traffic emissions based on vehicle kilometres travelled (VKT), as shown in Equation 2-8 (Rahman & Idris, 2017).

$$Emissions = VKT \times EF. \tag{2-8}$$

Table 2.7 presents GHG emission factors which were extracted from BC Community Energy and Emissions Inventory (BC Ministry of Environment, 2014). In addition, Table 2.8 presents (BC Ministry of Environment, 2014) other traffic air pollutants' emission factors which were obtained from the United States Environmental Protection Agency's Motor Vehicle Emission Simulator (MOVES) (Cai, Burnham, & Wang, 2013).

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[1] Merali, F. (2020, December 17). In landmark decision, coroner rules air pollution contributed to nine-year-old girl's death in the U.K. | CBC News. Retrieved December 18, 2020, from https://www.cbc.ca/news/world/coroner-rules-air-pollution-contributed-to-young-girls-death-1.5845117

Table 2.7 GHG Emission Factors

Vehicle type	Fuel	No. of Vehicles	Average VKT	CO_2 (eq. ton)	EF (kg/km)
Small Passenger Cars	Hybrid	58	21,100	144	0.118
	Gasoline	25,125	16,600	89,728	0.215
	Diesel	682	23,900	2,913	0.179
Large Passenger Cars	Hybrid	243	25,300	776	0.126
	Gasoline	12,350	16,500	52,202	0.256
	Diesel	123	14,500	440	0.247
Light Trucks, Vans, SUVs	Hybrid	118	26,400	612	0.196
	Gasoline	32497	20,100	212,846	0.326
	Diesel	970	19,800	8,190	0.426
	Other	120	11,700	365	0.260

Table 2.8 Other Air Pollutant Emission Factors

Vehicle type	Fuel	Emissions Factors (kg/km)				
		VOC	CO	NO_x	PM_{10}	$PM_{2.5}$
Passenger Cars	Gasoline	8.6×10^{-05}	2.2×10^{-03}	1.5×10^{-04}	4.9×10^{-06}	4.5×10^{-06}
	Diesel	5.2×10^{-05}	9.8×10^{-04}	4.2×10^{-04}	1.4×10^{-05}	1.3×10^{-05}
Light Trucks, Vans, SUVs	Gasoline	1.7×10^{-04}	3.9×10^{-03}	3.5×10^{-04}	8.6×10^{-06}	7.9×10^{-06}
	Diesel	1.6×10^{-04}	1.0×10^{-03}	1.5×10^{-03}	5.6×10^{-05}	5.5×10^{-05}

2.6.3 **Noise Pollution**

Noise pollution is a major concern for many urban areas. Gandelman et al. (2012) suggested that eliminating noise pollution significantly improves individuals' leisure and social life satisfaction. In addition, epidemiologic studies indicate that noise exposure can induce annoyance, sleep disturbance, reduction in children's cognitive ability, hearing impairment, hypertension, and ischemic heart diseases (Öhrström & Skånberg, 2004; Passchier-Vermeer & Passchier, 2000; World Health Organization, 2011).

WHO has established noise level guidelines of maximum 55 A-weighted decibel levels (dBA) during daytime and 45 dBA during nighttime (World Health Organization, 1999). A study conducted by Toronto Public Health found that the average noise levels in Toronto, ON in 2016 were around 63 dBA, of which 60% were attributed to traffic noise (Drew et al., 2017). The study also found that over 60% of residents during daytime and 92% of residents during nighttime are exposed to traffic noise levels above 55 and 45 dBA, respectively. In addition, they found that residents in areas with low-income households are more likely to experience high noise levels compared to the rest of the population. Similarly, an environmental equity assessment in Montreal, QC revealed that low-income and visible minority groups are more likely to inhabit a neighbourhood with a higher than average noise level during the night (Carrier, Apparicio, & Séguin, 2016).

Traffic noise is a complex phenomenon that is influenced by several factors including traffic speed, volume and composition, road surface, meteorological factors, ground surface, tire type, etc., most of which are country specific (Garg & Maji, 2014). As a result, several noise forecasting models have been developed around the world. In Canada, the Ontario Ministry of Transportation proposed a statistical traffic noise model (Khalil, 2015) that accounts for traffic composition, volume, and speed, as illustrated in Equation 2-9 (Khalil, 2015).

$$L_{eq} = 42.3 + 10.2 \times \log(V_C + 6 \times V_T) - 13.9 \times \log(D) + 0.1S, \qquad 2\text{-}9$$

where L_{eq} is the one-hour equivalent sound level at a point of reception, V_C is the light-vehicle traffic volume per hour, V_T is the heavy-vehicle traffic volume per hour, D is the distance from the road to the observation point, and S is the average traffic speed (km/hr).

2.6.4 **Walkability**

Up till the end of the twentieth century, the primary focus of transportation (traffic) engineers has been on utilizing the transportation right of way (ROW) for motorized modes. On the other hand, including pedestrians in the transportation planning process is only a recent addition (Lo, 2009). With this addition, the term "walkability" has emerged as a new area of research that aims at identifying metrics of the level to which the built environment, including transportation ROW, is walking friendly.

A number of approaches have been previously proposed to measure walkability (Dobesova, 2012; Frank, L. D. et al., 2009; Krambeck, 2006; Stockton et al., 2016). A common theme between most of the proposed walkability indices is that they try to capture three components of the built environment: 1) network connectivity, 2) residential density, and 3) land use diversity. The most widely used walkability index was proposed by Frank et al. (2009) for a quality of life study. The index is a function of four components as follows:

- *Net residential density:* the number of dwelling units per land area of residential block groups.
- *Retail floor area ratio:* the floor area footprint of a retail building divided by the land lot area.
- *Intersection density:* the number of intersections in the walking network per block group area.
- *Land use mix:* measured in entropy score of five land use types: residential, retail (excluding big box stores), entertainment, office, and institutional.

The four variables were then normalized using z-score. Finally, the walkability index for each block group was calculated as the sum of the z-scores of the four components as shown in Equation 2-10.

$$\text{Walkability Index} = (2 \times \text{z-intersection density}) + (\text{z- residential density}) + (\text{z- retail floor area ratio}) + (\text{z-land use entropy}). \quad \text{2-10}$$

2.6.5 **Bikeability**

Similar to walkability, bikeability refers to the extent to which the urban built environment is cycling friendly. However, the development of a bikeability index has received relatively lesser attention than walkability. Nevertheless, few researchers have proposed a bikeability index (Arellana, Saltarín, Larrañaga, González, & Henao, 2020; Emery, Crump, & Bors, 2003; Harkey, Reinfurt, Knuiman, Stwetart, & Sorton, 1998; Winters, Brauer, Setton, & Teschke, 2013), of which the index developed by Winter et al. (2013) was the most cited and widely used. This index measures bikeability based on metrics of five components: 1) cycling route density, 2) cycling route separation level, 3) connectivity of cycling friendly streets, 4) topography, and 5) destination density. The index value is computed by first creating a high-resolution surface of 10m grid-cell raster in ArcGIS for each of the five components, as follows:

- *Cycling route density:* the line density of designated cycling facilities within a 400 m radius circular buffer of each grid-cell. The resulted values were then converted to the length of designated cycling facilities within a 400m radius buffer.
- *Cycling route separation level:* A 200m buffer around physically separated cycling facilities.
- *Connectivity of cycling friendly streets:* the point density of all intersections that are connected to at least one cycling friendly link (i.e. local road and designated cycling facility) within a 400m radius circular buffer of each grid-cell. The resulted values were then converted to the number of intersections within a 400m radius buffer.

- *Topography:* the value of the maximum slope between each grid-cell and its neighbouring grid-cells using a Digital Elevation Model.
- *Destination density:* the point density of potential cycling friendly destinations within a 400 m radius circular buffer of each grid-cell. Cycling friendly destinations are defined as parcels with either of the following land uses: neighbourhood commercial, education, entertainment, and office.

Second, each surface was reclassified to deciles with a scale from 1 to 10, where 1 is least cycling friendly and 10 is the most cycling friendly. Finally, the bikeability index for each grid-cell is computed by summing the score of the five components as shown in Equation 2-11.

$$\begin{aligned} \text{Bikeability Index} = {} & (\text{cycling route density}) + (\text{cycling route separation level}) \\ & + (\text{connectivity of cycling friendly streets}) \\ & + (\text{topography}) + (\text{destination density}). \end{aligned} \tag{2-11}$$

2.6.6 **Transitability**

Public transit is a critical service that provides a more affordable alternative mode of transportation to the public, especially disadvantaged groups (Zuo, Wei, & Rohne, 2018). In addition, public transit is widely viewed as a mean to alleviate traffic congestion, reduce GHG emissions, and promote healthier lifestyles (Wang, K. & Woo, 2017; Zuo et al., 2018). Most transit users start their trips as pedestrians or cyclists (Bhat, Chandra R., Guo, Sen, & Weston, 2005) which emphasizes the importance of evaluating the accessibility of transit stops using actual pedestrian and cyclist networks. To address this point, Foda and Osman (2010) proposed the Stop Coverage Ratio Index (SCRI) to estimate transit stops access coverage. The SCRI for a transit stop can be calculated as the 400 m pedestrian network buffer divided by the 400 m circular buffer around the stop as shown in Equation 2-12.

$$SCRI = \frac{Transit\ Stop\ Network\ Buffer}{BTransit\ Stop\ Circular\ Buffer}. \qquad 2\text{-}12$$

While the index was proposed as a measure of pedestrians' accessibility to transit, it is important to account for cyclists' accessibility as well. The integration of cycling and public transit, also known as bike and ride, can minimize total travel time and thus become a strong competitive alternative to driving (Martens, 2004). The SCRI can be easily modified to account for cyclists' accessibility by changing the transit stop catchment buffer distance. While there is no agreement on the cycling threshold distance to transit, the literature indicates that it ranges from 1.2 to 5km with an average of 3 km (Lee, Jaeyeong, Choi, & Leem, 2016; Rietveld, 2000; Zuo et al., 2018; Zuo, Wei, Chen, & Zhang, 2020).

2.6.7 **Playability**

The Canadian 24-hour movement guidelines identify four key elements that are associated with notable health and cognitive benefits for children and youth: 1) accumulation of no less than 60 minutes per day of moderate to vigorous physical activity, 2) several hours of a variety of structured and unstructured light physical activities, 3) uninterrupted sleep of eight to 11 hours, and 4) no more than 2 hours per day of recreational screen time (Tremblay et al., 2016). However, only less than one-fifth of Canadian children and youth adhere to these guidelines (ParticipACTION, 2020) . This figure could be partially attributed to children's retreat from the street to indoors as walking to school and playing outside is no longer the norm in many urban areas (Brussoni et al., 2020). Hart (2002) pointed to the irony that children in underdeveloped countries have more opportunities to play outside than children in middle-class areas in many developed nations. Hart also argued that the rapid growth in playgrounds is motivated by public agencies attempt to keep children away from streets and make room for high speed, high traffic roads, in what Hart's call "the battle for sidewalks and streets". However, children's desire to experience and explore their surroundings cannot be accommodated by only providing public playgrounds (Hart, 2002). In fact, this approach of focusing primarily on playgrounds and excluding children from the planning process of all other built environment elements has resulted in counterproductive results of children spending enormous time indoors and on screens (Brussoni et al., 2020; Hart, 2002).

While there is no recognized playability index for the built environment, several studies in the literature have identified key elements of the built environment that are associated with children playability, including:

1. *Destinations* – playability is positively associated with close proximity to destinations, such as schools and parks (Page et al., 2010; Waygood et al., 2020).
2. *Walkability* – playability is positively associated with high walkable neighbourhoods (Kurka et al., 2015).
3. *Traffic safety* – higher perception of traffic safety is associated with higher playabilities for girls (Page et al., 2010).
4. *Green space* – close proximity to open green spaces is positively associated with playability (Lambert et al., 2019).
5. *Residential density* – playability is positively associated low residential density (Lambert et al., 2019).

2.6.8 **Social Interaction**

As discussed in section 2.4.2, built environment does not have a direct effect on the content and quality of social interactions; however, it does increase possibilities of passive contacts. As a result, the existing literature on the relationship between social interaction and the built environment focused particularly on social interaction potential (Farber, Neutens, Miller, & Li, 2013; Germann-Chiari & Seeland, 2004; Jin, 2010; LEE, JAE YONG & KWAN, 2011; Neutens, Farber, Delafontaine, & Boussauw, 2013; Wood, Frank, & Giles-Corti, 2010). For instance, Neutens et al. (2013) and Farber et al. (2013) utilized space–time prism intersection to model social interaction potential. In addition, Jin (2010) defined social interaction potential as two pedestrians passing within 25m of each other during a simulation time step (20 second).

2.6.9 **QoL Concluding Remarks**

Overall, the varied results of these numerous studies suggest that measuring the influence of land use and transportation systems on quality of life is exceedingly complex. In addition, the wide variation of the proposed indicators reflects how there is no global agreement on the definition of quality of life nor the importance of the factors that influence quality of life. Nevertheless, it is clear from these studies that neighbourhood design influences our quality of life in two ways. First, it directly influences our travel behaviour which in turn influences some quality of life indicators such as air and noise pollution, traffic volume, and traffic safety. Second, neighbourhood design indirectly influences other aspects of human behaviour that are related to quality of life such as social interactions and child development as discussed in sections 1.1 and 2.4.2. This dissertation will not attempt to develop the perfect neighborhood system design that ‘maximizes’ human quality of life, as humans by nature are each unique, experience life differently, and thereby value the quality of their life experiences differently. Rather, what is most practical, would be to identify a reliable suite of empirical tools that could be utilized by community planners and engineers to objectively evaluate key factors of a neighbourhood's design using previously researched quality of life metrics.

Chapter 3 Framework for Learning-based Travel Behaviour Model

This research presents an agent-based model to simulate agents' daily trip activities for morning commuting trips, with mode choices that include: driving, transit, walking, and cycling. The model (see Figure 3.1) has been constructed using the Recursive Porous Agent Simulation Toolkit (Repast), which is an open-source agent-based simulation platform that was first authored by researchers at the University of Chicago (Collier, Howe, & North, 2003) and then established as a reusable software infrastructure by the Argonne National Laboratory (North et al., 2013). Repast has been widely used in various transportation-related studies, such as commute travel patterns (Jin, 2010), network traffic controls (Abdul Aziz & Ukkusuri, 2016), walking behaviour (Yang, Diez Roux, Ana V.,PhD, MD, Auchincloss, Rodriguez, & Brown, 2011), and decision evaluation for AT infrastructure investment (Aziz et al., 2018b).

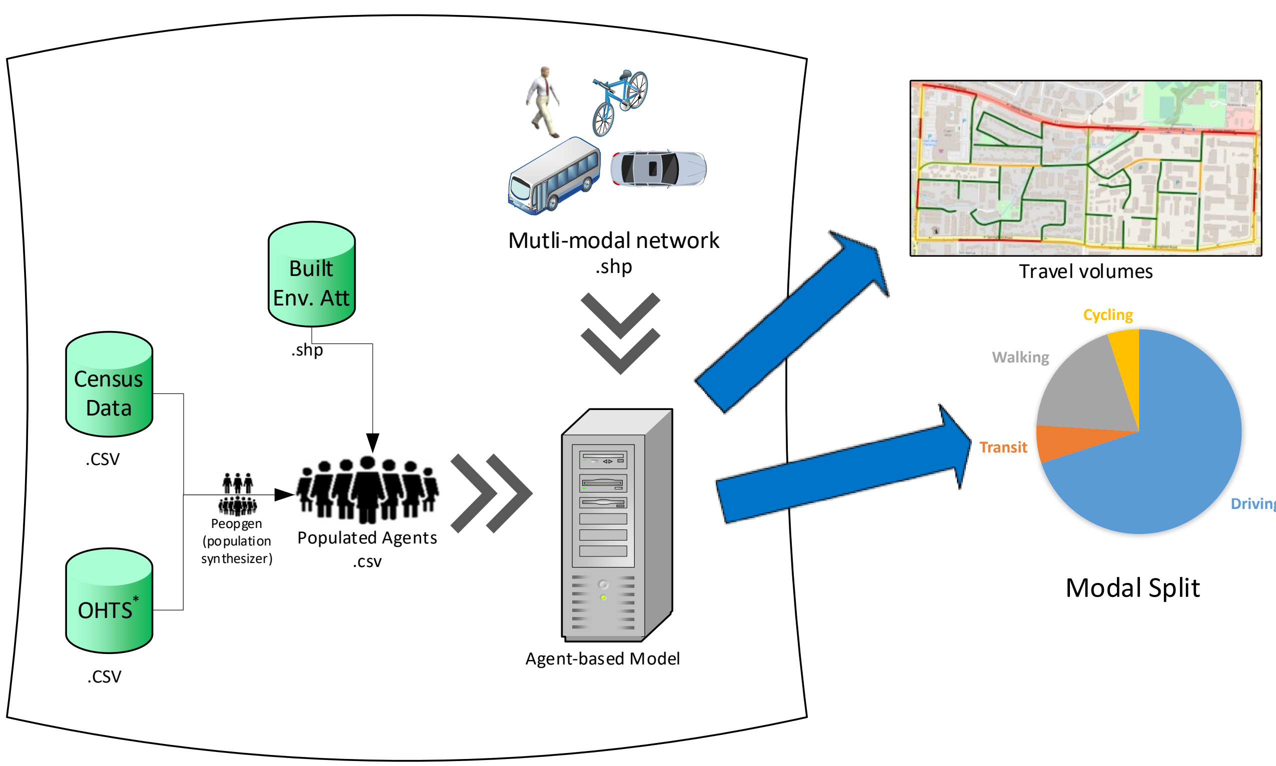


Figure 3.1: Agent-based model Framework

Following a typical structure of the agent-based framework, the presented model consists of three major components: environment, agents, and interaction rules as discussed below.

3.1 Agents

Agents in this model represent autonomous (i.e. make independent decisions based on their own goals) and adaptive transportation system users that seek to optimize their utility by learning and adapting a new behaviour based on experience. Each agent has its own characteristics (e.g. income, age, gender, occupation, and residential location) and a daily trip plan that includes trips origins, destinations, purposes, and cost. Agents were grouped into households where they share some characteristics such as available number of vehicles and income. Households were randomly allocated in the neighbourhood as a point feature according to each parcel land use zoning, density, and dwelling type. This means that households were only allocated on parcels that were classified as residential or mix land use and the number of households in each parcel was determined by the parcel density.

3.1.1 Mode Choice Behaviour

The developed agent-based model simulates agents' mode choice behaviour using decision rules based on the RUM Theory. As discussed in section 2.2, the utility function consists of two components: a deterministic component and a random error term. In this model, the deterministic component takes into account 1) characteristics of agents, 2) attributes of alternative modes, 3) the interaction between these two components, 4) the influence of built environment, 5) safety factors, and 6) agents' social interactions. With these factors included, the deterministic component can be formulated as:

$$V_{qm} = V(X_q) + V(Z_m) + V(X_q, Z_m) + V(B) + V(S), \quad 3\text{-}1$$

where $V(X_q)$, $V(Z_m)$, $V(X_i, Z_m)$, $V(B_m)$, $V(S_q)$, and $V(I_{qm})$ refer to characteristics of agent (q), attributes of alternative mode (m), the interaction between the characteristics of individual (q) and the attributes of alternative mode (m), built environment characteristics, and safety factors, respectively.

Built environment measures considered in the model include density (e.g. population and employment), diversity (e.g. land use entropy), design indicators (e.g. availability of public spaces and AT facilities), and transit service. The built environment measures were quantified at a fine spatial resolution of 1 km (max) area from trip origins and destinations to avert any spatial aggregation bias as well as to account for people's perceived limit of neighbourhood (Lee, Chanam & Moudon, 2006). In addition, this approach makes it possible to capture the effect of micro land use changes on mode choice behaviour.

For traffic safety measures, numerous studies found that AT crashes have a significant effect on AT mode choice behaviour, such that less AT crashes increases the likelihood of walking and cycling. However, while the importance of collision data is undeniable, there are still concerns regarding collision data accuracy and availability (Burns & Wilde, 1995; Shaw & Ison, 2018). Collision data is not always available due to the infrequency of collision events and when a new infrastructure is proposed, where no previous data is available (e.g. SMARTer Growth) (Guo, Klauer, Hankey, & Dingus, 2010; Wei & Lovegrove, 2013). For these reasons, this study utilizes indirect measures of safety such as intersection density, availability of sidewalk/bike lane, and proportion of pedestrian actuated traffic signal. These factors do not only influence mode choice behaviour, but they also influence route choice for those who decide to walk or bike as will be discussed in Section 3.2.

Similar to traffic safety measures, it was also hypothesized that social interaction measures influence both route and mode choices. For route choice, it was assumed that agents prefer routes with high AT and low automobile traffic. For mode choice, the Diffusions of Innovations theory (Rogers, 2003) was utilized to simulate how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. According to the Diffusions of Innovations theory, people were classified into five categories based on their level of social influence: 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards. Innovators are characterised by strong social influence and are very eager to seek information about new alternatives, while laggards lack social influence and are the last to adopt new alternatives. Similar to the work of Aziz (2018) and Doo (2012), agents in the model were randomly assigned to one of the five categories, while keeping the number of agents in each category as per the proportions proposed by Rogers (2003) as shown in Table 3.1. Rogers proposed these proportions based on the time element of adopting innovations, which was found to follow a normal, bell-shaped curve. In addition, an influence probability was assigned to each group to capture how agents in different categories vary in terms of willingness to seek and propagate information. Finally, it was hypothesized that the choice probability of the predominant mode (P_{qd}) is an indicator of the level of satisfaction towards that mode. In other words, higher choice probability implies higher satisfaction level, and thus agents are more willing to propagate their choices with others.

Table 3.1 Agents Categories (Rogers, 2003; Doo, 2012)

Category	Proportion	Social influence probability (ω)
Innovator	2.5%	0.9
Early Adopters	13.5%	0.45
Early Majority	34%	0.23
Late Majority	34%	0.1
Laggards	16%	0.05

3.1.2 **Knowledge Learning Process**

As discussed in section 2.2, the RUM framework has been criticized for its lack of consideration for humans' bounded rationality, as well as its lack of consideration for psychological factors that influence mode choice behaviour such as habit. Several techniques have been proposed to address the aforementioned gaps in the RUM theory. This study utilizes a conceptual framework presented by Idris et al. (2012), which proposed an adaptive learning-based mode choice model that integrated the RUM Theory with reinforcement learning concepts. The proposed model employed various reinforcement learning concepts to model decision-making behaviour considering the bounded rationality assumption. In particular, the proposed framework addresses three properties of bounded rationality: habit formation, awareness level, and information provision.

Agents' decision-making policy in the proposed agent-based model was to choose the transportation mode that maximizes their rewards in the long run. Rewards were defined as an agent's perceived utility for each of the available transportation modes. Agents in the model use adaptive behaviour to form their beliefs about the available transportation modes through an iterative process. In each iteration, agents choose the transportation mode that has the greatest probability based on the RUM Framework. During the iteration, agents acquire new information (e.g. traffic conditions) by interacting with other agents and the environment, which then were used to update agents' perceived utility for the subsequent iteration based on the following reinforcement learning algorithm:

$$V(s_{t+1}) \leftarrow V(s_t) + \alpha_i[R(s_t) - V(s_t)], \qquad 3\text{-}2$$

where:

$V(s_{t+1})$: Cumulative rewards at time step (t+1),

$V(s_t)$: Cumulative rewards until time step (t),

$R(s_t)$: Immediate reward gained at time step (t),

α_q: Step size parameter ($0 \leq \alpha_q \leq 1$), associated with agent (i).

Equation 3-2 includes an adaptive step size parameter (α) to simulate habitual tendency and its influence on learning from previous experience. Idris et al. (2012) hypothesized that the habitual tendency of a particular mode can be indicated by the choice probability of that mode, such that the greater the choice probability, the greater the habitual tendency. Since habitual tendency acts against learning from previous experience, Idris et al. (2012) formulated the step size parameter to be inversely proportional to the previous dominating mode choice probability as shown in equation 3-3. This formulation implies that the greater the habitual tendency towards a certain mode, the lower the step size parameter, and thus the less the agent learns from previous experience.

$$\alpha_q = 1 - P_{qd}, \qquad 3\text{-}3$$

where:
α_q: Step size parameter for agent (q),

P_{qd}: Previous mode choice probability that agent (q) selects the dominating mode (d).

In addition, a soft-max selection policy based on the Boltzmann distribution was used in this research to ensure an appropriate trade-off between exploitation and exploration as shown in Equation 3-4.

$$P_{qa} = \frac{e^{\frac{Q_t(a)}{\tau}}}{\sum_{b=1}^{n} e^{\frac{Q_t(b)}{\tau}}}, \qquad 3\text{-}4$$

where:
P_{qa}: Probability of individual (q) selecting action (a),

$Q_t(a)$: value of action (a) at time step (t),

τ: temperature parameter.

Within this selection policy, agents choose whether to exploit or explore an action to explore based on three components: 1) dominating mode choice probability, 2) agents' utility value for each available mode, and 3) the weighted average effects of social influence. First, a greater choice probability indicates a greater habitual tendency, which hinders an agent's willingness to explore new alternatives. Thus, the temperature parameter was assumed to be inversely proportional to the choice probability of the recent dominating mode, ($\alpha_q = 1 - P_{qd}$) (Idris et al., 2012). Second, it was hypothesized that agents choose which action to explore based on the combined effect of their formed beliefs about each available mode (i.e. utility values) and the level of social influence from an agent's social network. Thus, the value of choosing action (a) can be estimated using a weighted average as shown in Equation 3-5.

$$Q_t(a) = (1 - \omega_q) \times V_{qa} + \omega_q \times \lambda_{qa}, \quad 3\text{-}5$$

where the ω_q is the social influence probability assigned to agent (q) as in Table 3.1, λ_{qa} was calculated based on the social influence of those in agent (q) social Network (j) if their predominant mode choice was action (a), as follows:

$$\boldsymbol{\lambda_{qa}} = \frac{\sum_{j=1}^{J}(\boldsymbol{V_{jd}} \times \boldsymbol{\omega_j})}{\sum_{j=1}^{J}(\boldsymbol{\omega_j})}, \ \forall\, \boldsymbol{d} \in \{\boldsymbol{a}\}. \quad 3\text{-}6$$

3.1.3 **Information Provision**

In this research, agents were grouped into three categories based on their information acquisition and response behaviour. The first category conceptualized the state of partial information provision, in which agents do not have global information (i.e. imperfect knowledge) and thus can only adapt new behaviour based on their own experience. In other words, at the end of each iteration, agents only update the utility of the selected mode while the utility of unselected modes remained unchanged as shown in equation 3-7.

$$V_{qm}(t+1) = V_{qm}(t) + \alpha_q\left[R_{qm}(t) - V_{qm}(t)\right],\ V_{qn}(t+1) = V_{qn}(t), for\ all\ n \neq m, \quad 3\text{-}7$$

where:

$V_{qm}(t)$: Utility that agent (q) obtained from mode (m) until time step (t),

$V_{qn}(t)$: Utility that agent (q) obtained from any other mode (n≠m) until time step (t),

$R_{qm}(t)$: Immediate utility that agent (q) obtains from mode (m) at time step (t),

$V_{qm}(t+1)$: Updated utility that agent (q) obtains from mode (m) at time step (t+1),

$V_{qn}(t+1)$: Updated utility that agent (q) obtains from any mode (n≠m) at time step (t+1),

α_q: Step size parameter ($0 \leq \alpha_q \leq 1$), associated with agent (q).

The model expressed in equation (3.10) utilized a temporal-difference learning method to simulate an agent's behaviour, such that an agent updates its long-term utilities $V_{qm}(t+1)$ based on the difference between the immediate utility obtained at the current time step $R_{qm}(t)$ and the accumulated utility until the current time step $V_{qm}(t)$. Note that agents only update the utility for the selected mode, as information about the other modes would not be available.

The second category also conceptualized the state of partial information provision; however, the updating rules were revised to incorporate how agents become unfamiliar with unselected modes. Thus, an agent's mental and cognitive efforts to explore unselected modes declines over time as shown in Equation 3-8:

$$V_{qm}(t+1) = V_{qm}(t) + \alpha_q\left[R_{qm}(t) - V_{qm}(t)\right],$$

$$V_{qn}(t+1) = \begin{cases} V_{qn}(t) + [\alpha_q * V_{qn}(t)], & V_{qn}(t) < 0 \\ V_{qn}(t) - [\alpha_q * V_{qn}(t)], & V_{qn}(t) \geq 0 \end{cases} \quad for\ all\ n \neq m. \qquad \text{3-8}$$

On the other hand, the evolution of new Advanced Traveller Information Systems (ATIS) gives transportation users access to real-time information about different modes simultaneously. Thus, people are now capable of gaining knowledge and updating their preferences for each available travel mode prior to each trip (i.e. including unselected modes). Under this assumption the updating rules could be re-written as follows:

$$V_{qm}(t+1) = V_{qm}(t) + \alpha_q\left[R_{qm}(t) - V_{qm}(t)\right], \qquad for\ all\ m = 1\ to\ M. \qquad \text{3-9}$$

Agents were randomly assigned to one of the three information provision categories as will be discussed in section 5.5. Previous research showed that information provision has a relatively small impact on travel behaviour, with an estimated impact that varies between 30-40% (Englisher, Juster, Bregman, Koses, & Wilson, 1996; Khattak, Yim, & Prokopy, 2003; Peirce & Lappin, 2003; Wang, X., Khattak, & Fan, 2009).

3.2 Environment

The environment represents the space where agents make activities and interact with each other. In the developed agent-based model, the environment was comprised of several GIS datasets including a transportation system (e.g. roads and sidewalks), activity locations (e.g. households and workplaces), and built-environment (e.g. parks). The transportation system was modelled as a multi-layer network where different transportation modes were represented by different layers. This makes it possible to simulate multi-modal trips where agents might need to use different transportation modes to reach their destinations (e.g. walking from home to transit stop, then riding the bus to a destination). In a multi-layer network, any node that is coincident with a node of another layer acts as a point of transfer between the two layers as shown in Figure 3.2.

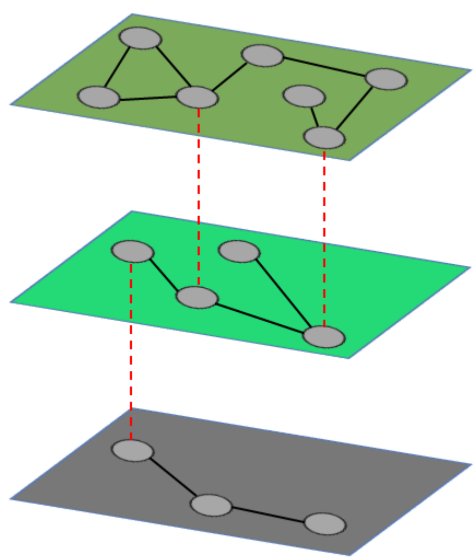


Figure 3.2: Example of a multi-layers network

In addition, the transportation system was represented in the model by two separate classes; both classes extend super classes from JgraphT, which is a Java library of graph structures and algorithms (Michail, Kinable, Naveh, & Sichi, 2020). The first network class was an undirected weighted graph class that was used to calculate the number of walking and cycling agents and their social interactions on each road segment. The second network class was a directed weighted graph class that was used to map the network and calculate the best route for each trip according to the selected travel mode. For automobiles, a customized Dijkstra algorithm was used to calculate the best route based on travel time as shown in Equation 3-10. The algorithm was customized to express travel time as a function of road segments volume to capacity ratio based on the Bureau of Public Roads (BPR) Volume Delay Function (VDF) (Spiess, 1990).

$$\boldsymbol{t = \sum_{i=1}^{n} t_o \left[1 + \left(\frac{v}{c}\right)^{\alpha}\right]}, \qquad \text{3-10}$$

where:

t_o: free flow travel time,

v: hourly traffic volume when the trip occurs,

c: road capacity,

α: congestion effect coefficient.

Similarly, a Dijkstra algorithm was customized to determine the shortest route for AT users based on a perceived length function which accounts for the influence of 1) AT volume, 2) traffic volume, 3) and AT infrastructure type, as shown in Equation 3-11. In addition, Jin (2010) suggested that AT users are less sensitive to any change in AT and automobile volumes in already congested segments. Thus, the influence of automobile and AT volumes on perceived length were calculated as per Equation 3-12

$$D_i = \sum_{i=1}^{n} D_i \left[\frac{P_{auto}}{P_{AT}} - w_{im}\right], \qquad 3\text{-}11$$

where:

D_i: perceived length of a road segment,

w: the influences of AT infrastructure type (m) on link (i),

P: the influence of AT and automobile volume,

D_i: actual length of a road segment.

$$P_{ij} = \left(V_{ij} + 1\right)^{\alpha}, \qquad 3\text{-}12$$

where:

V_{ij}: Traffic volume of mode (j) on link (i),

α: refers to the influence level coefficient.

3.3 Population Synthesis

Agent-based models usually require a fully disaggregated dataset about the entire population in a study area. However, acquiring such data is impractical due to time constraint, high cost, low response rates, and privacy laws. To tackle this issue, agents in the developed model were synthesized at the parcel level for the entire study area based on the following four steps: 1) generation of agents at the finest zonal level using a population synthesizer 2) allocation of the synthesized households at the parcel level, 3) assignment of the synthetic agents to workplace dissemination area, and 4) assignment of the synthetic agents to workplace parcel. First, agents were generated at the finest zonal level by matching the joint distribution of key attributes from a disaggregate sample of the population with known marginal distributions of the actual population in the study area. Typically, the disaggregate sample is obtained from regional household travel surveys while the marginal distributions are obtained from aggregate census data. In the developed model, synthetic agents were generated using PopGen, an open-source population synthesizer that employs the iterative proportional updating (IPU) algorithm. The IPU is a heuristic iterative procedure that was proposed by Ye et al. (2009) to fill the gap in the standard iterative proportional fitting (IPF) procedure of not controlling for both household and personal level attributes. In the IPU algorithm, weights are adjusted iteratively among households of the same type until they match the known distributions of households and personal level attributes of interest, such as dwelling type, household income, gender and age. Second, synthesized households were randomly assigned to a home parcel within their dissemination area (based on the results of the first step).

Third, synthesized persons were assigned to workplaces using a disaggregate destination choice model with nonlinear multinomial logit formulation. The alternatives for the destination choice model are aggregated zones (dissemination areas), not elemental alternatives (parcels). Nevertheless, the alternative choice set for each person is still large which makes it difficult to estimate the model's parameters. Assuming that choice probabilities satisfy independence from irrelevant alternatives assumption (i.e. error term is independent and identically distributed), the model parameters could be estimated using random subset of the full choice set (McFadden, 1978; Pozsgay & Bhat, 2001). Assuming that the number of elemental alternatives in each zone is large and their systematic utility is homogeneous, the utility of individual (q) in zone (i) choosing alternative (j) can be expresses as (Bhat, Chandra, Govindarajan, & Pulugurta, 1998):

$$U_{qij} = \beta' x_{qij} + \eta \log(D_j) + \varepsilon_{qij}, \qquad \text{3-13}$$

where:

x_{qij}: Vector of explanatory variables including travel impedance (e.g. cost or time), zonal attributes and attractiveness, and interaction of travel impedance with socio-economic characteristics of individuals (q),

β': Vector of coefficients to be estimated,

D_j: Number of elemental alternatives in zone (j),

η: Scale parameter.

The number of elemental alternatives, D_j, in each zone is difficult to quantify; however, it could be modelled by a set of size variables such as the zone area and number of employments. Thus, utility function can be rewritten as:

$$U_{qij} = \beta' x_{qij} + \eta \log(\delta' d_j) + \varepsilon_{qij}, \quad \text{3-14}$$

where d_j is a vector of proxy variables and δ' is a vector of corresponding parameters. After assigning destination zones to the agents, the last step is to randomly assign each agent to a parcel within its destination zone.

3.4 Simulation Setup

In period 0, the initialization process, the model reads the shapefiles that contain information about the transportation system (e.g. network layout, speed limits, and one-way roads), as well as the synthesized agents' information and locations for an entire region. The next step in the model initialization process was to compute base utility and the corresponding probability of choosing available modes for each agent. In the first iteration, agents choose the travel mode with the highest probability and travel on the map according to the calculated shortest path. During each iteration, agents acquired new information (e.g. traffic conditions, volume of pedestrians and automobiles encountered) by interacting with other agents and the environment, which then were used to update agents' perceived utility for the subsequent iteration as presented in Equation 3.10, 3.11, or 3.12, depending on the agents' information provision category. In the following iterations, agents chose whether to explore or exploit, based on a generated random number; if the number was less than the exploration rate, then agents chose to explore new alternatives using the soft-max selection process described in the previous section. On the other hand, if the generated random number was greater than the exploration rate, agents exploited the action with the highest Q-value, as shown in Figure 3.3.

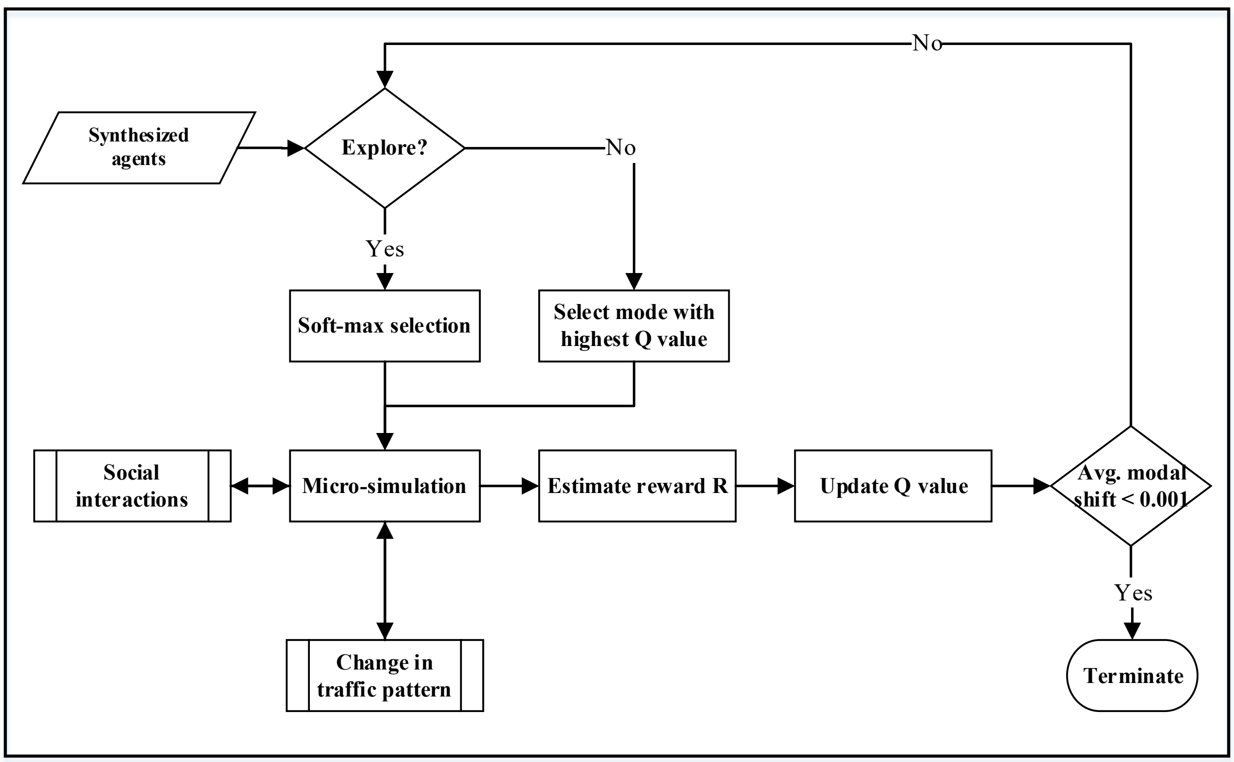


Figure 3.3: The proposed framework flowchart

Chapter 4 Dataset Description

4.1 Study Area

The city of Kelowna is part of the Regional District of Central Okanagan (RDCO) in the southern interior of the province of British Columbia, as illustrated in Figure 4.1. The city is located on the traditional and unceded territory of the Syilx Okanagan people. It encompasses 21,779 hectare and a population of 127,380 individuals and 53,925 households distributed at 167 dissemination areas. Kelowna's population is growing rapidly at an annual rate of 1.51%, which means that the city's population is expected to grow to 161,701 by 2030 and 179,200 in 2040. Given that the average household size is expected to decline, it is projected that around 20,084 dwellings will be needed to accommodate the growth in the city. Further, the city is expected to experience substantial growth in older age groups compared to younger age groups (City of Kelowna, 2018).

To limit urban sprawl, the city has mandated to accommodate 44 percent of future growth in five urban centres, as shown in Figure 4.1. In addition, the city has identified eight pseudo SMARTer Growth principles to guide the planning process of the urban centers as follows:

- *Mix it up:* promote high density, mix land use, and active streets (e.g. commercial usage on ground floors) within close proximity to high quality transit service.
- *Places for people:* creating a pedestrian friendly design through consistent street-wall heights and setbacks that relate to the width of sidewalks.
- *Healthy housing mix:* promote mix of housing types, affordable housing, and family-oriented units.
- *Social spaces:* promote Social Interaction in public spaces.

- *Placemaking:* promote local character of communities and sense of identity in public spaces.
- *Going green:* promote the integration of greenways, parkways, and parks.
- *People first transportation:* prioritize alternative modes of transportation.
- *Make it walkable:* improve pedestrian connectivity through short blocks and/or mid-block pathways and promote pedestrian friendly sidewalk landscaping.

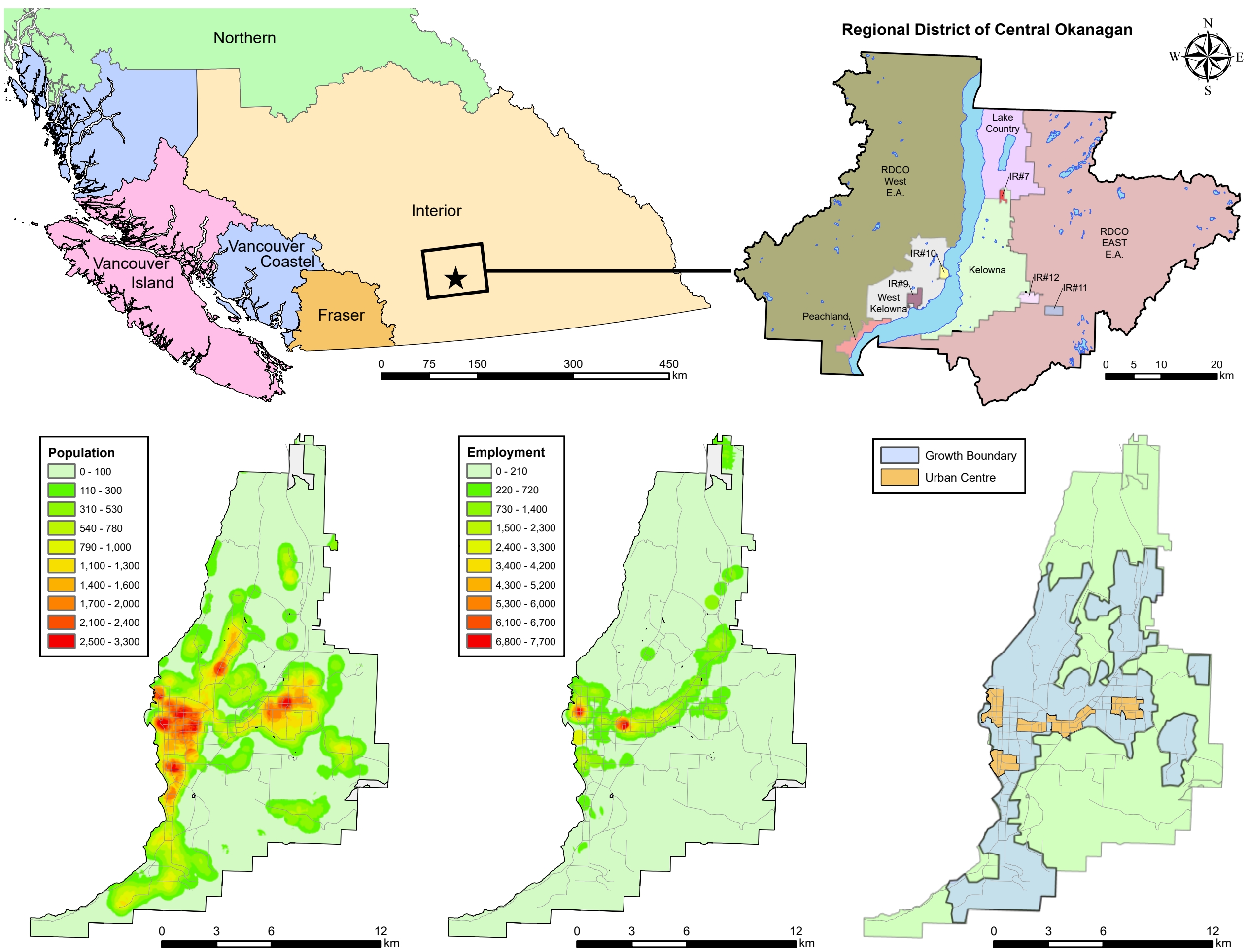


Figure 4.1: Location of the City of Kelowna

Three urban centres are examined in this study: Capri-Landmark, South Pandosy, and Rutland, as shown in Figure 4.2. The Capri-Landmark neighbourhood is approximately 98 hectares with a total population (density) of 2,886 residents (30 people/hectare) and a total employment (density) of 8,523 jobs (87 jobs/hectare). Of the five official urban centres, Capri-Landmark has been identified as top priority for a new comprehensive urban centre plan due to its lack of previous comprehensive planning, increasing development pressure, and several built-environment challenges including limited green spaces and disconnected AT infrastructure (City of Kelowna, 2016). The neighbourhood is serviced by a rapid bus service on its north boundary (Harvey Avenue) and a frequent bus service on its south boundary (Springfield Road).

The South Pandosy neighbourhood is approximately 156 hectares with a total population of 4,184 residents (27 people/hectare) and 3,895 jobs (25 jobs/hectare). The neighbourhood is characterized by unique pedestrian-oriented streetscape and concentration of retail on one of its major corridors (Pandosy Street) as well as several waterfront public spaces and parks. The neighbourhood is serviced by several frequent bus services.

The Rutland neighbourhood is approximately 169 hectares with a total population of 5,607 residents (33 people/hectare) and 1,400 jobs (8 jobs/hectare). It is characterized by the availability of several public parks and a community market. However, a major highway (Hwy 33) cuts through the neighbourhood. Similar to the South Pandosy neighbourhood, Rutland is also serviced by several frequent bus services.

All the three neighbourhoods were hypothetically retrofitted using the SMARTer Growth (SG) principles as shown in Figure 4.3 to Figure 4.8. The retrofitting process involved a series of local road closures to preclude through traffic on local roads and direct it to the perimeter, without altering the existing non-motorized network. Moreover, some areas that resulted from road closures were used to provide green spaces in the neighborhood. These green spaces eventually supplemented the local road network to provide more ambiant off-road pathways that allow convenient walking and cycling across the neighborhood. Finally, the distribution of population and employment within the neighbourhood was changed according to the SG Principles such as higher density and mixed land use located along the perimeter arterial and major collector corridors. Table 4.1 presents a summary of the transportation and land use metrics for the existing scenarios and the proposed retrofits.

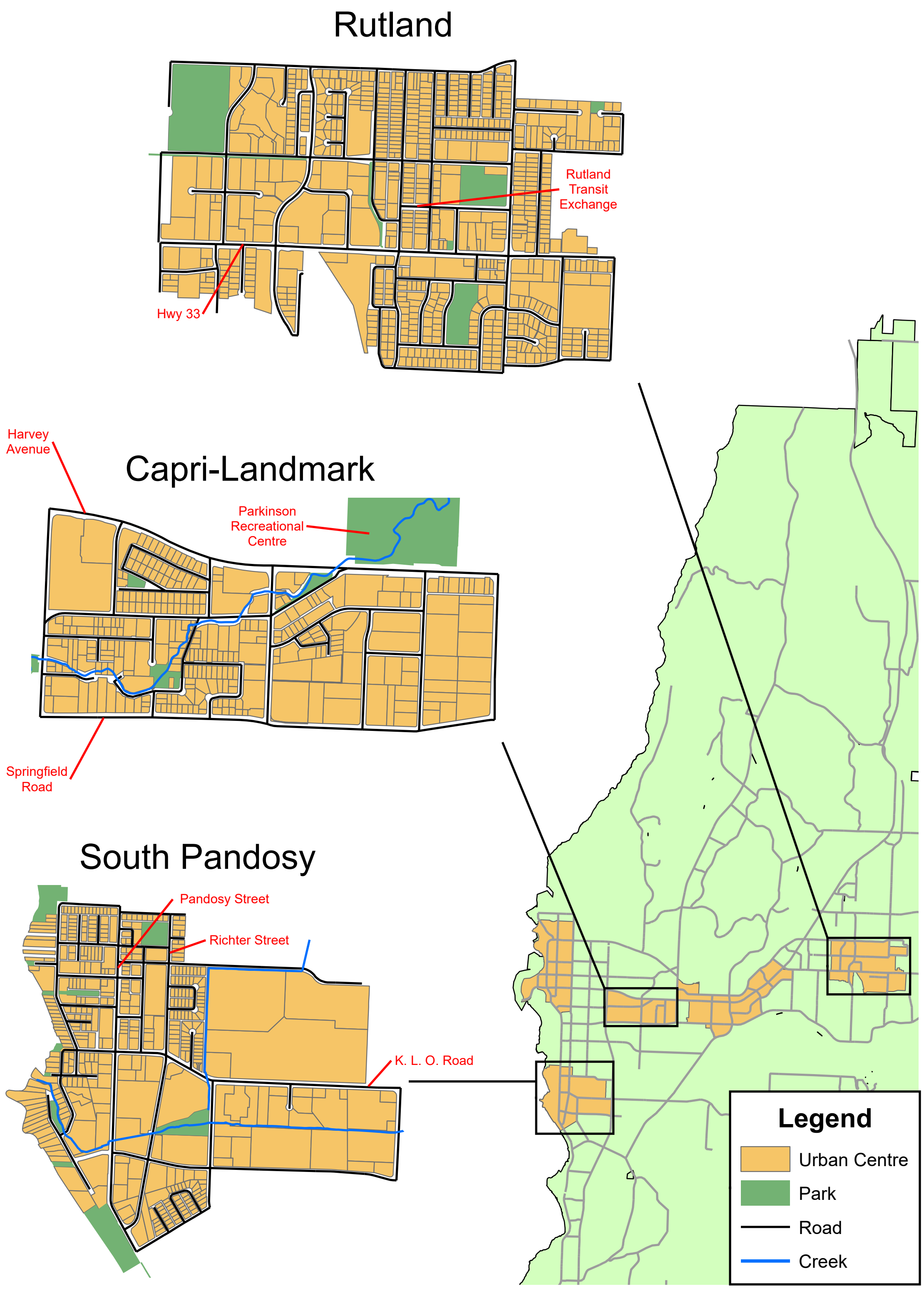


Figure 4.2: Locations of the study areas & existing roads and land use

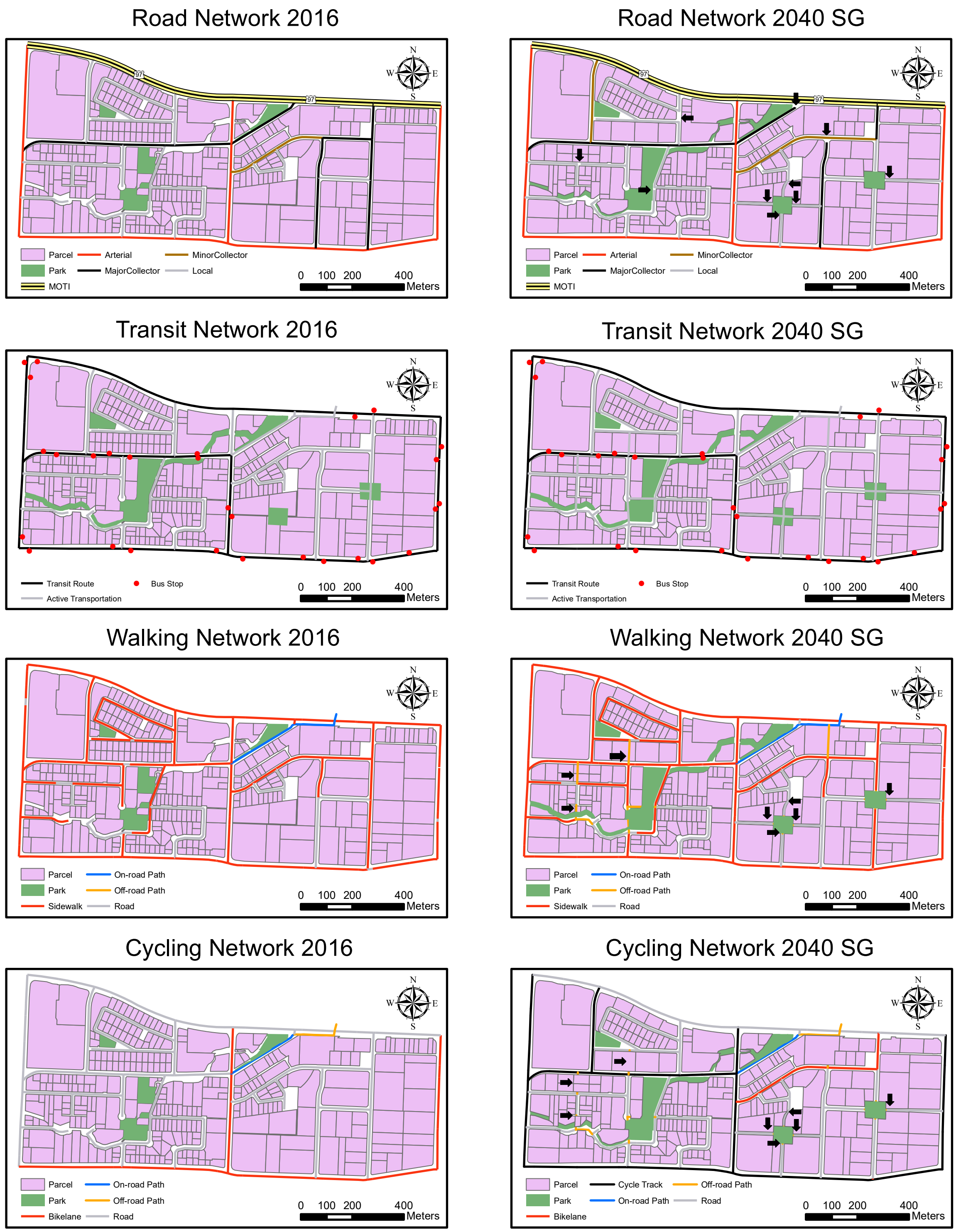


Figure 4.3: SMARTer Growth transportation retrofit of the Capri-Landmark neighbourhood

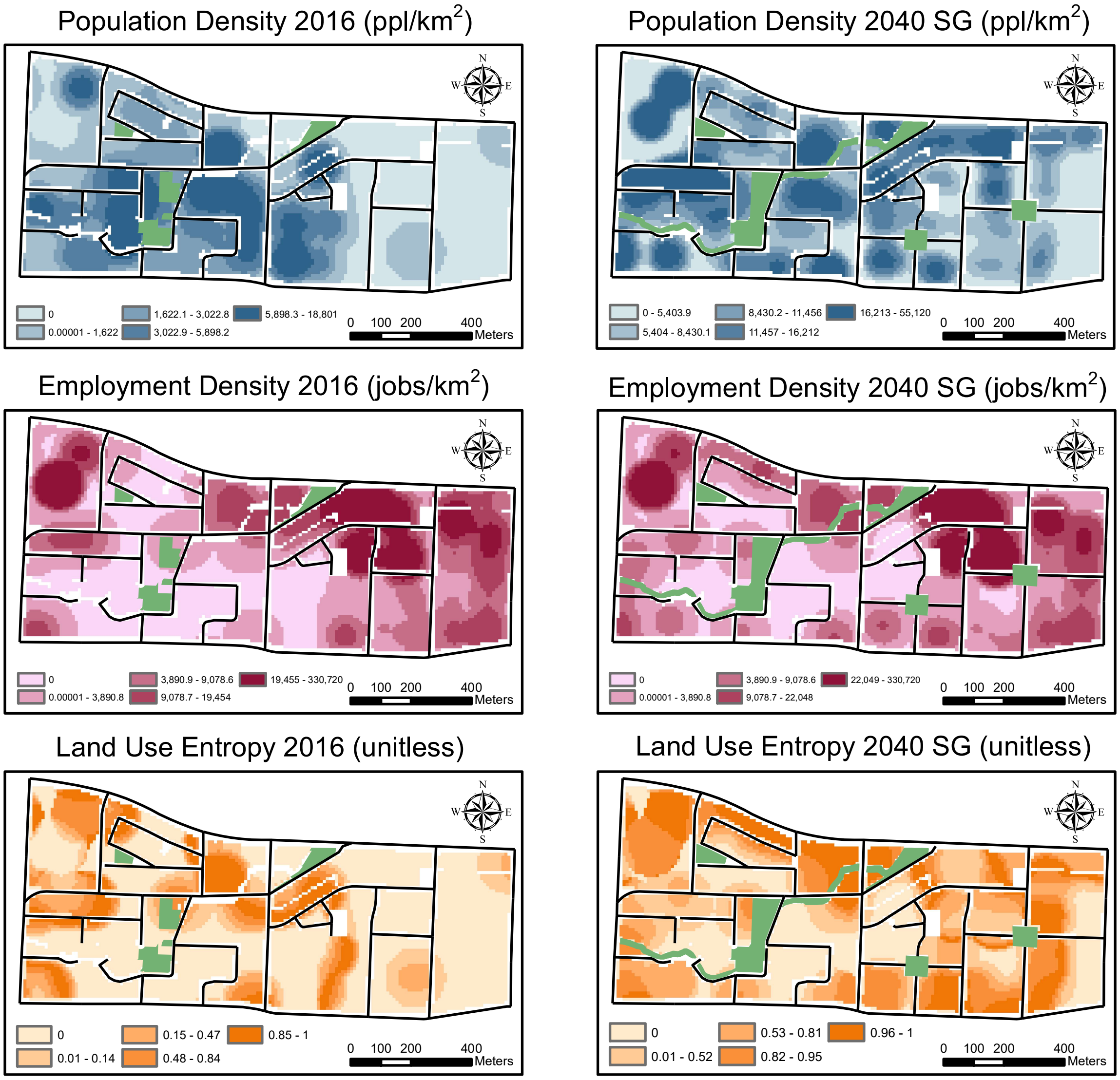


Figure 4.4: SMARTer Growth land use retrofit of the Capri-Landmark neighbourhood

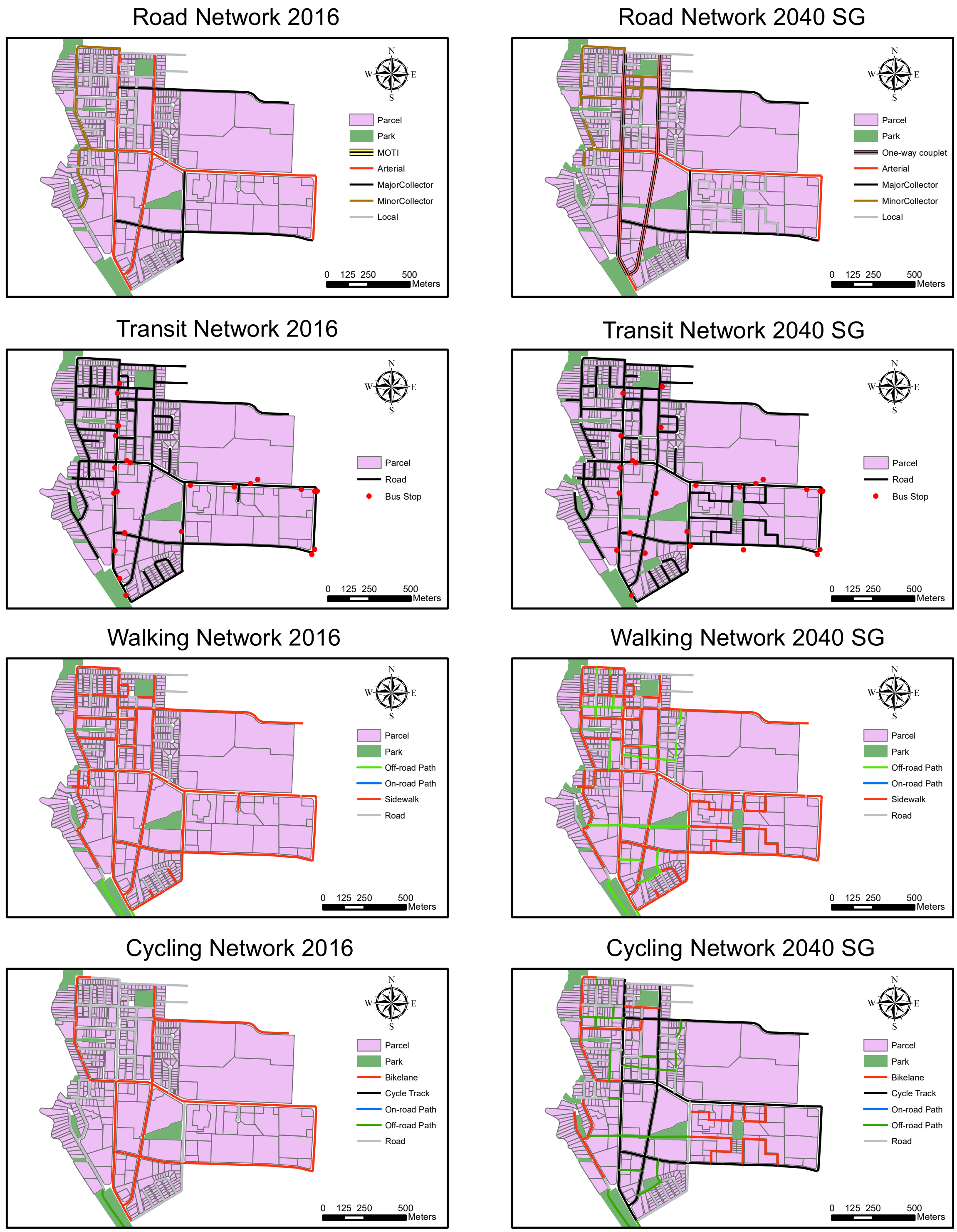


Figure 4.5: SMARTer Growth transportation retrofit of the South Pandosy neighbourhood

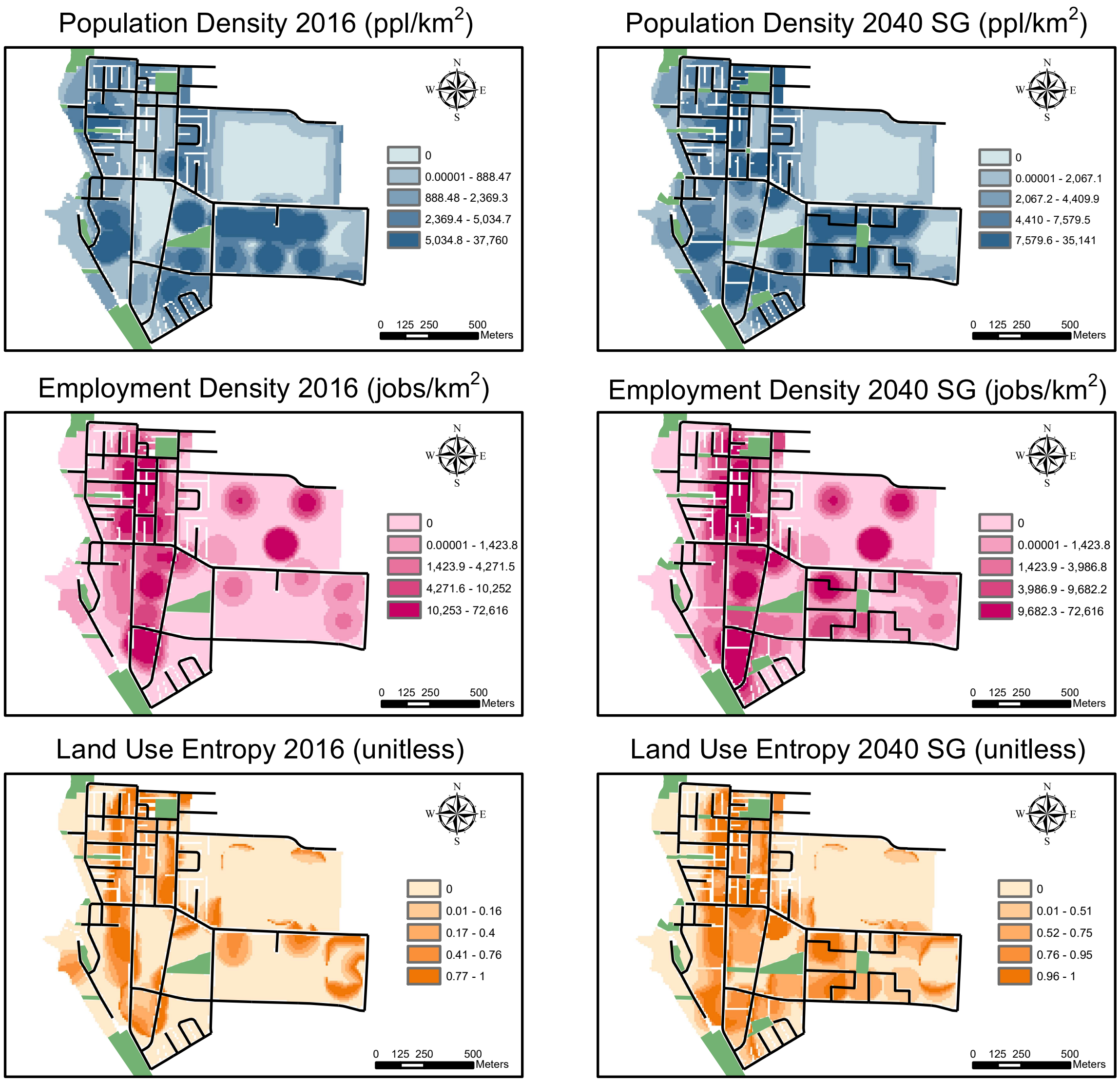


Figure 4.6: SMARTer Growth land use retrofit of the South Pandosy neighbourhood

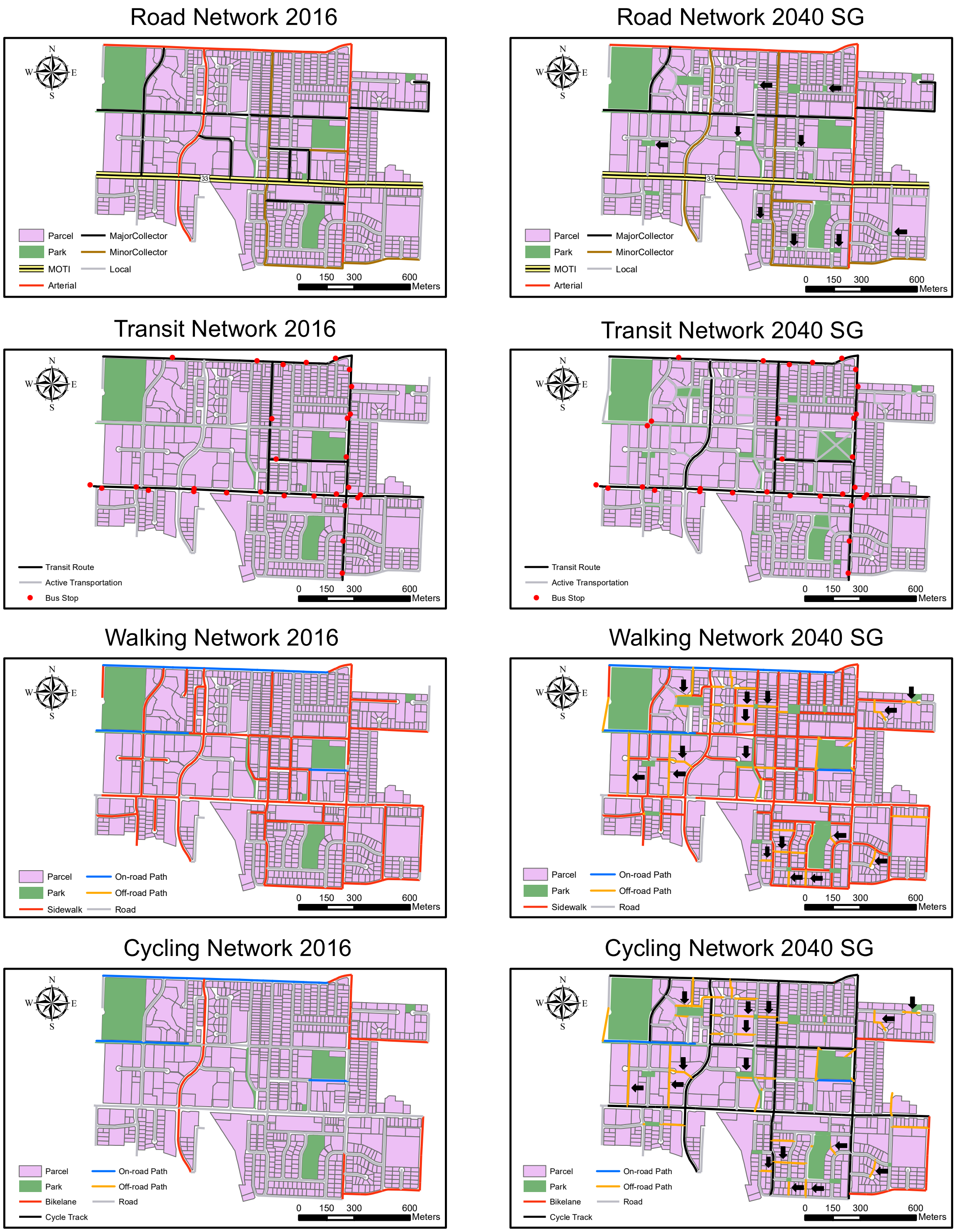


Figure 4.7: SMARTer Growth transportation retrofit of the Rutland Neighbourhood

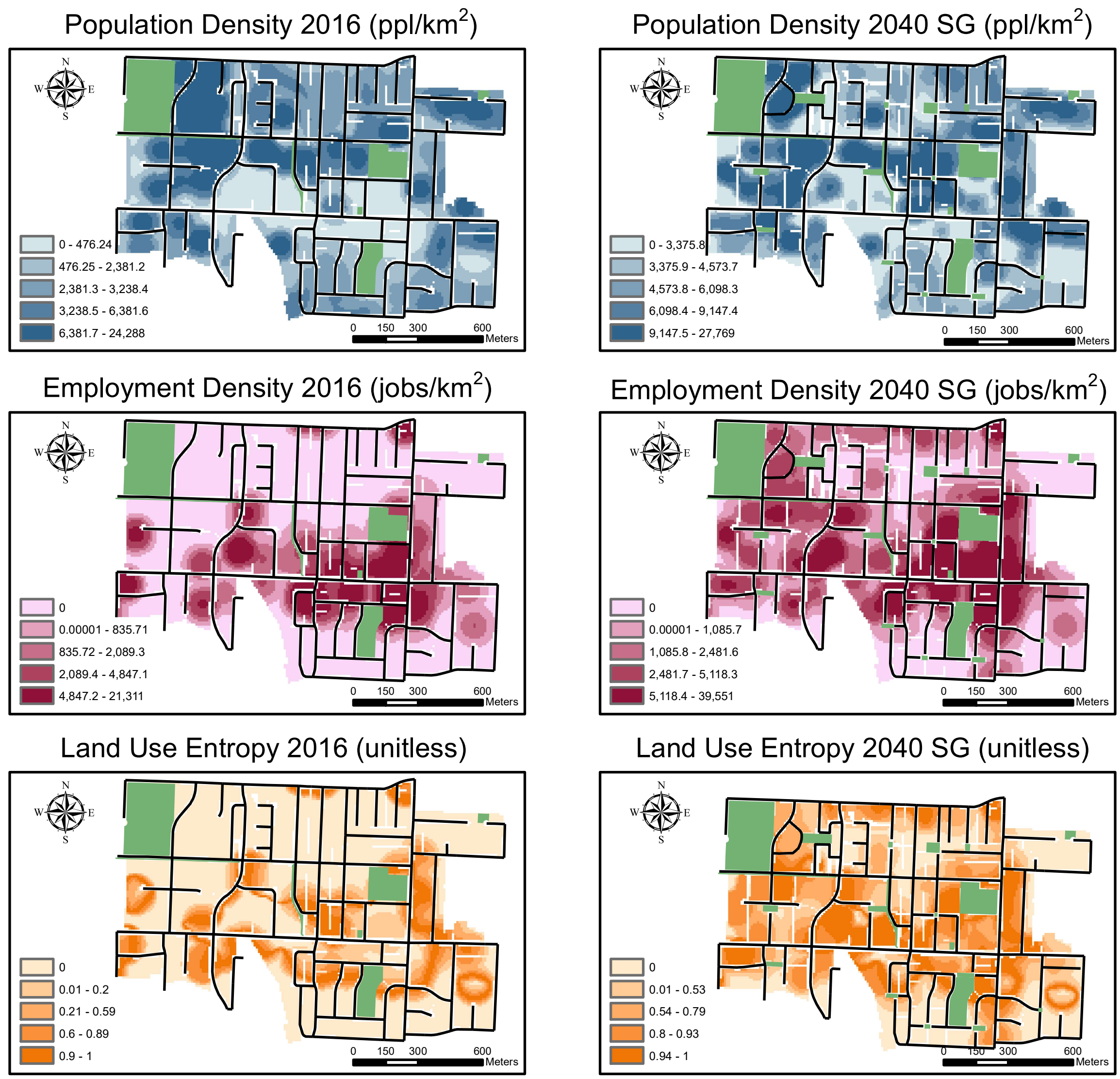


Figure 4.8: SMARTer Growth land use retrofit of the Rutland Neighbourhood

Table 4.1 A summary of the transportation and land use metrics for the existing scenarios and the proposed retrofits

Metric	Capri-Landmark		South Pandosy		Rutland	
	Existing	2040 SG	Existing	2040 SG	Existing	2040 SG
Population density (pop/hectare)	23.7	107.7	25.7	43.7	35.6	57
Employment density (jobs/hectare)	106	118.1	27.3	37.4	13.8	28.3
Green area (hectare)	2.2	5.6	8.8	11.3	12.8	15.1
TLKM (km)	17.9	18.3	15.1	16.2	22.5	22.0
Road connectivity (links/nodes)	1.33	1.12	1.30	1.18	1.31	1.10
Sidewalk length (km)	9.3	9.7	11.6	13.3	12.3	15.7
Bike lane length (km)	2.8	0.8	6.8	5.5	3.2	1.3
Cycle track length (km)	0	4.6	0	5.5	0	7.8
On-road Path (km)	0.3	0.3	0	0	1.9	0.7
Off-road Path (km)	0.2	1.1	0.35	2.9	0.89	5.2

4.2 Dataset Description

This research utilized four types of data for the development and calibration of the proposed adaptive ABM including: 1) a disaggregate sample of the population at the household and person level, 2) socio-economic marginal distributions of the population, 3) transportation networks, and 4) land use information. A description of each of the four data types and their sources is presented below.

4.2.1 Disaggregate Sample of Population

The disaggregate sample was obtained from the Okanagan Travel Survey (OTS). The OTS is a household-based travel survey for the residents of the RDCO and the City of Vernon. The OTS data includes both socioeconomic and demographic characteristics (e.g. auto ownership, income, age, and sex) as well as information on travel patterns (e.g. travel mode, trip purpose). In addition, travel time and distance for all reported trips were generated for car, transit, walking, and cycling using the Google Directions API, given the respondents' residential and work postal codes (Idris, 2013).The survey was conducted during weekdays in the fall of 2013, with a response rate of 3.3 percent, total responses of 3,050 households, and 22,500 trip records. In this research, only observations where both trip ends were located in Kelowna were used for the development of models. In addition, the dataset was cleaned to exclude observations with missing data, such as the chosen mode and trip information. Figure 4.9 and Figure 4.10 show the number of excluded observations by reason for mode and destination choice models and population synthesis, respectively.

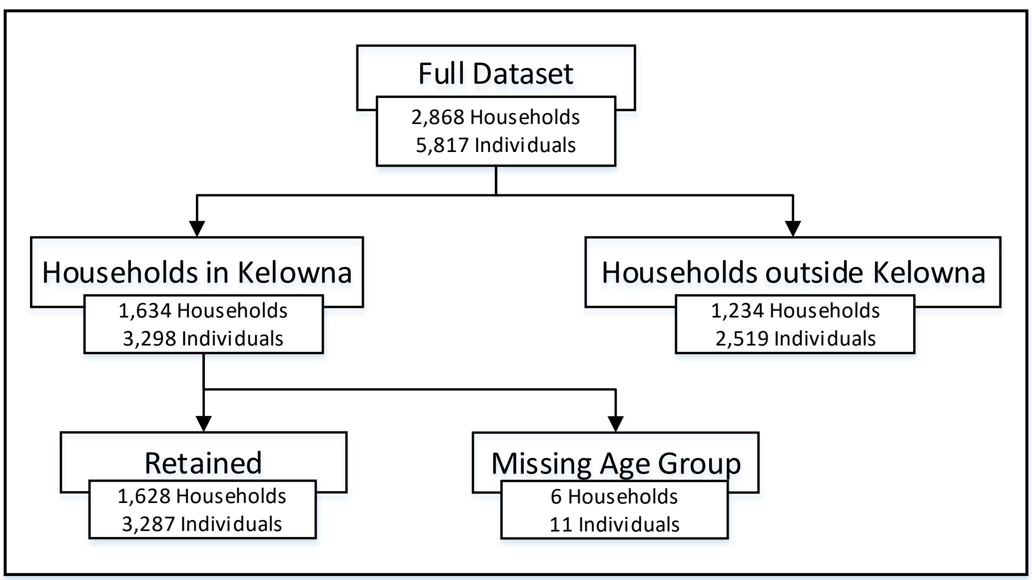


Figure 4.9: Description of the sample used for population synthesis

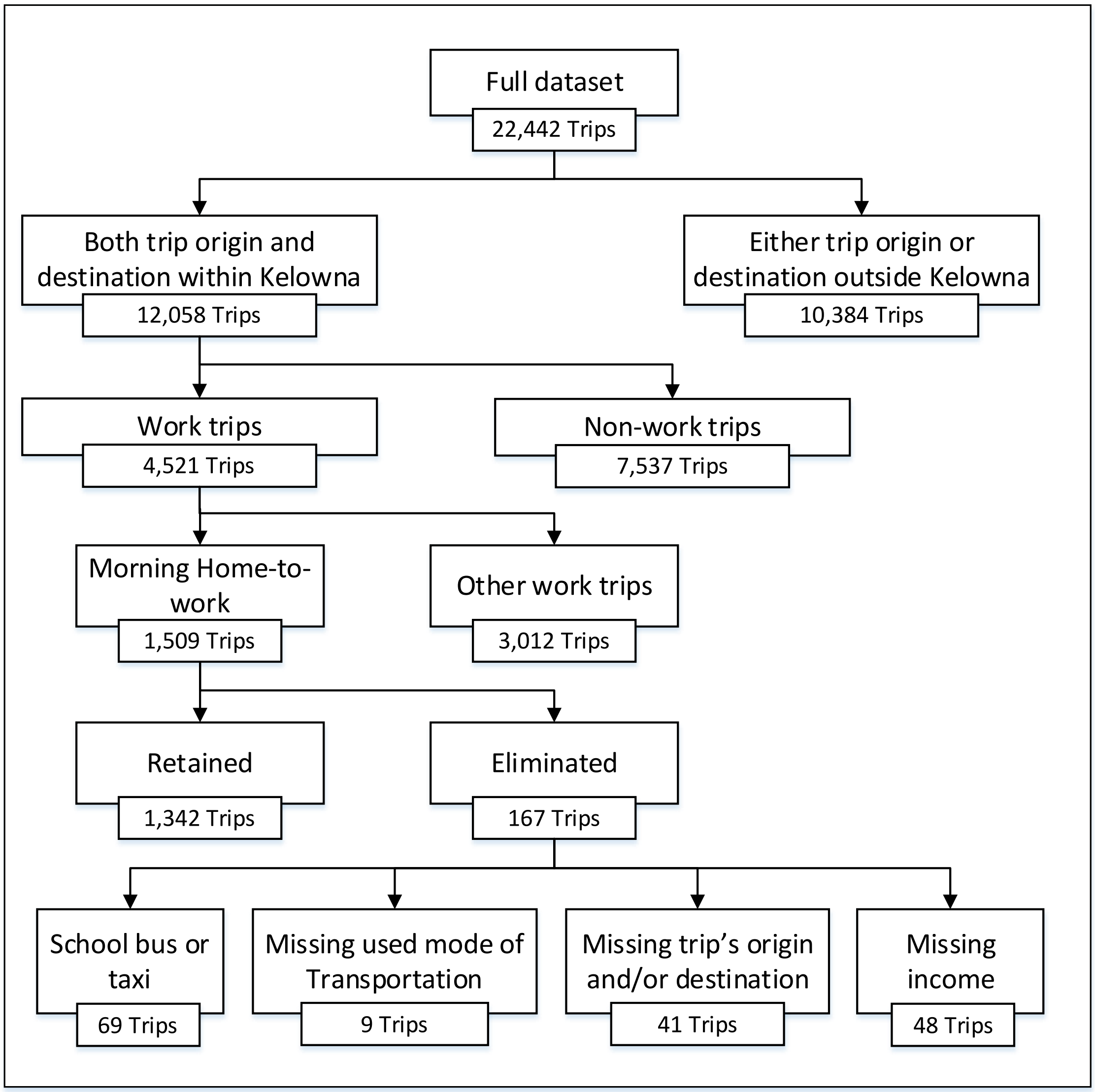


Figure 4.10: Description of the sample used for transport mode and destination choice models

For population synthesis, the OTS data was filtered to only include households located within the city boundary (1,628 households and 3,287 persons). For the development and validation of the MNL mode and destination choice models, the data was filtered to only include home-to-work trips during the morning peak (6 am - 9 pm) for which both trips ends are in Kelowna (1,344 trips). Home-to-work trips were used in this study due to their permanence, non-discretionary nature, and resemblance of long-term decisions. Table 4.2 and

Table 4.3 show the characteristics of the sample used for mode and destination choice models and population synthesis, respectively.

Table 4.2 Socio-economic Characteristics of the OTS Subsets Used for Model Development and Validation

Variable	Category	N	%
Number of vehicles in a household	0	29	2.2
	1	366	27.2
	2	603	44.9
	3+	346	25.7
Number of bicycles in a household	0	162	12.1
	1	183	13.6
	2	351	26.1
	3+	648	48.2
Household dwelling type	Single Detached House	905	67.3
	Apartment or Condo	214	15.9
	Townhouse or Row House	156	11.6
	Duplex	54	4.0
	Mobile Home	15	1.1
Age	(05-14)	249	18.5
	(15-24)	207	15.4
	(25-34)	247	18.4
	(35-44)	219	16.3
	(45-54)	234	17.4
	(55-64)	173	12.9
	65 and over	15	1.1
Sex	Men	627	46.7
	Women	717	53.3
Monthly or annual transit pass	Yes	159	11.8
	No	1185	88.2
Driver’s license	Yes	1020	75.9
	No	324	24.1

Table 4.3 Socio-economic Characteristics of the OTS Subsets Used for Population Synthesis

Variable	Category	N	%
Households Characteristics			
Household size	1	334	20.5
	2	823	50.6
	3	212	13.0
	4+	259	15.9
Household dwelling type	Single Detached House	960	59.0
	Apartment or Condo	370	22.7
	Townhouse or Row House	206	12.7
	Duplex	63	3.9
	Mobile Home	29	1.8
Persons Characteristics			
Age	(05-14)	365	11.1
	(15-24)	436	13.3
	(25-34)	511	15.5
	(35-44)	482	14.7
	(45-54)	525	16.0
	(55-64)	534	16.2
	65 and over	434	13.2
Sex	Men	1506	45.8
	Women	1781	54.2

4.2.2 **Marginal Distributions of the Population**

The socio-economic marginal distributions of the population were based on aggregate census data at the dissemination area level, which is the smallest geographic area for which census data are disseminated. The dataset was extracted from Statistics Canada 2016 Census Profiles files using the Canadian Census Analyser tool (Statistics Canada, 2017). It included various explanatory variables at the household and individual level such as age, sex, dwelling type, employment, modal share, etc. Table 4.4 shows summary statistics of the characteristics of the population in Kelowna in 2016.

Table 4.4 Socio-economic Characteristics of the population in Kelowna in 2016

Variable	Category	N	%
Households Characteristics			
Household size	1	15,740	29.2
	2	20,985	39.0
	3	7,385	13.7
	4+	9,730	18.1
Household dwelling type	Single Detached House	24,740	45.8
	Apartment or Condo	16,390	30.4
	Townhouse or Row House	8,100	7.3
	Duplex	3,920	15.0
	Mobile Home	810	1.5
Persons Characteristics			
Age	(00-04)	5,565	4.4
	(05-14)	12,250	9.6
	(15-24)	15,980	12.5
	(25-34)	17,030	13.4
	(35-44)	14,710	11.5
	(45-54)	17,300	13.6
	(55-64)	18,105	14.2
	65 and over	26,440	20.8
Sex	Male	61,605	48.4
	Female	65,735	51.6

4.2.3 **Transportation Networks**

Transportation networks data was obtained from the City of Kelowna's open data portal. The data includes spatial and temporal (built year) dimensions of road centerlines, road intersections, sidewalks, bike lanes, cycle tracks, on-road paths, off-road paths, and walkways.

Figure 4.11, Figure 4.12 and Figure 4.13 depict the road, walking, and cycling networks in Kelowna, respectively, in 2016.

In addition, transit routes and stop locations were created using the General Transit Feed Specification (GTFS) dataset for Kelowna. The GTFS is a data specification that allows public transport agencies to publish transit data in a format that can be easily consumed by wide range of applications, including google maps. It was developed by Google in collaboration with TriMet. The GTFS is comprised of a series of at least six tables (formatted as text files .csv) including: routes, trips, stop_times, stops, calendar, and shapes. The transit network for the city of Kelowna with frequency levels for bus stops appended as a temporal dimension is illustrated in Figure 4.14. The frequency level for each bus stop was determined by computing the headway for all transit routes utilizing the bus stop during the morning working-day hours (6 am – 9 am), and then calculating the average headway of all these transit routes. The frequency classification of bus stops is divided into five categories based on average headway as shown in Table 4.5.

Using the city and GTFS datasets, two multi-modal transportation networks were constructed to imitate the transportation network in the city of Kelowna for two years of interest: 2014 and 2016.

Table 4.5 Bus Stops Frequency Classification by Average Headway

Level	**Average Headway**
High service	Less than 20 min
Medium service	From 20 min to 30 min
Low service	From 30 min to 45 min
Very low service	More than 45 min
No service	—

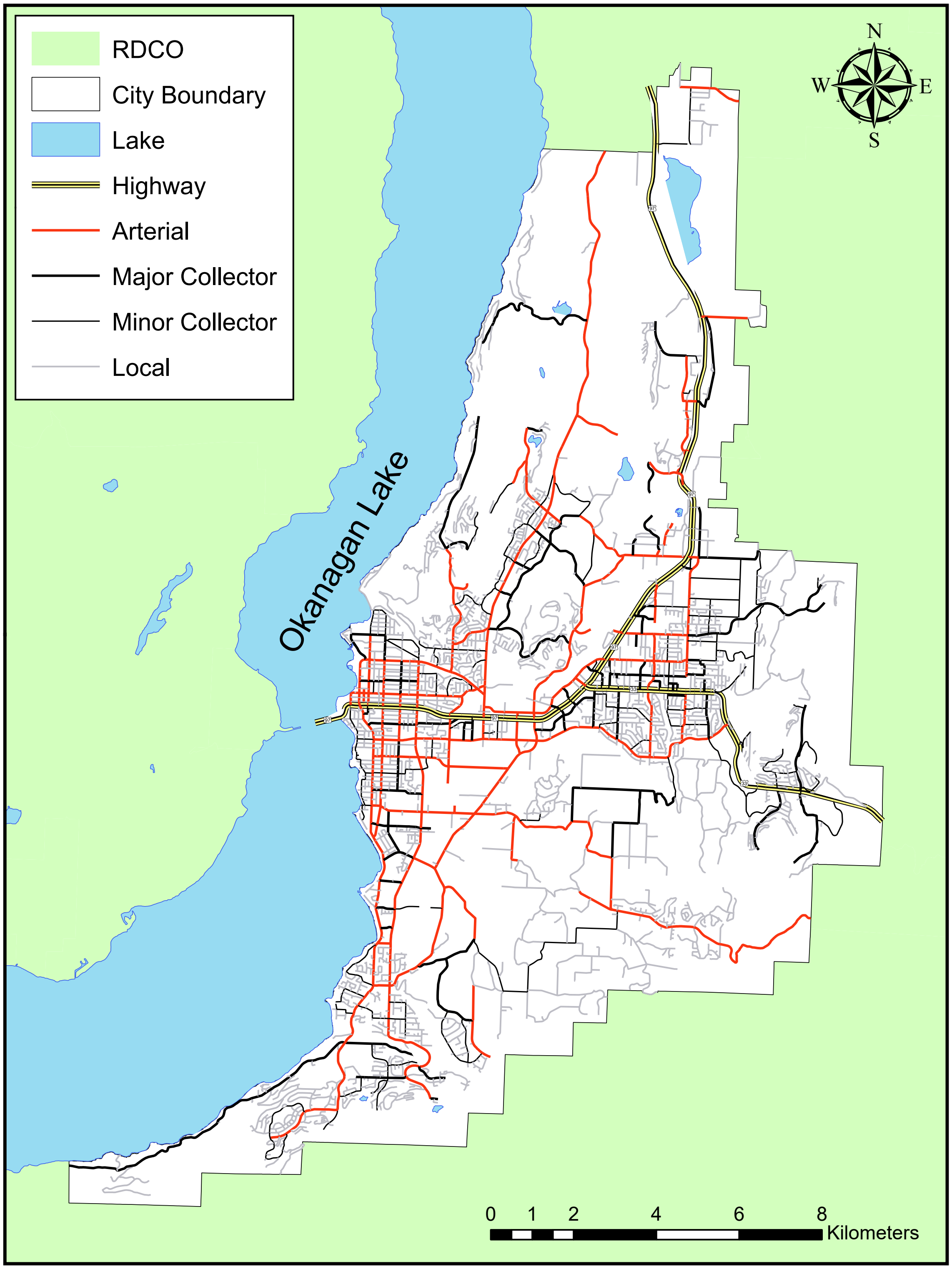


Figure 4.11: City of Kelowna's road network

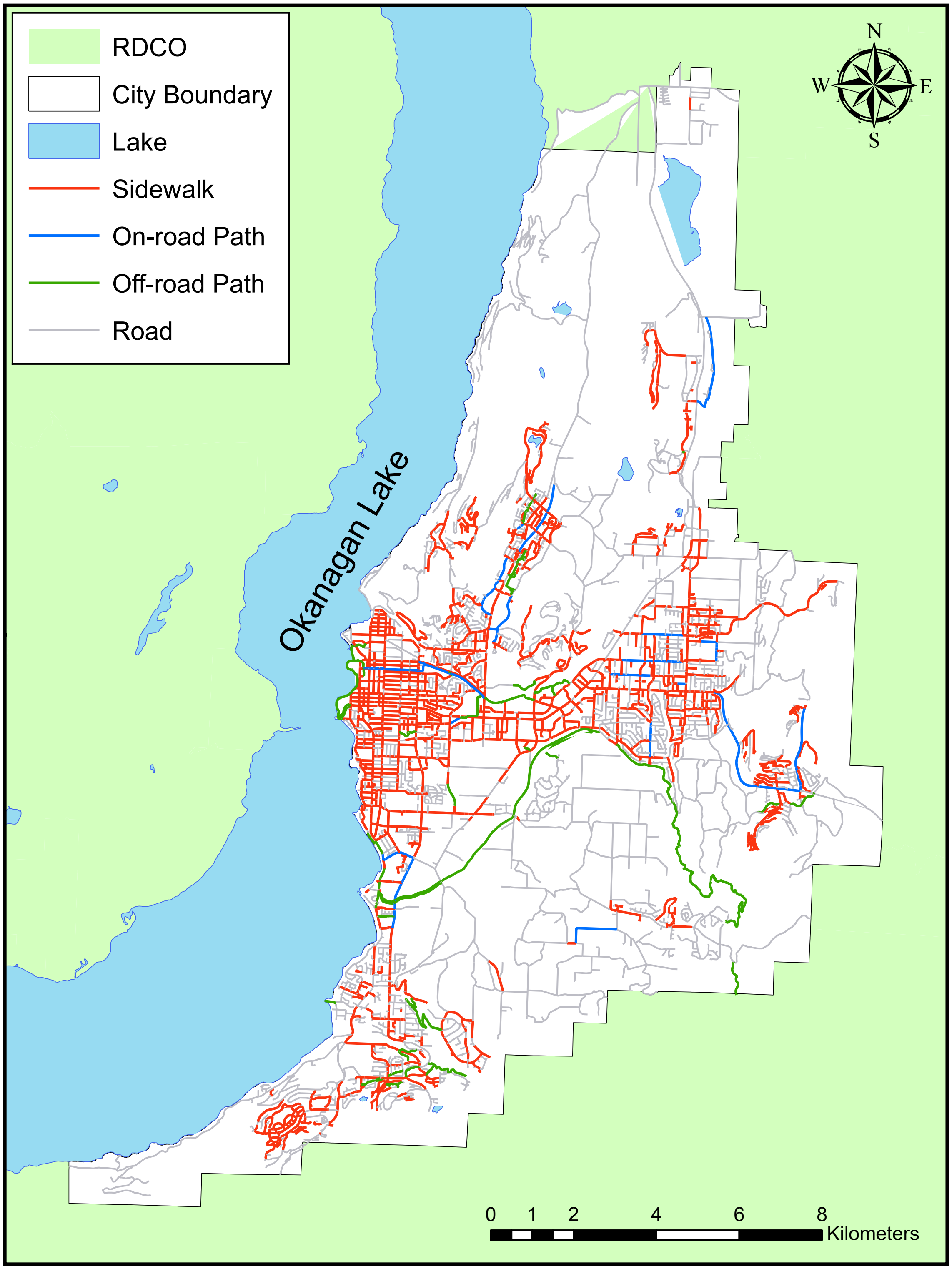


Figure 4.12: City of Kelowna's walking network

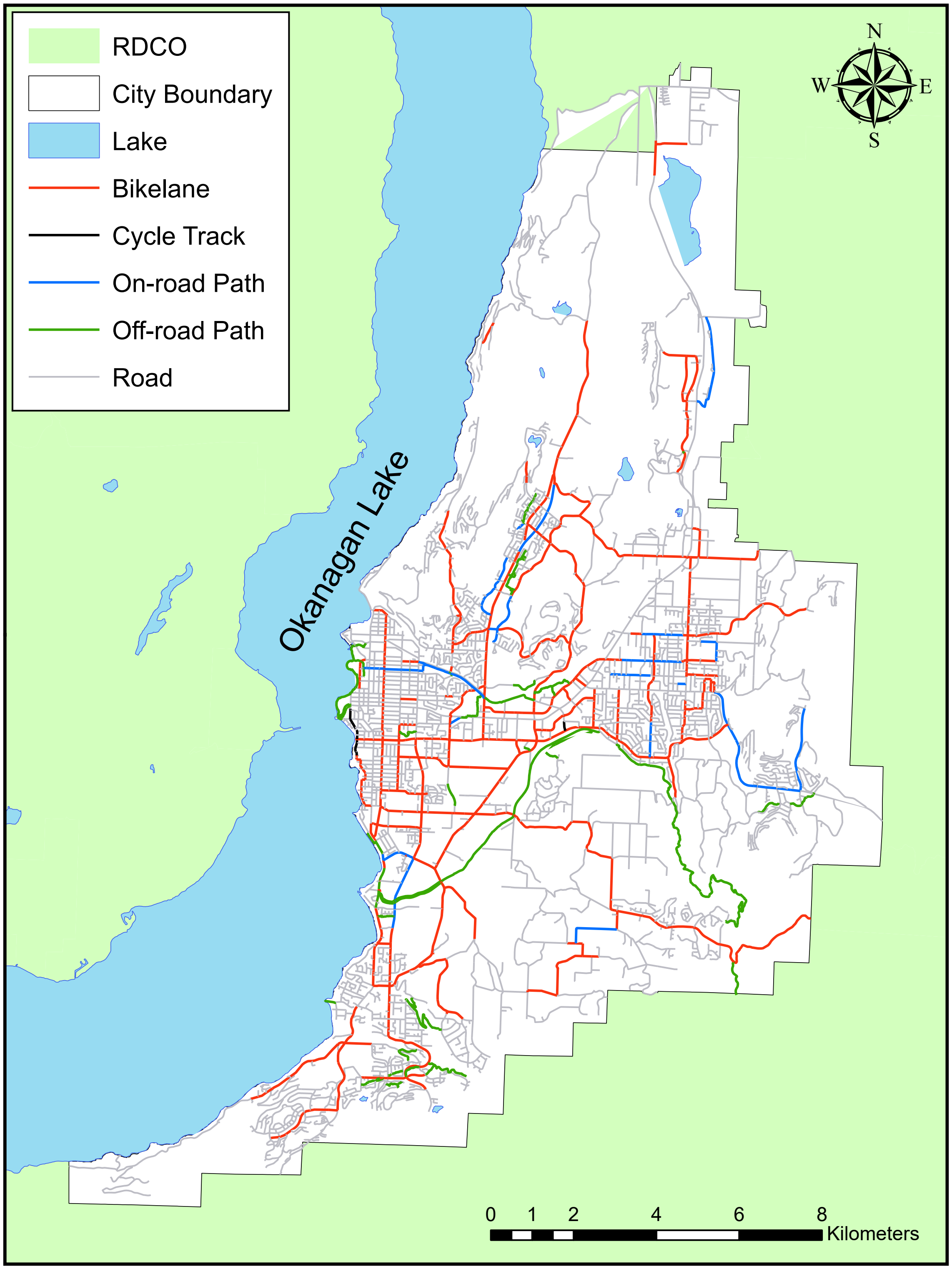


Figure 4.13: City of Kelowna's cycling network

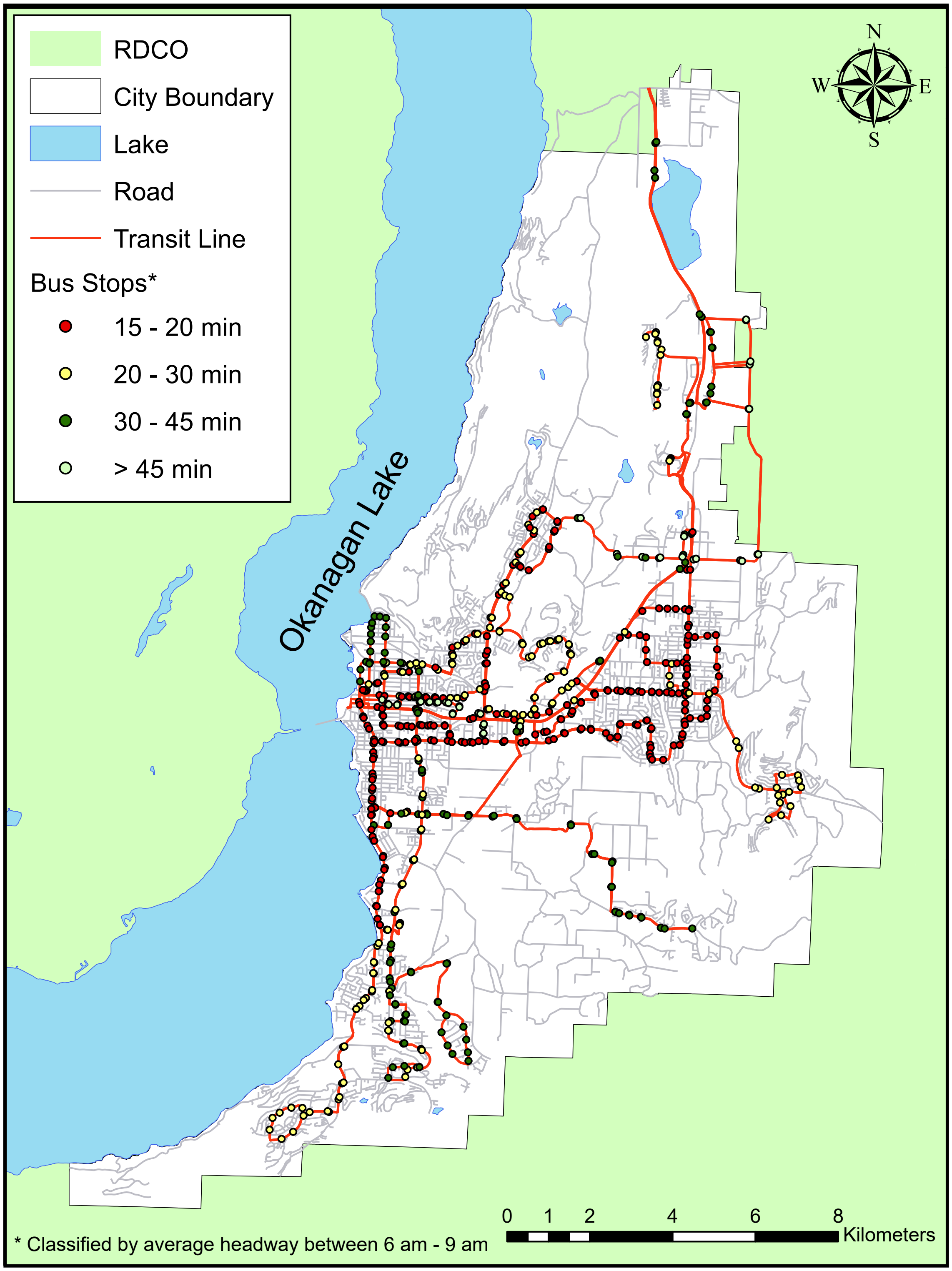


Figure 4.14: City of Kelowna's transit network

4.2.4 Land Use Information

Finally, land use data for the study area in 2014 were obtained from the city of Kelowna. The data was compiled at the parcel level using various sources including Census Canada profiles, BC Assessment, Canada Business Points, and the Central Okanagan School District's enrollment counts. Figure 4.15 shows several land use characteristics of Kelowna aggregated at the dissemination area level; a parcel was associated with a dissemination area if its centroid falls within the dissemination area boundary.

The land use data at the parcel level for the year of 2016 were not available to the researcher. Thus, there were approximated by assuming a uniform rate of change for all parcels in a dissemination area. The rate of change for each dissemination area was calculated using the aggregated number of population and employment in each dissemination area in 2014 and 2016.

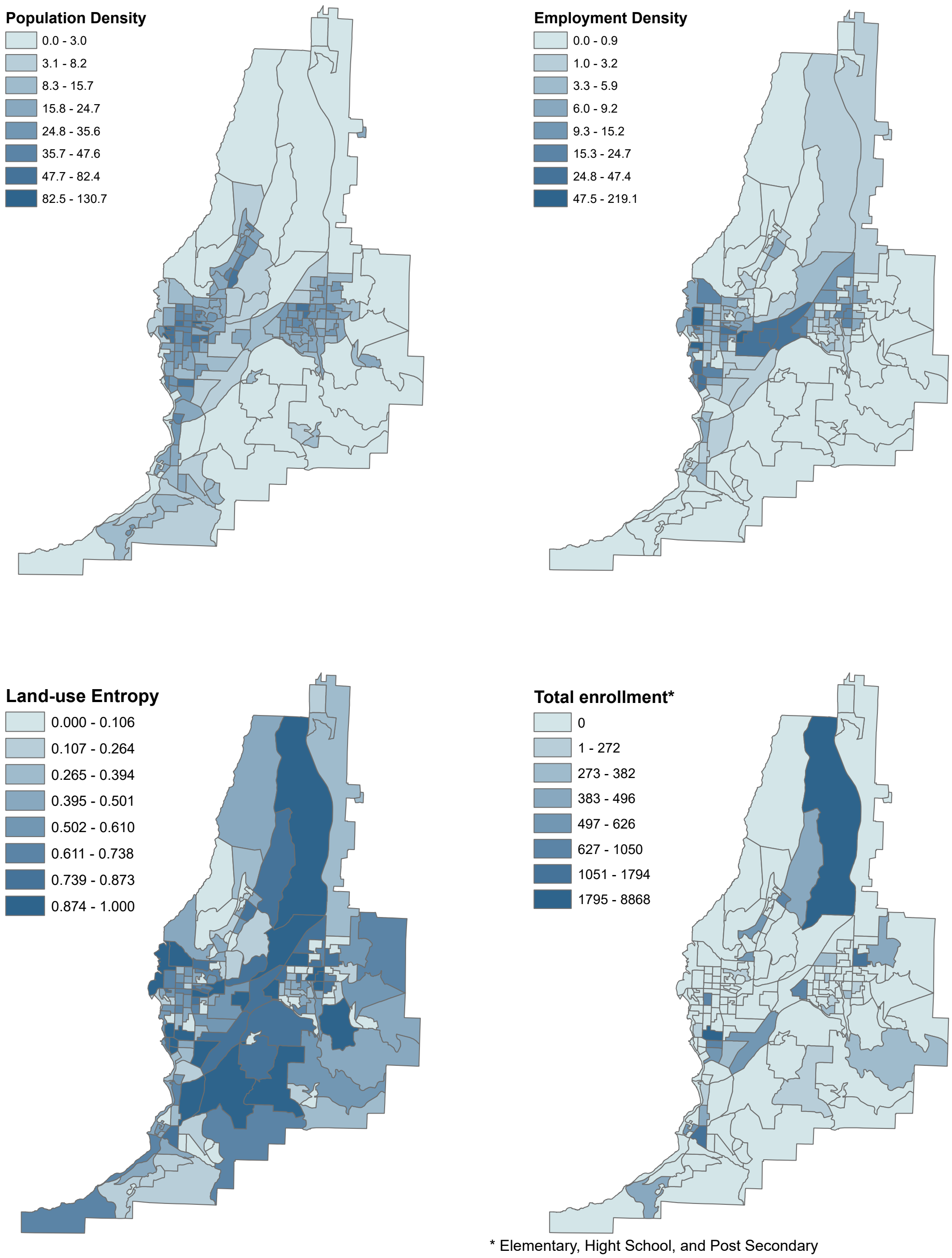


Figure 4.15: Land use Characteristics of Kelowna

Chapter 5 Model Development & Calibration

5.1 Population Synthesis

A population synthesizer, namely Popgen, was used to generate a population for the city of Kelowna using the disaggregate OTS data and the aggregated census data. PopGen is an open-source population synthesizer that employs the iterative proportional updating (IPU) algorithm (Bar-Gera, Konduri, Sana, Ye, & Pendyala, 2009; Konduri, You, Garikapati, & Pendyala, 2016; Ye, Konduri, Pendyala, Sana, & Waddell, 2009b). It adjusts weights iteratively among households of the same type until they match the known marginal distributions of households and personal level attributes of interest. In this research, the household level attributes included dwelling type and number of people per household; the person level attributes included age and sex.

Table 5.1 compares the characteristics of the synthetic agents with the observed population. It can be seen from the data in this table that the maximum difference between the synthetic and observed population was 0.7%, which was for the sex variable, while the lowest difference was 0%. While this preliminary comparison suggests that the population synthesis module generated a representative synthetic population, further empirical testing was required to support this hypothesis.

Several goodness-of-fit measures were found in the literature for evaluating the fit between the actual and synthetic population. The most commonly used indicator in the literature is the standardized root mean square error (SRMSE), as illustrated in Equation 5-1 (Farooq, Bierlaire, Hurtubia, & Flötteröd, 2013; Fatmi & Habib, 2018; Pritchard & Miller, 2012; Saadi, Mustafa, Teller, Farooq, & Cools, 2016). The SRMSE is a distance-based statistic. It has a lower limit of zero, which represents a perfect fit, and a variable upper limit depending on the distribution of T_{ij}, that is usually assumed to be 1 (Pritchard & Miller, 2012). While the SRMSE is superior over traditional goodness-of-fit measures (e.g. R^2 and chi-square), it can only be used when the totals match (i.e. $\sum_{i,j} \hat{t}_{ij} = \sum_{i,j} t_{ij}$) (Knudsen & Fotheringham, 1986).

$$\text{SRMSE} = \frac{\sqrt{\frac{1}{I \times J} \sum_i^I \sum_j^J \left(\hat{t}_{ij} - t_{ij}\right)^2}}{\frac{1}{I \times J} \sum_i^I \sum_j^J \hat{t}_{ij}}, \qquad \text{5-1}$$

where:

$\hat{t}_{ij}$: is the synthesized number of agents with the combination of the attributes i, j,

t_{ij}: is the observed number of people with the combination of the attributes i, j.

The population synthesis results show that Popgen generated a synthetic population of 54,355 households, compared to 54,445 observed households, and 123,135 individuals, compared to 123,035 observed individuals. These results reveal an insignificant under-representation of the number of households and a slight over- representation of the number of individuals by 0.17% and 0.08%, respectively. Thus, the SRMSE cannot be used to evaluate the synthetic population in this research.

An alternative approach is to use the statistic $\overline{\psi}$ (Equation 5-2), an information-based statistic, which was among the three goodness-of-fit measures recommended by Knudsen and Fotheringham (1986). Similar to the SRMSE, the lowest limit for the statistic $\overline{\psi}$ is zero, which indicates a perfect fit. The resulted statistic $\overline{\psi}$ for the synthetic population was calculated to be 0.037, which indicates a realistic synthetic population.

Table 5.1 Socio-economic Characteristics of the OTS Subsets Used for Model Development

Variable	Category	Observed %	Synthetic %	Difference %
Households Characteristics				
Household size	1	29.2	29.2	0.00
	2	39.0	39.0	0.01
	3	13.7	13.7	0.01
	4+	18.1	18.1	0.02
Household dwelling type	Single Detached House	45.8	45.9	0.02
	Apartment or Condo	30.4	30.4	0.01
	Townhouse or Row House	7.3	7.3	0.02
	Duplex	15.0	15.0	0.03
	Mobile Home	1.5	1.5	0.01
Persons Characteristics				
Age	(05-14)	10.1	10.1	0.06
	(15-24)	13.1	13.2	0.11
	(25-34)	14.0	13.9	0.09
	(35-44)	12.1	12.4	0.28
	(45-54)	14.2	14.2	0.03
	(55-64)	14.9	15.0	0.16
	65 and over	21.7	21.2	0.55
Sex	Men	48.4	47.7	0.66
	Women	51.6	52.3	0.66

$$\overline{\Psi} = \sum_i \sum_j p_{ij} \left| \log \frac{p_{ij}}{s_{ij}} \right| + \sum_i \sum_j q_{ij} \left| \log \frac{q_{ij}}{s_{ij}} \right|, \qquad 5\text{-}2$$

where:

$$p_{ij} = \frac{t_{ij}}{\sum_i \sum_j t_{ij}}, \qquad 5\text{-}3$$

$$q_{ij} = \frac{\hat{t}_{ij}}{\sum_i \sum_j \hat{t}_{ij}}, \tag{5-4}$$

$$s_{ij} = \frac{(p_{ij} + q_{ij})}{2}. \tag{5-5}$$

In addition, statistic $\overline{\psi}$ was computed at the dissemination area level to assess the spatial distribution of the synthetic population matrix compared to the observed population matrix. The results, as shown in Figure 5.1 (a), show that around 72% of the dissemination areas have a $\overline{\psi}$ less than 0.1 and a maximum $\overline{\psi}$ value of 0.166, which is consistent with levels found in the literature to be acceptable goodness of fit.

Similarly, the second measure used to assess goodness of fit, the standardized absolute error (SAE) goodness-of-fit measure, Equation 5-6, was also computed at the dissemination area level to assess the spatial distribution of the total number of synthetic agents in comparison with the observed population. The results, as depicted in Figure 5.1, reveal that around 64% and 92% of the dissemination areas have SAE values of less than 5% and 10%, respectively. Overall, the results from both measures show that the population synthesis module used in this research generated a synthetic population that yields a high level of goodness of fit.

$$SAE_k = \left| \frac{T_k - \hat{T}_k}{T_k} \right| \times 100, \tag{5-6}$$

where:

T_k: is the total number of observed population in dissemination area (k).

$\hat{T}_k$: is the total number of synthetic agents in dissemination area (k).

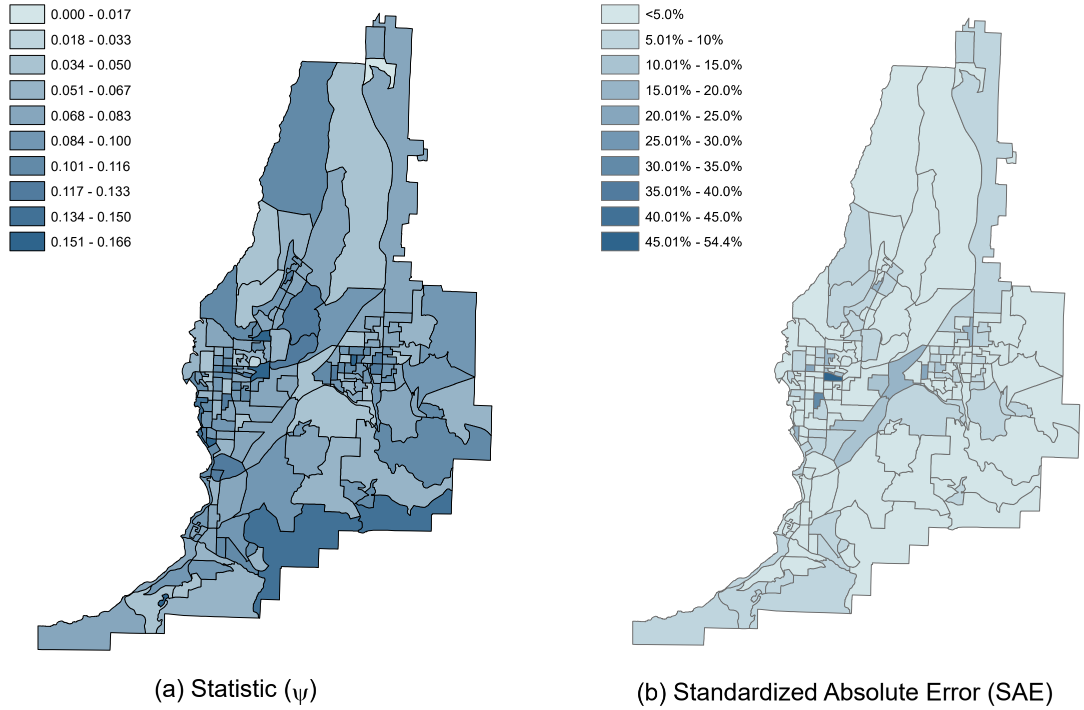


Figure 5.1: Goodness-of-fit measures of the synthetic population at the dissemination area level

5.2 Discrete Morning Home-to-work Attraction-end Choice Model

5.2.1 Modelling Methods

This section discusses variable selection, parameter estimation, and choice subset size determination for the discrete morning home-to-work attraction-end choice model. Several explanatory variables are considered for the model including travel impedance, zonal attributes and size measures, and the interaction of travel impedance with socio-economic characteristics of individuals.

A composite travel impedance was utilized in this study to account for modal availability between zones, such as the unavailability of a travel mode should increase the impedance value for a zone pair (Bhat et al., 1998). While driving was available for all zone pairs in the study area, transit, walking, and cycling were not available for several zone pairs. In theory, walking and cycling are also available for all zone pairs; however, practically, there is a threshold distance that people are willing to commute. One approach to estimate the walking/cycling threshold distance is by calculating the 95th percentile of walking/cycling commuting trip distances. In this research the walking and cycling threshold distances are estimated to be 1.9 km and 10 km, respectively, as shown in Figure 5.2 and Figure 5.3. The composite travel impedance was calculated as the following (Bhat et al., 1998):

$$\text{imp} = \frac{TT_c}{1 + \left(y_t \times \frac{TT_c}{{TT_t}^{\beta}}\right) + \left(y_w \times \frac{TT_c}{{TT_w}^{\gamma}}\right) + \left(y_b \times \frac{TT_c}{{TT_b}^{\lambda}}\right)}, \quad \text{5-7}$$

where y_t, y_w, and y_w are dummy variables that indicate the availability of transit, walking, and cycling modes, respectively (1 if available, 0 otherwise), and TT_c, TT_t, TT_w, TT_b are driving, transit, walking, and cycling travel times, respectively. The parameters β, γ, and λ have a positive value and they denote the importance of transit, walking, and cycling modes compared with driving mode. These parameters were determined empirically by estimating the model in Equation 5-8, assuming that the probability of a trip in zone i to be attracted to zone j is only influenced by composite impedance. The results reveal that β, γ, and λ were statistically significant with values of 5.86, 2.24, and 4.0, respectively.

$$P_{qij} = \frac{e^{\alpha f(imp_{qij})}}{\sum_{j \in C_q} e^{\alpha f(imp_{qij})}}. \quad \text{5-8}$$

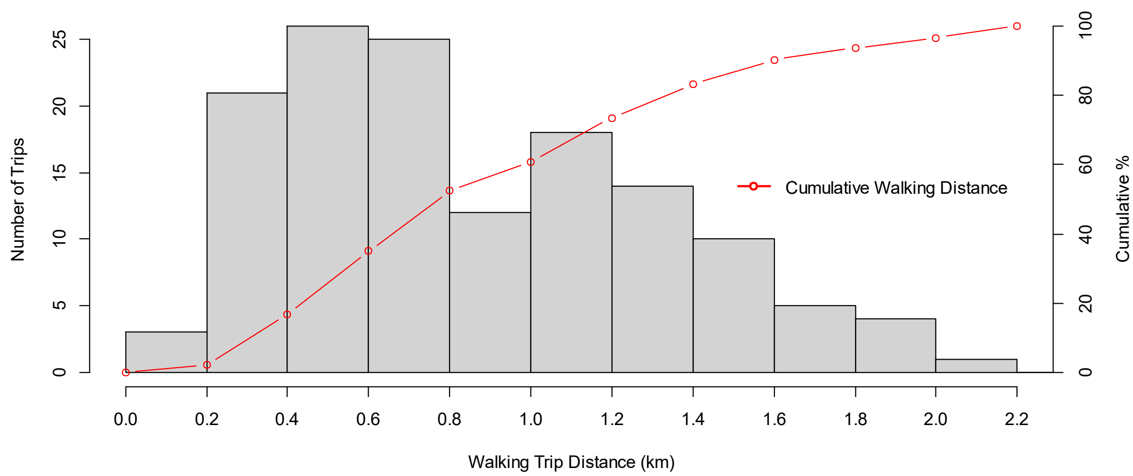


Figure 5.2: Cumulative walking distance distribution curve

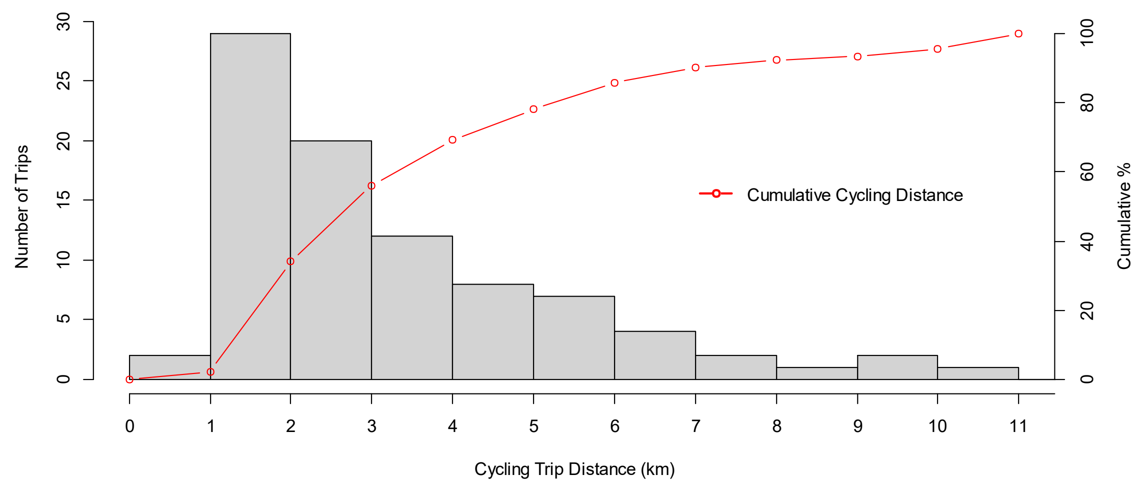


Figure 5.3: Cumulative cycling distance distribution curve

In addition, several zonal measures were considered for the model, which were classified as size and non-size measures. The size measures included total number of employments, number of non-retail employment, and number of retail employment. The non-size measures included land-use mix (population and employment), employment mix (retail and non-retail), and an urban core dummy variable (1 if located in the city's urban core, 0 otherwise). Both land-use mix and employment mix were measured in terms of entropy score and are computed as illustrated in Equation 5-9, where P_j is the proportion of land use development for type j and J is the number of land use types.

$$Entropy = \frac{\sum_j \lfloor P_j \times \ln P_j \rfloor}{\ln J}. \qquad 5\text{-}9$$

The last set of explanatory variables considered for the discrete attraction-end model is the interaction between travel impedance and individual attributes such as age, gender, and occupation.

The model parameters were estimated using the DONLP2 optimization algorithm (Spellucci, 1998a; Spellucci, 1998b) coded in Biogeme (2003), an open source package for maximum likelihood estimation; the DONLP2 algorithm is used due to the nonlinear form of the logit model. The choice subset was restricted to seven alternatives, including the chosen alternative. In addition, the forward stepwise method is used for variable selection based on three criteria: 1) statistical significance of the parameter estimates, 2) the parameter estimate signs are intuitive, and 3) the model goodness-of-fit. A variable is retained in the model if it exhibits statistical significance at the 95% confidence interval level, which corresponds to critical values of 1.96 for 2-tailed test and 1.645 for 1-tailed test. In addition, the parameter signs should be in the expected direction. For instance, a positive sign for a travel impedance parameter would imply that the probability of choosing an alternative will increase as travel impedance increases, which is contrary to expected travel behaviour and thus should be eliminated. Finally, a variable is selected if it increases the model goodness-of-fit. It has been well established that adding a variable to a model will always increase its training error regardless of the variable importance and thus measures such as the McFadden's pseudo ρ^2

cannot be used to compare models with different number of variables. Thus, a modeller should consider either directly estimating the test error or using a goodness-of-fit measure that accounts for overfitting bias (James et al., 2017). One popular approach is to use the adjusted ρ^2 (Koppelman & Bhat, 2006), as presented in Equation 5-10, which places a penalty for adding a new variable. Therefore, if the decrease in the training error due to adding a variable is less than the penalty, then the value of the adjusted ρ^2 will decrease.

$$\text{Adjusted } \rho^2 = 1 - \frac{LL(\hat{\beta}) - K}{LL(0)}, \quad \text{5-10}$$

where $LL(\hat{\beta})$ is the log-likelihood for the estimated model, $LL(0)$ is the log-likelihood with zero parameters, and K is the number of estimated parameters.

5.2.2 **Modelling Results**

The final model parameter estimates result of the attraction-end choice model and their corresponding statistical significance are shown in Table 5.2. The negative coefficient for the composite impedance measure indicates that the probability of choosing a candidate destination decreases with the increase between the production zone and the candidate zone. In addition, the results show that individuals in the higher income groups are less sensitive to travel impedance than those in the lower-income groups. Similarly, the number of vehicles per person in a household reduces individuals' sensitivity to travel impedance. The coefficient of the zonal size measures indicates that individuals are more likely to choose zones with a high number of total employments. Moreover, the positive coefficient for the Urban Core dummy variables indicates zones that are located in the urban core are more likely to attract work activities.

Table 5.2 Parameter Estimation Results for the Discrete Morning Home-to-work Attraction-end Choice Model

Null log-likelihood	-4881.142	
Final log-likelihood	-2736.256	
Adjusted ρ^2	0.438	
Variable	**Parameter**	**t-stat.**
Composite impedance	-0.225	-25.33
Urban Core	0.295	3.36
Log of zonal size measures		
Size of the zone (hectare)	1.0	—
Total number of Employment	0.434	2.46
Socio-economic interactions with composite impedance		
Household Income ($100,000 or more)	0.0182	3.05
Vehicles/person in a household	0.0251	3.54

In addition, Figure 5.4 shows that the projected travel time distribution from the discrete choice model mimics the actual travel time distribution observed in the OTS dataset.

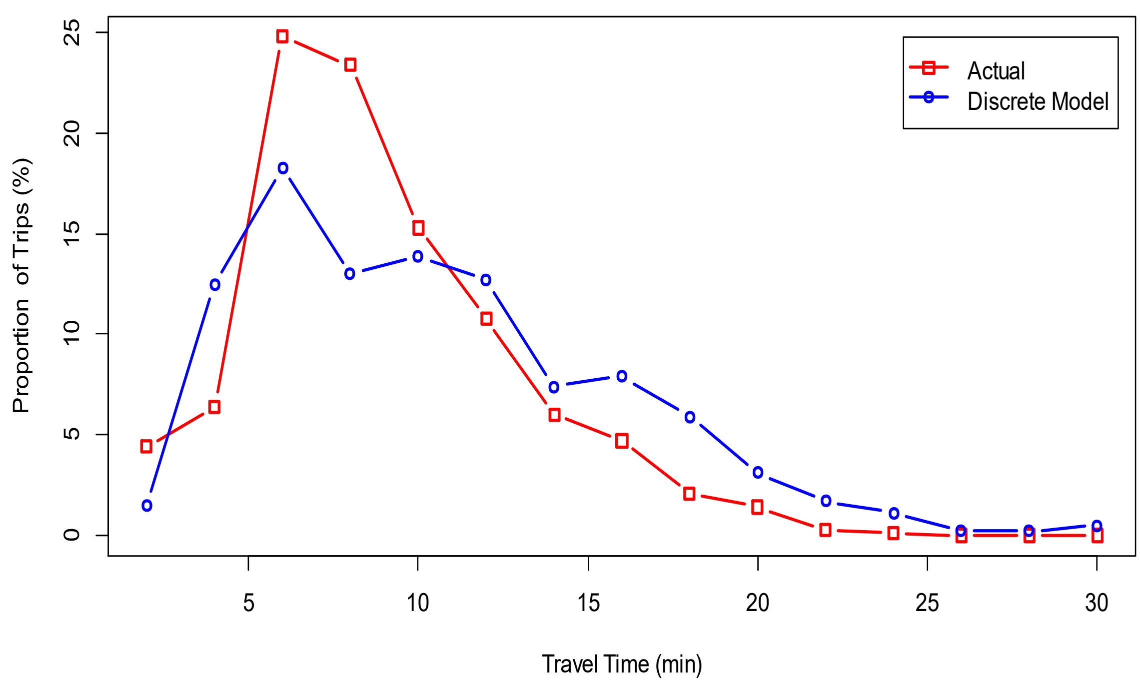


Figure 5.4: Trip time distribution comparison between the actual and estimated trips

5.3 Discrete Morning Home-to-work Mode Choice Model

5.3.1 Modelling Methods

An MNL model for morning home-to-work mode choice decisions was developed for the city of Kelowna. The model accounts for socioeconomic characteristics, level of service attributes, and built-environment measures. The built-environment measures were quantified at various buffer distances (300, 400, up to 1,000 m) for all trips' origins and destinations. Two type of buffers were used in this study including circular and road network buffers (Figure 5.5). Population density, employment density, land use diversity, employment diversity, and length of AT infrastructure were quantified using circular buffers while proximity to bus stops and green spaces were quantified using road network buffers.

Figure 5.5: Network buffer vs circular buffer

Four utility functions were estimated for the four travel modes considered in this research which are: 1) automobile, 2) transit, 3) walk, and 4) bike; these travel modes represent the universal choice set. However, not all alternatives in the universal choice set were feasible for the entire population, which could be due to legal regulations, the individual's characteristic, and trip attributes. The subset of the universal choice set that is available for an individual is called the feasible choice set, and it was used for model calibration.

Several assumptions were made regarding the availability of the four travel modes considered in this research. For instance, the automobile mode is assumed to be available for individuals since it comprises both drive-alone and shared-ride alternatives. Transit is assumed to be available for all trips, unless transit travel time cannot be calculated using the Google Maps Directions API, which indicates that trip origin and/or destination is at least 3 km away from the nearest bus stop. Finally, walking and cycling availability is determined using the 95th percentile of walking/cycling commuting trip distances as discussed in Section 4.2.1.

The model parameters were estimated using the BIerlaire's Optimization (BIO) algorithm adapted in Biogeme. Similar to the attraction-end choice model, the forward stepwise method is used for variable selection based on the three criteria: statistical significance, intuitive parameter sign, and goodness-of-fit. Nevertheless, explanatory variables that provide significant behavioural insights and policy implications were retained in the model even if they were below the 95% confidence interval level (Fatmi, 2017; Rahman, 2016). In addition, in light of numerous studies suggesting a non-linear relationship between non-motorized modes and their predictors (Cervero, Denman, & Jin, 2019; Hanson & Giuliano, 2017), several non-linear forms for walking and cycling utilities were examined including exponential, logarithmic and quadrant functions. However, the results indicated that a linear utility function for walking and cycling modes provides better goodness-of-fit for the mode choice model.

5.3.2 **Modelling Results**

The final model parameter estimates result of the mode choice model and their corresponding statistical significance values are shown in Table 5.3. The modelling results show that travel distance and time are negatively associated with all travel modes, as one would expect. However, females are more sensitive to the increase in cycling distance than males. In addition, the results show that those in the age range from 15 to 24 years are less likely to use the auto mode and more likely to walk to work, which could be explained by youth having limited access to a driving license and/or a vehicle. The number of vehicles and bikes per person in the household has a significant negative association with auto use and bike use, respectively; however, the influence of the increase in the number of vehicles per person is much stronger and more significant than the increase of the number of bikes per person.

For the built environment measures, the results indicate that higher employment density within a 400m buffer of trip destinations increases the likelihood of using transit and cycling modes. In addition, land use diversity, measured by entropy at a 700m buffer of trip origins, is found to be positively associated with the increase of the likelihood of walking. The availability of high frequency bus stops within 800m of trip origins has a significant positive association with transit use. On the other hand, the availability of medium frequency bus stops within 500m of trip origins has a positive association, but not statistically significant, with the increase of the likelihood of using transit. These results indicate that people are willing to walk longer distances, than usually assumed in transportation studies, to reach bus stops with high frequency service. Moreover, the length of bike lanes within an 800m buffer of trips origins and a 600m buffer of trip destinations decreases the likelihood of using the auto mode. Finally, the availability of green spaces and off-road paths are positively associated with the cycling mode, which could be attributed to the higher perceived level of safety on off-road paths compared to on-road facilities.

Table 5.3 Parameter Estimation Results for the Discrete Morning Home-to-work Mode Choice Model

Null log-likelihood	- 1856.379			
Final log-likelihood	- 600.114			
Adjusted ρ^2	0.663			
Variable	**Auto**	**Transit**	**Walking**	**Cycling**
Alternative Specific Constant	—	-3.69	1.77	-2.78
level of service				
Travel Time	-0.144 (-3.36)	-0.0188 (-1.57)	—	—
Travel Distance	—	—	-2.33 (-10.53)	-0.361 (-5.35)
Socio-economic				
Age Group (15-24)	-1.17 (-4.06)	—	0.902 (2.15)	—
Age Group (55-64)	-0.551 (-1.91)	—	—	—
Driver's license	0.632 (2.32)	—	—	—
Monthly transit pass	—	3.82 (12.23)	—	—
Vehicles/person in the household	1.77 (6.38)	—	—	—
Bikes/person in the household	—	—	—	1.23 (7.22)
Female × Distance	—	—	—	-0.132 (-2.38)

Variable	Auto	Transit	Walking	Cycling
Built Environment				
Employment density 400 m (at destination)	—	0.00588 (1.61)	—	0.0105 (3.42)
Land use entropy 700 m (at origin)	—	—	1.27 (2.31)	—
# high frequency bus stops 800 m (at origin)	—	0.0601 (2.07)	—	—
# medium frequency bus stops 500 m (at origin)	—	0.117 (0.83)	—	-0.270 (-1.64)
Green spaces availability 500 m (at origin)	—	—	—	0.860 (1.84)
Bike lane length 800 m (at origin)	-0.119 (-1.91)	—	—	—
Sidewalk length 300 m (at destination)	—	—	0.307 (2.21)	—
Off-road path length 800 m (at destination)	—	—	—	0.194 (1.32)

values within parenthesis () show t-stat value

5.4 Calibrating Route Choice

The complex nature of agent-based models makes them difficult to calibrate and validate, especially with the lack of significantly detailed datasets for various components of the system. In such cases, pattern-oriented modelling (POM) becomes an extremely useful tool, in which multiple patterns are used to guide the calibration process (O'Sullivan & Perry, 2013; Wiegand, Jeltsch, Hanski, & Grimm, 2003). Grimm et al. (2005) described patterns as "defining characteristics of a system and indicators of essential underlying processes and structures". As participants in the OTS were not asked to report their trips routes, pedestrian and cyclists route choice algorithms in this research are calibrated by comparing ABM simulation's predicted walking and cycling traffic patterns with those found in the literature, as discussed below.

5.4.1 **Pedestrian Route Choice**

Several studies have examined the route choice behaviour of pedestrians. Seneviratne and Morrall (1985) conducted a survey to evaluate the factors affecting the route choice of walking trips within the CBD of Calgary, Alberta, Canada. With 2,685 valid questionnaires, they found that the shortest path was the most important factor that influences pedestrians route choice and that people unconsciously try to minimize their walking trips. Similarly, Schlossberg et al. (2007) found that pedestrians' first priority is to minimize travel time and distance (i.e. choosing the most direct and shortest route). In addition, Verlander and Heydecker (1997) found that around three quarters of pedestrians chose the shortest path. On the other hand, the increase in trip length for the other quarter was highly variable.

The results of the simulation using the calibrated pedestrian route choice model estimated that around 79% of walking trips are using the shortest route. The increase in the number of walking trips that are using the shortest path compared to the literature is attributed to the fact that neighbourhoods in the city of Kelowna have mixed street patterns (e.g. grid, loops and lollipops, cul-de-sacs, etc.), which means that some pedestrians do not have the option to choose among several comparable route options (i.e. they only have one feasible route from origin to destination, so they take it, and, it is the shortest route); previous research have studied neighbourhoods with a grid street pattern. In addition, walking trips are, on average, 21 m longer than the shortest route, which represents a 1.54% increase over the shortest distance. Figure 5.6 shows that the increases in trip distance are fairly well distributed over the length of the shortest path with a poor least square fit of $-2.3 + 0.017x$ and $R^2 = 0.06$.

These results are in accord with the literature indicating that pedestrians tend to minimize their physical effort by choosing the shortest path.

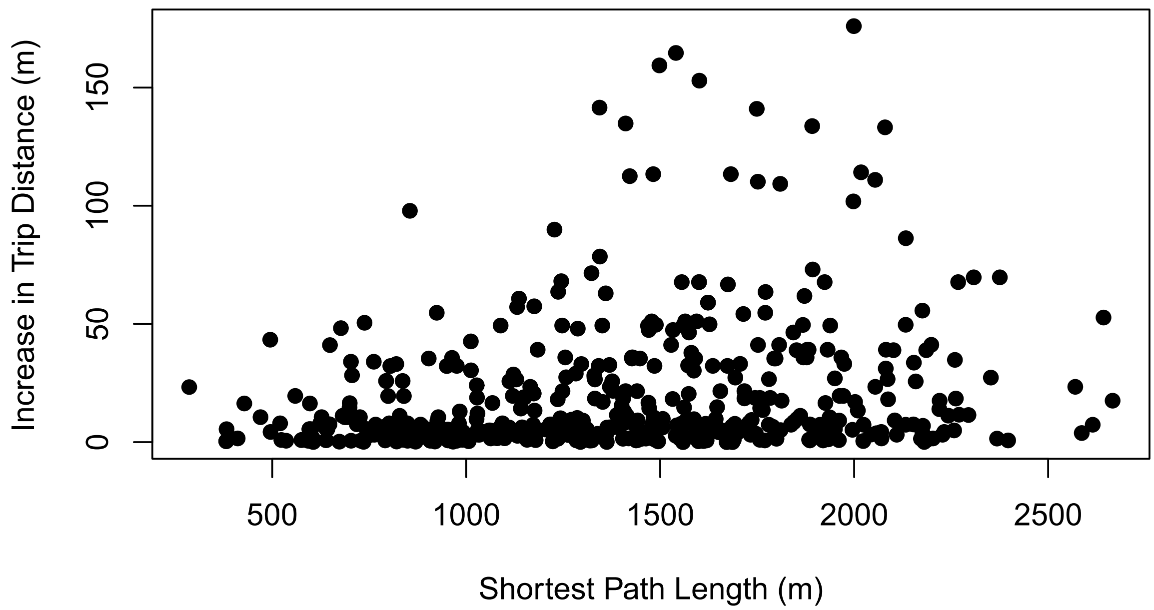


Figure 5.6: Scatter plot of the increase in trip distance over the shortest path length

5.4.2 **Cyclist Route Choice**

In contrast to pedestrians' route choice behaviour, minimizing travel time and distance is not the sole element that determines cyclists' route choice. Cyclists generally prefer using off-street paths and lower-volume roads (Winters, Teschke, Grant, Setton, & Brauer, 2010). Li et al. (2017) tracked the route choice of about 4,600 cyclists in Toronto, Ontario, Canada using a smartphone application that collects cyclists' GPS data. They found that the average overlap between the chosen route and the shortest route was around 29 percent, which indicates that other factors, such as bicycle facilities, play an important role in determining cyclists' route choice. Upon further investigation, they found that cyclists were willing to detour around 6% in distance from the shortest route to avoid high traffic volume. In addition, Li et al. (2017)

found that increasing the proportion of the route along off-road facilities by 1% is perceived by cyclists as decreasing the trip's distance by around 5%. These findings were supported by Larsen and El-Geneidy (2011), who also found that cyclists would ride farther to travel along off-road facilities as compared to bike lanes. Additionally, the research found that the availability of cycling facilities within 400 m of the home and destination increases the odds of using the facility by 129% (Larsen & El-Geneidy, 2011). Likewise, Stinson and Bhat (2003) estimated that cyclists are willing to increase their travel time by 10% to travel along routes with cycling facilities. In addition, Krizek et al. (2007) found that cyclists endured, on average, a 67% additional travel distance to use off-road facilities. Furthermore, Winters (2010) found that 75% and 90% of cycling trips are within 10% and 20% of the shortest distance, respectively. In contrast, a study in Guelph, Ontario, Canada found that the majority of cyclists prefer using on-road facilities rather than using off road paths (Aultman-Hall, Hall, & Baetz, 1997)—this is an old study that may have had significant confounding and masking factors; it may also have been a local cultural effect related to the relatively low-volume, rural roads and the high number of university students typical in the Guelph community population. On a side note, the classification of the road where the AT facility is located also influences AT use as well as driver attitudes. Audirac (2008) showed that drivers would be annoyed the most to share the road with cyclists on an arterial road (83 percent), followed by highways (80 percent), and finally collector and local roads (58 percent).

My simulation predicted that around 33% of cycling trips are using the shortest route, while the remaining trips are, on average, 322 m longer than the shortest route, which represents a 9.5% increase over the shortest distance. Figure 5.7 shows that around 77% of cycling trips are within 10% of the shortest distance and 90% of the cycling trips are within 20% of the shortest distance.

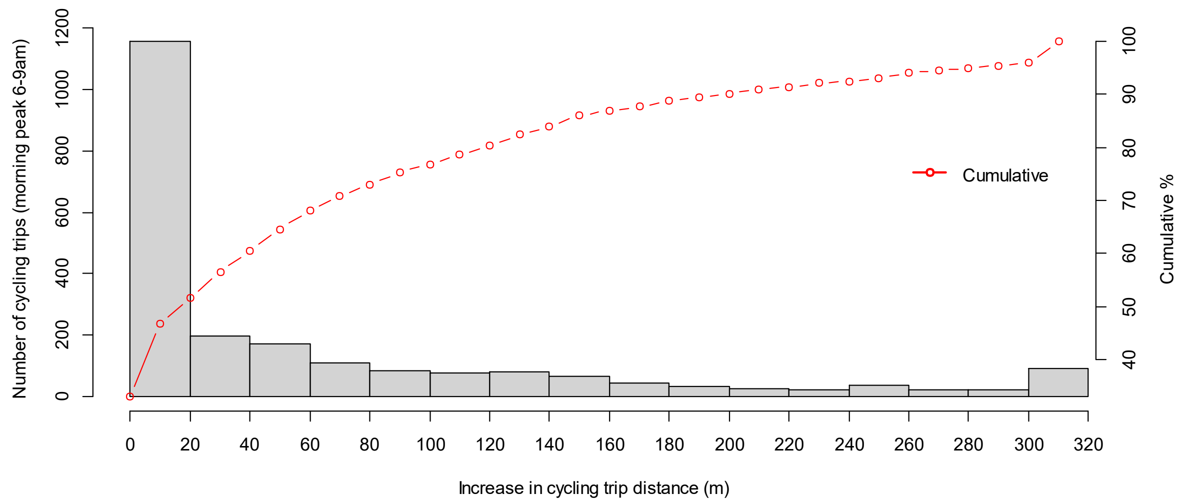


Figure 5.7: Distribution of the increase in predicted cycling trip distance comparted to the shortest path trip distance

In addition, distance-decay functions provide a robust way to understand travellers' spatial behaviour (Krizek et al., 2007). In this research, the distance examined in the decay function is the increase in trip distance relative to the distance of the shortest route. Figure 5.8 depicts distance-decay curves by three cycling facility types: off-road paths; on-road physically separated, and on-road bike lanes. Examining the decay curves revealed similar trends to those observed by Larsen and El-Geneidy (2011) who found that cyclists would ride farther to travel along an off-road facility than any on-road facility regardless of the level of separation. Similarly, they found that cyclists would ride farther to travel along a physically separated on-road facility (e.g. cycle track) than a bike lane. The simulation results show that cyclists, on average, traveled 249, 288, and 430 m further to use on-road bike lanes, on-road physically separated facility, and off-road paths, respectively.

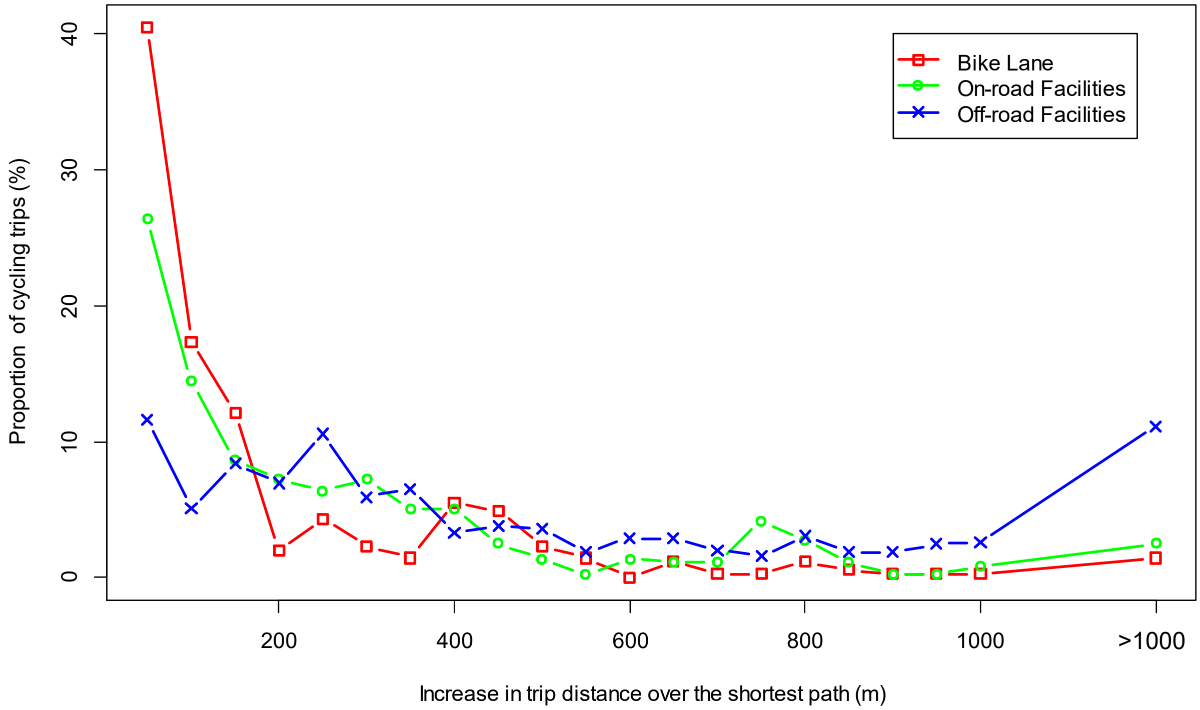


Figure 5.8: Distance-decay curves by facility type

5.5 Calibrating Information Provision

A genetic algorithm (GA) approach is utilized to automate the process of calibrating the proportions of information provision categories in the synthetic population. GA is used in this research due to its easy implementation, good performance, and robust response to dynamic changes (Liu & Fan, 2020; Sivanandam & Deepa, 2007). GA is an iterative and stochastic search process that attempts to mimic natural evolution (Sivanandam & Deepa, 2007). Moreover, GA uses genetic population terminology to describe a mathematical model. The model consists of a population of individuals that breed repeatedly to produce fitter individuals. Individuals are described by their genetic material, chromosomes, which contain a set of genes (parameters); each chromosome represents a solution to the problem at hand. During each iteration, GA works with a new population set that is commonly called generation.

The first step in a GA algorithm, as shown in Figure 5.9, is initializing the population variables: 1) population size and 2) initial population. The population size is determined based on the complexity of the problem. The initial population is usually randomly generated to explore a large search space and account for a wide range of possibilities. The second step is calculating the fitness of each individual of the population using a fitness function. The third step is breeding which consists of four operators, as follows:

1. *Parents selection:* is the process of choosing individuals that will be used to produce new offspring for the next generation. Since fitter parents are expected to produce fitter offspring, the basic parent selection method is to choose the two best individuals. Other parent selection methods include roulette selection, random selection, rank selection, and soft-max selection.

2. *Crossover:* is the process of recombining the genes of the parents to make new children. Crossover swaps two randomly selected subset of genes between two individual chromosomes. The crossover probability parameter describes the frequency of a crossover in a generation, such that a probability of 0% means that the offspring will be exact copies from their parents and a probability of 100% means that all offspring have genes from both parents.

3. *Mutation:* is a random tweak in the genes of a chromosome. Similar to exploration in RL, mutation prevents the algorithm from getting stuck at a local optimum and allows it to explore a new search space. In GA, mutation occur

randomly and does not happen often; the frequency of mutation could be decided by specifying the mutation probability (p_m) parameter.

4. *Replacement:* is the process of selecting individuals from the current generation and their offspring to survive and become part of the next generation. Choosing the replacement strategy is critical since it influences the convergence behaviour of the GA. Some of the commonly used convergence strategies include entire generation replacement, random replacement, both parents replacement, and elitism.

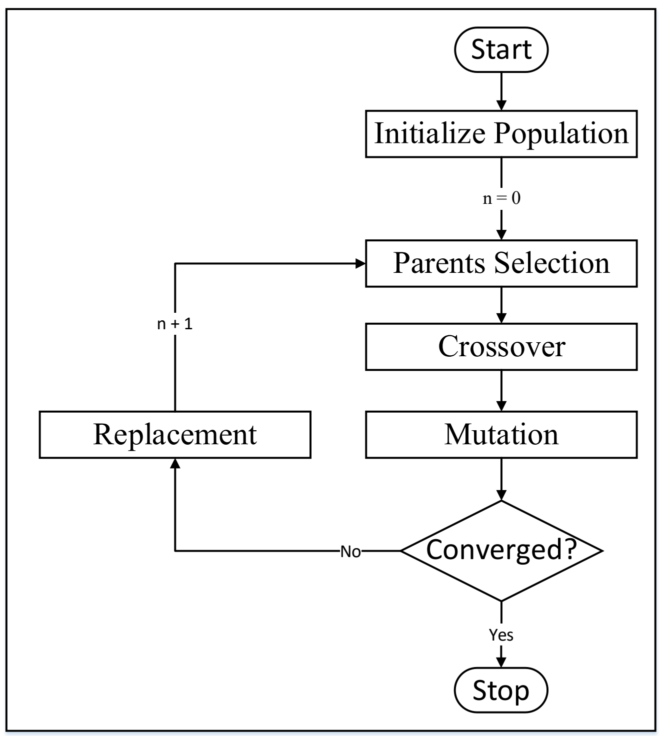


Figure 5.9: Flow chart of Genetic Algorithm

In this research, the GA population is initialized by randomly generating 10 chromosomes. Then, each of the chromosomes is evaluated using the SRMSE (fitness function), which measures the goodness-of-fit of the aggregated ABM simulation modal share output at the dissemination area level to the actual modal share reported in the Census Data. The next step was to select parents to produce offspring, which was done by selecting the two fittest individuals in the GA population. After that, offspring are created using the single point crossover with a crossover probability of 100%. In a single point crossover, the two selected parent chromosomes are cut at a randomly generated point and the genes before the point are exchanged. Next, a random number is generated to decide if an offspring will perform mutation, such that a mutation will occur if the random number is less than the mutation probability, which is 20%. Finally, the fitness values for the offspring are calculated and the least two fit individuals are be replaced by the newly created offspring. The stopping criteria was set to either reaching an SRMSE value of zero or after six iterations without a change in the SRMSE value.

Due to computational constraints, it was not possible to use all, or even a large number of, dissemination areas in the calibration process of information provision. Thus, the dissemination areas were randomly divided into two sets: training (51 dissemination areas) and validation (118 dissemination areas). A comparison between the characteristics of the dissemination areas in the training set, validation set, and the entire study area was conducted to ensure that both sets are representative of the land use (Figure 5.10) and demographic characteristics (Table 5.4) of the study area. The results show that the distribution of population density, employment density, and land use entropy in the training and testing sets have the same distribution as the original dataset (Figure 5.10). These results were further supported by conducting the Kolmogorov-Simirnov (K-S) test to compare the overall shape of the distribution of the two sets. The K-S results revealed a D value of 0.111, 0.114, and 0.149 and p-values of 0.771, 0.742, and 0.408 for population density, employment density, and land use entropy, respectively, which means that the null-hypothesis that both samples have the same distribution can be accepted. Moreover, the Fligner-Killeen test was computed to evaluate the homogeneity of the training and testing sets. The test results revealed a p-value of 0.377, 0.085, and 0.918 for population density, employment density, and land use entropy, all of which are greater than 0.05, which indicates that there is no significant difference in variance between the training and testing sets.

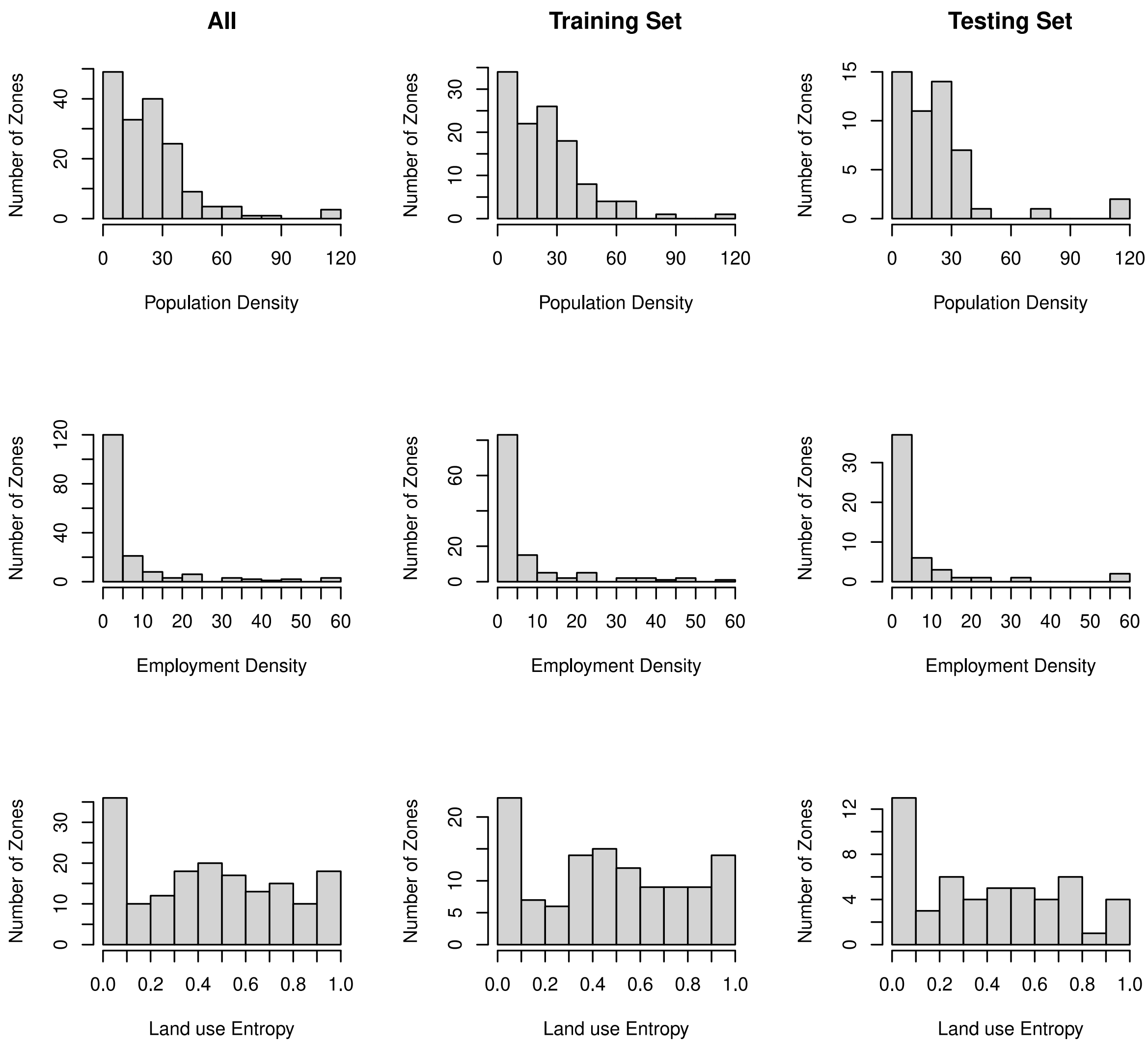


Figure 5.10: Comparison of the land use characteristics of the validation and testing datasets

For the demographic characteristics, Table 5.4 shows that the characteristics of training and testing sets at the individual level represent a negligible difference from the original dataset; however, the difference is slightly greater at the household level. For instance, single person households are over-represented in the training set by 1.2% and under-represented in the testing set by 2.6%. Similarly, the training set underrepresents the apartment dwelling type and overrepresents the single attached house dwelling type and vice versa for the testing test.

Table 5.4 Comparison of the Demographic Characteristics of the Validation and Testing Datasets

Variable	Category	All	Training		Testing	
		%	%	Δ	%	Δ
Households Characteristics						
Household size	1	29.3	30.5	1.20	26.8	2.57
	2	39.1	38.7	0.41	40.0	0.87
	3	13.6	13.3	0.37	14.4	0.80
	4+	17.9	17.5	0.42	18.8	0.90
Household dwelling type	Single Detached House	45.6	44.3	1.33	48.5	2.85
	Apartment or Condo	30.1	31.6	1.51	26.8	3.24
	Townhouse or Row House	7.2	7.0	0.10	7.4	0.22
	Duplex	14.8	14.4	0.35	15.5	0.75
	Mobile Home	2.4	2.7	0.27	1.8	0.58
Persons Characteristics						
Age	(05-14)	10.0	9.9	0.11	10.2	0.23
	(15-24)	13.0	12.9	0.11	13.3	0.23
	(25-34)	13.9	14.1	0.22	13.4	0.47
	(35-44)	12.0	11.9	0.07	12.2	0.15
	(45-54)	14.2	14.2	0.01	14.2	0.03
	(55-64)	14.9	14.9	0.00	14.9	0.00
	65 and over	21.9	21.9	0.05	21.8	0.11
Sex	Men	48.3	48.43	0.10	48.13	0.20
	Women	51.7	51.57	0.10	51.87	0.20

In addition, the statistic $\overline{\psi}$ was utilized to ensure that the OTS observations in the training and validation sets are representative of demographics and trip characteristics observed in the study area. It was computed based on four variables: 1) trip distance, 2) trip purpose, 3) age, and 4) gender. The resulted $\overline{\psi}$ for the training and testing sets is calculated to be 0.451 and 0.481, respectively, which indicates a good representation of the OTS observations in the study area.

The GA reached conversion after 14 iterations; Figure 5.11 shows the convergence of the GA procedure. The calibration process revealed the following information provision proportions: 32% partial information, 18% partial information with knowledge decay, and 50% perfect information. The proportion of users with perfect information is higher than that of previously reported in the literature. This difference could be attributed to significant advancement in digital technology and higher smartphone ownership over the years. For instance, household subscription to mobile services increased by 47.5% from 2004 to 2016 (CRTC, 2019).

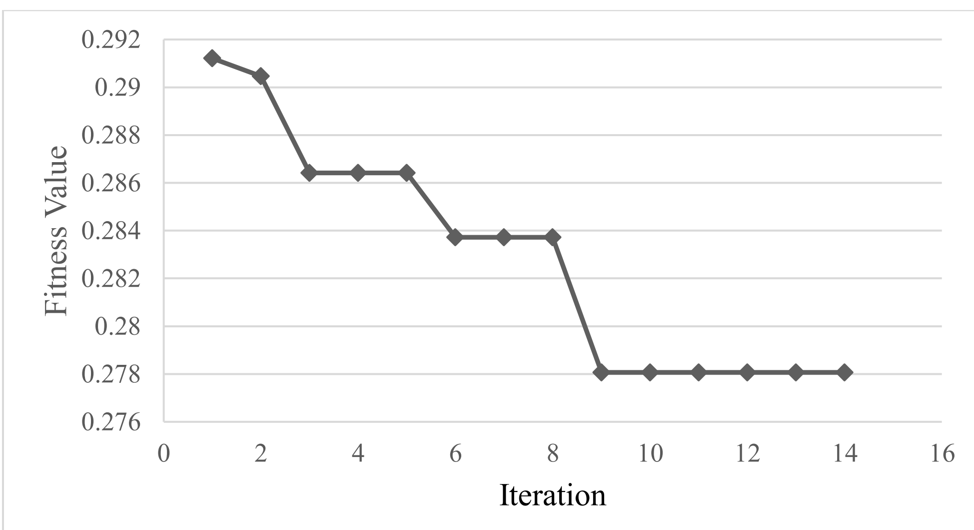


Figure 5.11: Convergence for calibrating information provision in the ABM simulation

5.6 Summary

This presented and discussed the development and calibration of the various components of the ABM simulation. First, a synthetic population was generated for the city of Kelowna, BC based on the following four steps: 1) generation of agents at the dissemination area level using an iterative proportional updating algorithm 2) random allocation of the synthesized households at the parcel level, 3) assignment of the synthetic agents to workplace dissemination area, and 4) random assignment of the synthetic agents to workplace parcel. The population synthesis goodness-of-fit results show that the population synthesis module used in this research generated a synthetic population that yielded a high level of goodness of fit, with a $\overline{\psi}$ value of 0.037. In addition, the results revealed 64% and 92% of the dissemination areas have standardized absolute error values of less than 5% and 10%, respectively. The next step in the population synthesis process was to assign workplace dissemination areas to the synthesized population using a multinomial logit attraction-end choice model. Several explanatory variables were considered for the model including composite travel impedance, zonal attributes and size measures, and the interaction of travel impedance with socio-economic characteristics of individuals. The model yielded an adjusted ρ^2 value of 0.438 and its parameter estimate indicated that individuals in the higher income groups are less sensitive to travel impedance than those in the lower-income groups. Similarly, the number of vehicles per person in a household reduces individuals' sensitivity to travel impedance.

Second, An MNL model for morning home-to-work mode choice decisions was developed for the city of Kelowna, BC. The model accounts for socioeconomic characteristics, level of service attributes, and built-environment measures. The built-environment measures were quantified at various buffer distances for all trips' origins and destinations. The model yielded an adjusted ρ^2 value of 0.663 and its parameter estimate indicate the following: 1) females are more sensitive to the increase in cycling distance than males, 2) the availability of high and medium frequency bus stops within 800m and 500m, respectively, of trip origins has a positive association with transit use, 3) the availability of green spaces and is positively associated with the cycling mode.

Third, section 5.4 presented the calibration process of the walking and cycling shortest path algorithms. For walking, the ABM simulation estimated that around 79% of walking trips are on the shortest path. In addition, walking trips are, on average 1.5% longer than the shortest path. As for cycling, the ABM estimated that around 33% of cycling trips are using the shortest path, while the remaining trips are, on average, 9.5% longer than the shortest route. In addition, 77% of cycling trips are within 10% of the shortest distance and 90% of the cycling trips are within 20% of the shortest distance.

Finally, section 5.5 presented and discussed the calibration process of the proportions of the information provision categories using a genetic algorithm. The algorithm reached convergence after 14 iterations and revealed the following information provision proportions: 32% partial information, 18% partial information with knowledge decay, and 50% perfect information.

Chapter 6 Results and Discussion

6.1 Overview

This chapter presents the modelling results of evaluating the impact of the SMARTer Growth (SG) neighbourhood design principles on transportation travel behaviour and quality of life (QoL). As described in Chapter 4, Three urban centres in the city of Kelowna are examined in this research including: Capri-Landmark, South Pandosy, and Rutland. Three scenarios were examined for each of the urban centres, as follows: 1) 2016 transportation and land use systems (S1), 2) 2040 projected transportation and land use systems based on city of Kelowna's endorsed official community plan (S2), and 3) 2040 projected transportation and land use systems utilizing SG design principles, given the city's projected urban growth (S3). Section 6.2 presents the results from an initial model of the ABM simulation. Section 6.3 examines the impact of the three scenarios on neighbourhood travel pattern using the proposed agent-based model, presented in Chapter 3. In addition, it presents and discuses the QoL evaluation of the three scenarios, for each of the urban centres, utilizing the suite of tools recommended in Section 2.6.

6.2 Preliminary Modelling Results

This section reports on results from an initial model of the ABM simulation. The model was applied to the Capri-Landmark urban centre. However, there were few actual internal trips reported in the City's provided dataset (i.e. where both trip ends were located in the Capri-Landmark urban centre). Hence, it would have been difficult to both calibrate the model and forecast the influence of the retrofitted design on internal trips. Therefore, 5,000 trips were randomly generated within the neighbourhood.

For further simplicity, only three travel modes were considered in this case study as follows: 1) automobile, 2) transit, and 3) non-motorized modes, with the MNL model specification shown in Table 6.1.

Table 6.1 Parameter Estimation Results for the Discrete Morning Home-to-work Mode Choice Model considering three transportation modes

Null log-likelihood		-2,378.191	
Final log-likelihood		-849.680	
Adjusted ρ^2		0.643	
Variable	**Auto**	**Transit**	**Non-motorized**
Alternative Specific Constant	—	-5.49	-0.346
level of service			
Travel Time	-0.159 (-3.83)	-0.012 (-1.09)	—
Travel Distance	—	—	-0.838 (-11.1)
Socio-economic			
Age Group (15-24)	-0.639 (-2.87)	—	—
Driver's license	—	-1.02 (-2.48)	—
Monthly transit pass	1.44 (-3.86)	3.11 (8.26)	—
Vehicles/person in the household	1.24 (5.30)	-1.06 (-2.34)	—
Bikes/person in the household	-0.433 (-1.86)	—	0.505 (2.06)
Female	—	—	-0.281 (-1.63)
Built Environment			
Employment Density 600 m (at Destination)	—	0.008 (1.88)	0.012 (3.21)
Land use entropy 600 m (at Destination)	—	—	—
Population Density 800 m (at Origin)	—	—	—
Bike Lanes Length 400 m (at Origin)	—	—	0.339 (1.84)

values within parenthesis () show t-stat value

This preliminary case study examined the influence of several policy scenarios on neighborhood travel patterns, including increased activity density and/or non-motorized to vehicle route directness ratio, and transportation demand management (TDM) strategies. The first set of scenarios examined the influence of transportation network connectivity on travel behaviour, including the influence of: 1) retrofitting the road network only, 2) retrofitting the non-motorized network only, and 3) retrofitting both the road and non-motorized networks, as depicted in Figure 4.3. To comprehend the magnitude of change in both networks, the percentage change in travel time and distance between the existing scenario and the proposed retrofit were estimated as follows: 19.3% increase in driving travel time and 9.2% decrease in non-motorized travel distance.

The second set of scenarios examined the influence of increasing population and employment densities on travel behaviour. The three cases considered in this scenario correspond to 10%, 20%, and 30% increase in activity density (i.e. population and employment densities combined). The third scenario examined the combined effect of retrofitting the transportation network and a 30% increase in activity density on travel behaviour.

The last set of scenarios explored the effect of transportation and land use changes (third scenario) coupled with TDM strategies. Contrary to traditional mode choice modelling techniques, this research assumes that people vary with regards to levels of information provision. One could argue that the most optimistic modal shift towards active transportation modes (transit and non-motorized) is achieved under the assumption that 100% of the agents have perfect information. While this assumption might not be practical, TDM strategies, such as improving ATIS and media awareness campaigns, can be used to increase information provision and awareness of the current state as well as any changes in transportation and land use systems. Three cases of increasing information provision are compared: practical-, medium-, and high-level scenarios. In addition, another scenario was designed to explore the effect of providing 25% and 50% of the population in the study area with a temporary free transit pass to gain familiarity with the transit service in the city. This scenario was coded in the simulation by assuming that the transit pass dummy variable is 1 when calculating the soft-max selection policy. This assumption results in increasing the probability of exploring the transit mode for agents that are enrolled in the free transit pass program.

The first three sets of scenarios (transportation, land use, and combined) were run four times in this case study. They were run once for each of the three information provision categories (i.e. all agents are assigned to a category). For the fourth run, agents were randomly assigned to information provision and social interaction categories as per the following proportions 60, 10 and 30%, respectively. On the other hand, the TDM strategy scenarios were run assuming the latter only. The assumed proportion value of each category were exogenous and were based on previous research that shows information provision has relatively small impact on travel behaviour, with an estimated impact that varies between 30-40% (Englisher, Juster, Bregman, Koses, & Wilson, 1996; Khattak, Yim, & Prokopy, 2003; Peirce & Lappin, 2003; Wang, X., Khattak, & Fan, 2009). It is also worth noting that earlier modelling experimentation showed that the perfect information category reflects traditional mode choice modelling. Thus, its modal share results can be used to compare traditional mode choice modelling with those of the proposed framework.

Figure 6.1 shows learning process of agents with various information provision rules, which demonstrates how agents are behaving in a unique and different based on their assigned learning updating rules, social network, and the randomness introduced in the model through the soft-max exploration technique.

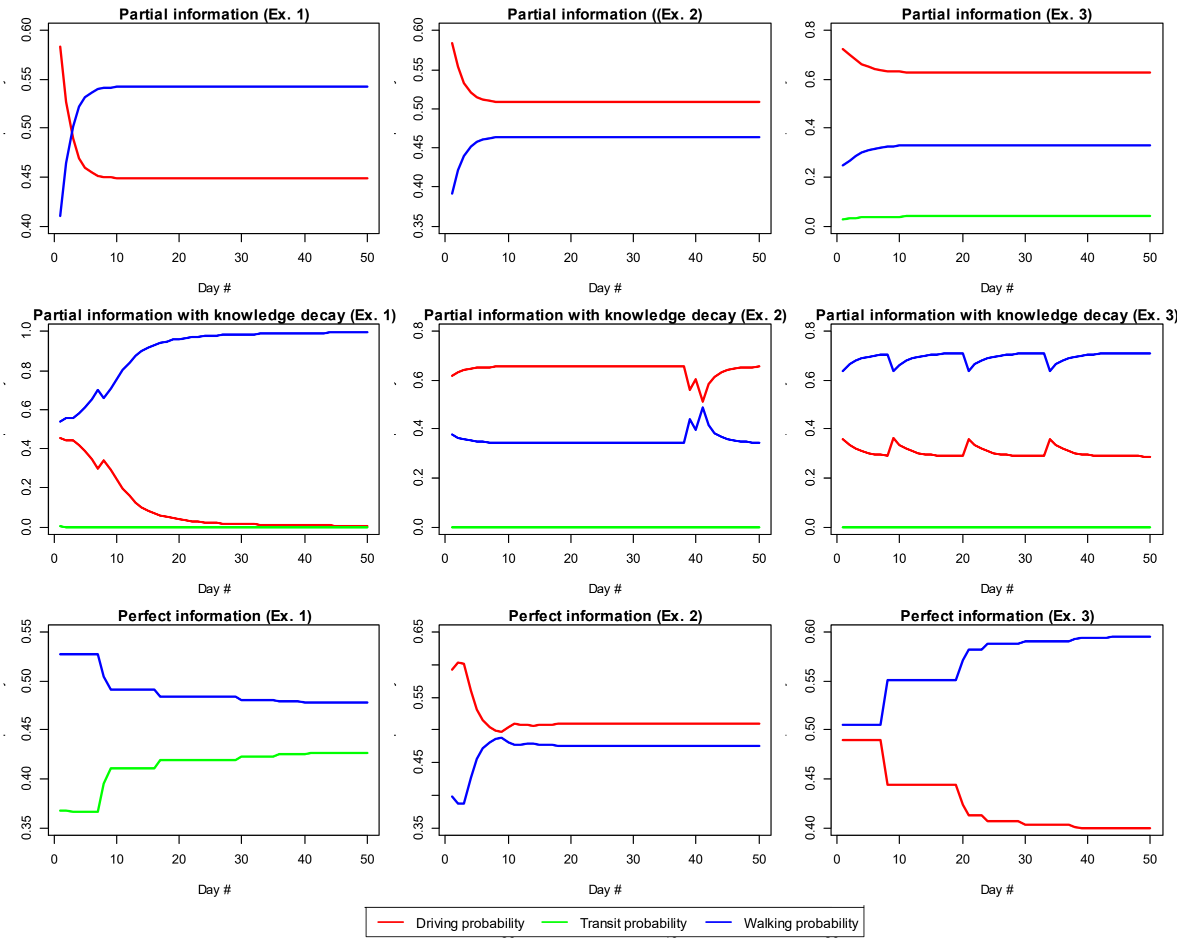


Figure 6.1: Learning process and habit formation for agents with various information provision categories

Figure 6.2 illustrates the percentage change in modal split for the proposed transportation and land use retrofits compared to the existing conditions. The figure shows that all proposed information provision scenarios produce almost similar modal shift trends except for the partial information with knowledge decay category. For this category, the results show a significant increase in the auto modal share despite the proposed hypothetical changes in the transportation and land use systems that were in favour of transit and non-motorized modes. Another unanticipated finding is the slight increase in auto modal share when retrofitting the road only in the random information provision assignment scenario, as shown in Figure 6.2d. A possible explanation would be that the reduction in auto utility due to retrofitting the road network was relatively small compared to the decline of unselected modes' utilities over time for agents with knowledge decay. This hypothesis can be validated by looking at the results of the perfect information run (see Figure 6.2c) which shows that the auto modal share decreases as expected.

Another interesting finding is that the modal shift in the non-motorized scenario was greater than the road network scenario despite the fact that the change in travel time in the former scenario was less than the latter scenario. This suggests that increased accessibility for non-motorized users has more impact on modal share than restricting car use. Nevertheless, the multi-modal, multi-prong retrofit strategies had the greatest beneficial influence on mode choice. These trends were observed in both the perfect information scenario (Figure 6.2c) and the random information provision assignment scenario (Figure 6.2d).

Moving to increasing the activity density scenarios, 10%, 20%, and 30% increase in activity density resulted in -0.44%, 5.2%, and 9.04% modal shifts toward transit, and they reduced auto modal share by 0.2%, 2.24%, and 4.29%, respectively. Finally, the combined transportation and land use scenario achieved the highest modal shift from auto towards transit and non-motorized modes. Note that the shift towards transit in this scenario is slightly less than the scenario of increasing activity density by 30%, which illustrates how transit competes with non-motorized modes.

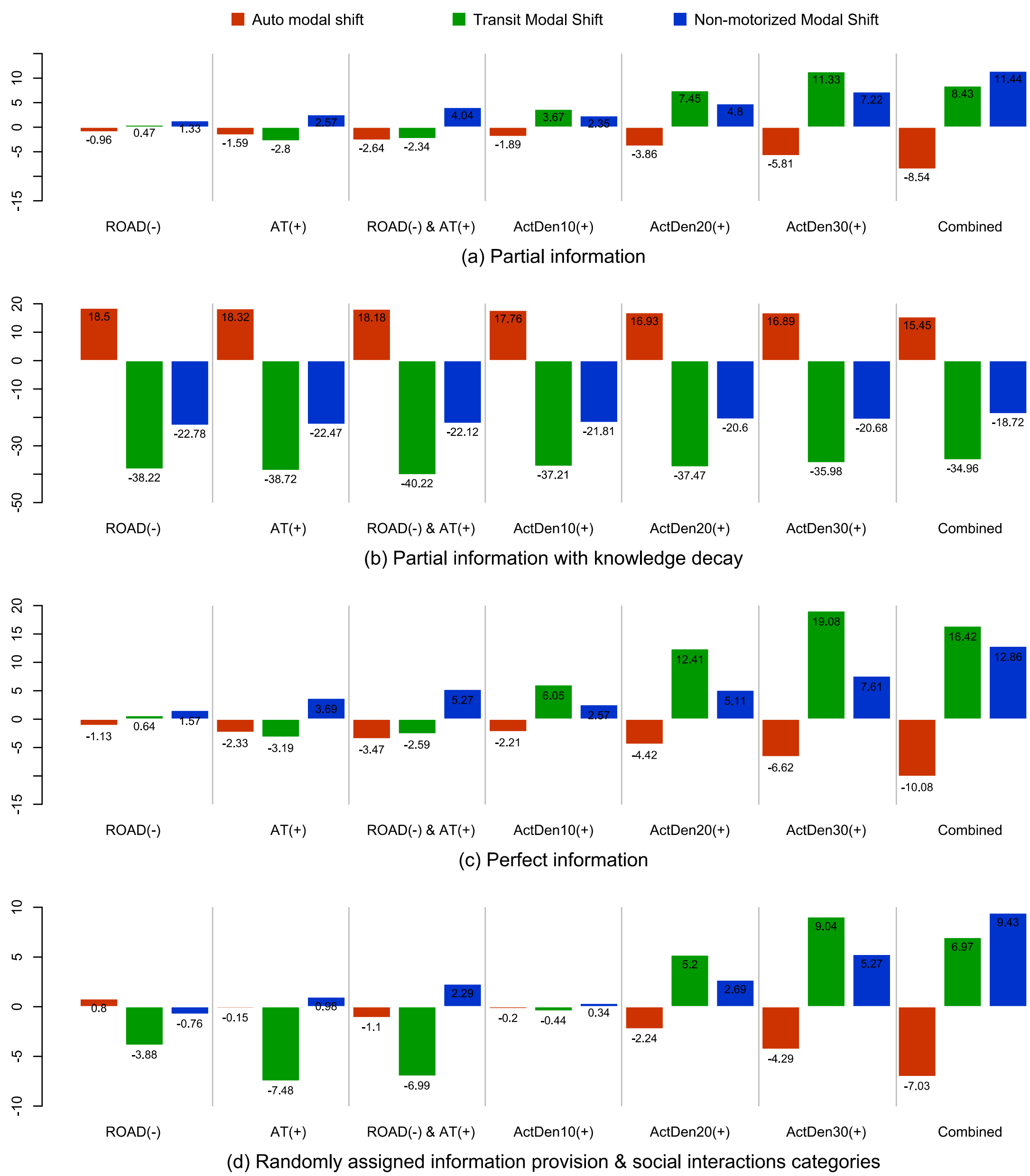


Figure 6.2: Modal shift for the transportation and land use scenarios of the preliminary analysis

In addition, the proposed framework adds a time dimension to the modal shift process. This dimension might not represent the actual time that it takes individuals to reform their beliefs about transportation modes. However, it could give a hint regarding the relative duration it would take to reap the full benefits of two proposed policies. This duration was calculated as the time steps it would take the simulation to terminate, which is when the average modal shift of all modes is less than 0.0001%. For this case study, our analysis shows that while land use policies are superior over retrofitting the transportation network, changing land use requires twice as much time as changing the network to reap the full benefits of land use policies.

Finally, using TDM policies to augment transportation and land use changes reinforces their effectiveness. For instance, running the simulation assuming the medium-level information provision scenario resulted in 10.13% and 10.6% increase in transit and non-motorized modal shares (Figure 6.3a). Similarly, the high-level information provision scenario resulted in 11.7% and 11.6% increase in transit and non-motorized modal share (Figure 6.3a). In addition, providing temporary transit pass for 25% and 50% of the population resulted in 8.12% and 8.79% increase in transit modal share, as shown in Figure 6.3b. This scenario was particularly useful for agents with knowledge decay as it increased their chances of exploring the transit mode and thus maintaining familiarity with the service as illustrated in Figure 6.4.

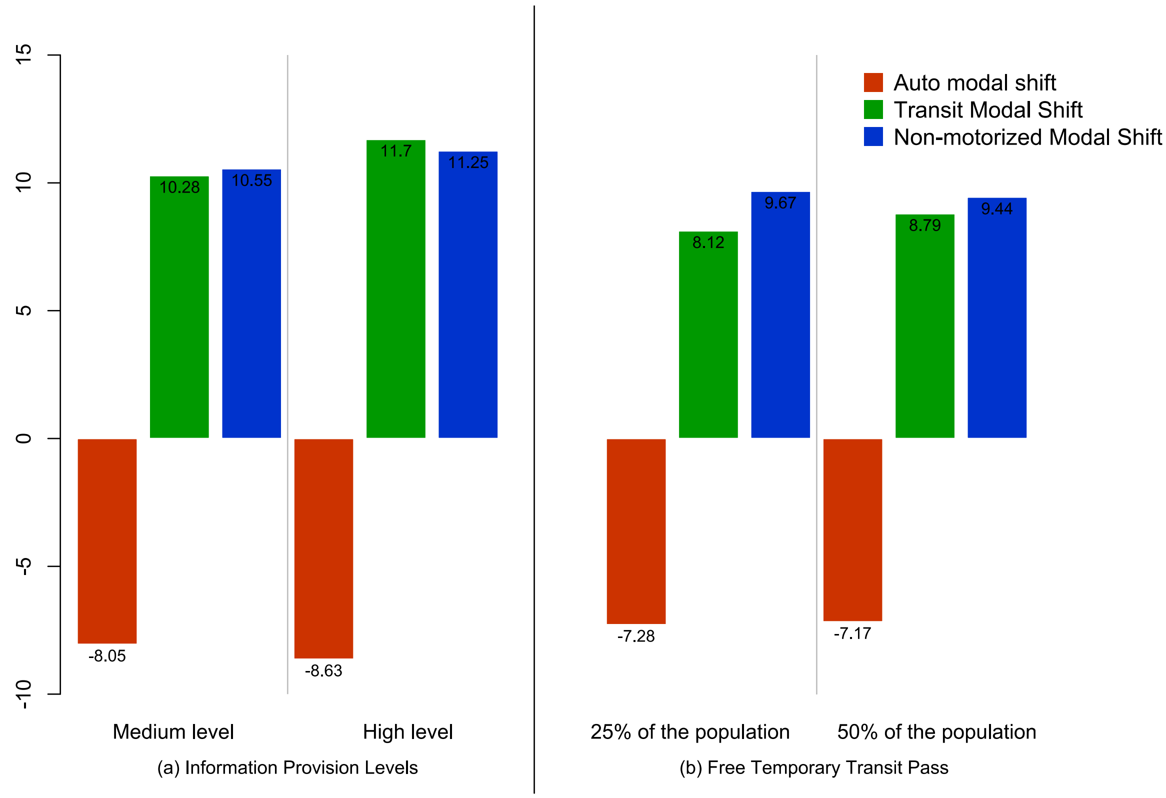


Figure 6.3: Modal shift for TDM strategy scenarios of the preliminary analysis

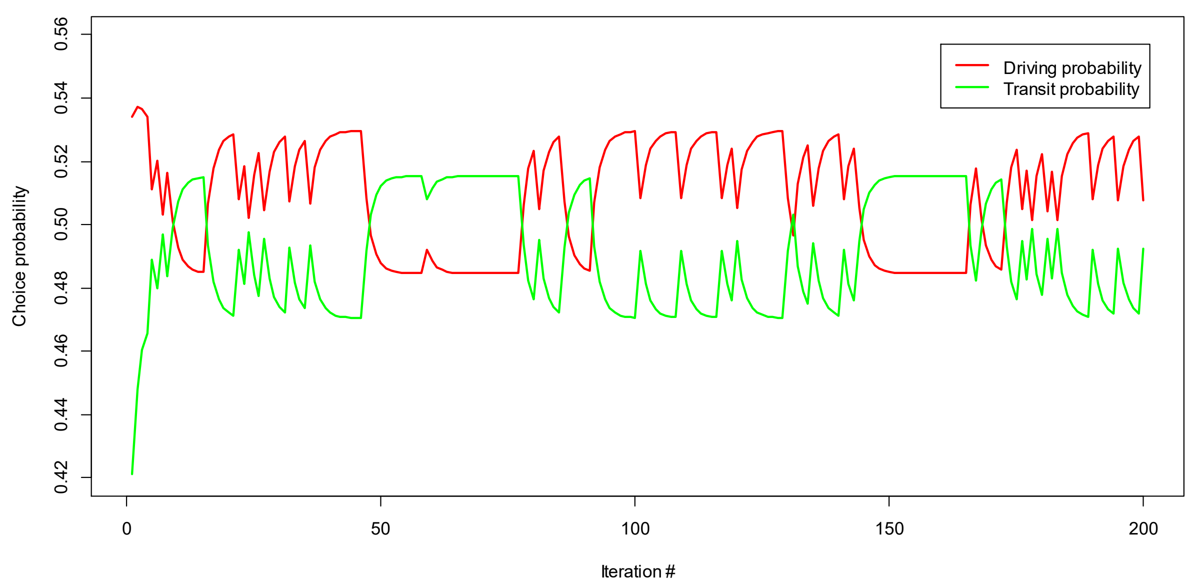


Figure 6.4: The change in auto and transit mode choice probability based on an agent's familiarity with the transit service

6.3 Case Study Results

6.3.1 Mode Choice Modelling Results

Table 6.2 shows the ABM modal shift forecasting results for the 2016, 2040 OCP and 2040 SG scenarios in the three urban centres. The results show that the Capri-landmark exhibited the highest modal shift towards non-motorized modes in both the 2040 OCP and SG scenarios. In particular, the 2040 OCP scenario resulted in 12% decrease in auto use, 70% increase in walking, and 17% increase in cycling. Similar but more pronounced modal shift was forecasted for the 2040 SG scenario with 22% decrease in auto use, 92% increase in walking, and 74% increase in Cycling.

Similarly, the 2040 OCP scenario in Rutland resulted in 5 and 24% decrease in auto use and cycling trips, respectively, and 36% increase in walking trips. Whereas the 2040 SG scenario resulted in 19% decrease in auto use, 76% increase in walking trips, and 82% increase in cycling trips.

For the South Pandosy urban centre, the results of the 2040 OCP scenario revealed a 4% increase in auto use, 6% decrease in walking, and 18% decrease in Cycling. On The other hand, the 2040 SG scenario resulted in 7% decrease in auto use and 48% increase in walking and cycling trips, respectively. A possible explanation for this low increase in walking trips is the already high number of walking trips in South Pandosy, which was estimated to be 27% in 2016, compared to 13 and 14% in Capri-Landmark and Rutland, respectively.

Table 6.2 Modal Shift in the Urban Centres

Scenario	Auto (%)	Transit (%)	Walking (%)	Cycling (%)
Capri-Landmark				
Existing 2016	68.7	12.3	13.4	5.6
2040 OCP	60.4 (-12.2%)	10.4 (-15.8%)	22.7 (69.8%)	6.5 (17.4%)
2040 SG	53.6 (-22.0%)	11.1 (-10.0%)	25.6 (91.5%)	9.7 (73.6%)
South Pandosy				
Existing 2016	60.1	8.0	26.9	5.0
2040 OCP	62.6 (4.2%)	8.2 (2.4%)	25.1 (-6.6%)	4.1 (-18.7%)
2040 SG	55.8 (-7.3%)	9.2 (14.3%)	27.7 (3.1%)	7.4 (47.7%)
Rutland				
Existing 2016	71.7	11.0	13.7	3.6
2040 OCP	68.2 (-4.9%)	10.4 (-4.8%)	18.7 (36.0%)	2.7 (-24.5%)
2040 SG	57.4 (-20.0%)	11.9 (9.0%)	24.1 (75.7%)	6.5 (81.6%)

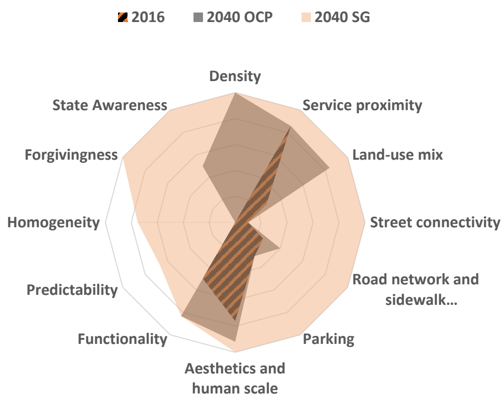
values within parenthesis () show modal shifts compared to the 2016 scenario

6.3.2 QoL Evaluation Results

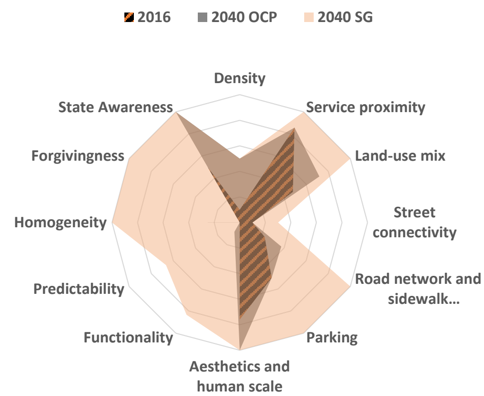
Eight tools and indicators are utilized in this research to evaluate the QoL of a neighbourhood, including: 1) i-THRIVE , 2) air quality, 3) noise pollution, 4) walkability, 5) bikeability, 6) Transitability, 7) playability, and 8) Social Interactions. The following subsections will report and discuss the results of each of the QoL evaluation tools for study areas.

6.3.2.1 i-THRIVE

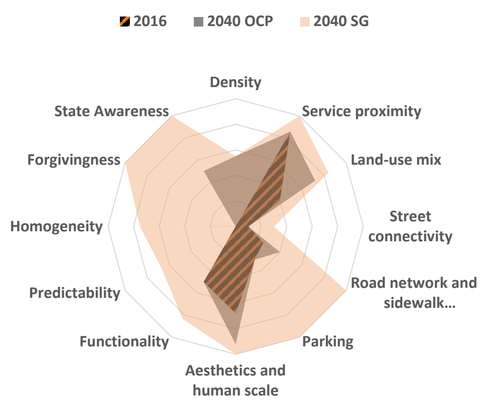
The i-THRIVE Tool consists of 12 elements, including 1) density, 2) service proximity, 3) land use mix, 4) street connectivity, 5) road network and sidewalk characteristics, 6) parking, 7) aesthetics and Human Scale, 8) functionality, 9) predictability, 10) homogeneity, 11) forgivingness, and 12) state awareness. A summary of the i-THRIVE evaluation is presented in Figure 6.5 and Appendix B and discussed below.



(a) Capri-landmark



(b) Pandosy



(c) Rutland

Figure 6.5: i-THRIVE evaluation of the study area

6.3.2.1.1 The 2016 Scenario (S1)

The existing scenario (S1) for all three urban centres scored poorly on the i-THRIVE, with a total score of 33%, 38%, and 35% for Capri-Landmark, South Pandosy, and Rutland, respectively. The following will discuss individual i-THRIVE elements evaluation:

Density: the average dwelling unit density for Capri-landmark, South Pandosy, and Rutland are 23, 27, and 26 units/hectare, well below the minimum i-THRIVE requirement of 35 units/hectare. In addition, the non-residential floor area ratio (FAR) in the three urban centres are 0.62, 0.94, and 0.54, respectively. The low FAR values are attributed stand-alone parkade structure in the Capri-Landmark, and strip malls with vast parking lots in all three urban centres.

Service proximity: to be rated highly in the service proximity element, i-THRIVE requires that 1) 100 % of residential units within 800m of at least 20 neighbourhood services, including at least three food markets one park, 2) at least 90 % of residential units within 800m, and 70 % of residential units within 400m of a suitable transit stop, and 3) be within 4 km of an existing or planned employment centre. In the three urban centres, more than 75% of the residential units are within 800m of 20 neighbourhood services, three food markets, and a park. In addition, 100% of residents are within 800m of a bus stop and 96, 84, and 88% are within 400m of a bus stop.

Land-use mix: the i-THRIVE has several metrics related to land use mix, including 1) providing outdoor public spaces; 2) providing new services to an existing neighbourhood, 3) providing a mix of housing types, and 4) including ground floor pedestrian use along commercial, mixed-use, and multifamily buildings. In the three urban centres, outdoor public spaces comprise approximately 2, 4, and 7% of the total neighbourhood land, which means that only the Rutland neighbourhood meets the i-THRIVE requirement of dedicating at least 5% of the total community land as an outdoor public space. In addition, all three urban centres provide new services to the community and a mix of three housing types while only the South and Rutland has a public school within 800m of the community centre. On the other hand, none of the urban centres provide pedestrian use on the ground floor of all mixed-use buildings and 50% of multifamily residential buildings.

Street connectivity: all three urban centres barely meet the i-THRIVE's street connectivity requirement of achieving active transportation to vehicle route directness ration of 1; the lower the value, the higher the score.

Road network and sidewalk characteristics: to achieve high score in this element, the i-THRIVE requires traffic calming measures to control speed and eliminate vehicles shortcutting. In addition, it requires implementing complete street designs, as well as having a comprehensive AT network augmented by off-street AT pathways and lighting. All three urban centres performed poorly on this element due to the lack pedestrian and cyclists' friendly street designs. For instance, none of the neighbourhoods has at least 4 traffic calming measure/hectare nor pedestrian-priority local roads with a posted speed limit of 15 km/hr.

Functionality: this element encourages eliminating grey roads, such as each road fulfills only a single function. Both Capri-Landmark and Rutland scored relatively higher on this element than South Pandosy as more than 75% of the roads in both neighborhoods are categorized based on the single function they fulfill with a good access management on collector roads of 25-30 access/km.

Predictability: this element aims to reduce human errors by creating a predictable road environment for each road type in terms of expected speed, acceptable maneuvers, and type of road users. All three urban centres performed poorly on this element as current road designs do not create distinguishable environments for road users.

Homogeneity: the criterion aims to prevent serious injuries in traffic collisions by minimizing differences in mass, speed and direction between road users. With the current road design in the three neighborhoods separate pedestrians from both cyclists and vehicles, they provide little to no separation between cyclists and motorists.

Forgivingness: this criterion aims to reduce the consequences of human error by providing a forgiving road environment (e.g. rumble strips, wide shoulder, etc.). All three urban centres did not achieve the minimum requirement of having at least one forgiving road environment measure on more than 60% of arterial and collector roads.

State awareness: this criterion aims to reduce the road users' perception of a driving task compared to their capabilities. The i-THRIVE requires that at least 20% of intersections to be either 3-way or roundabout with at least one treatment that decreases task demand for pedestrians and cyclists. Both Capri-Landmark and Rutland did not achieve minimum requirement for this element. On the other hand, more than 40% of the intersections in the south Pandosy neighborhood are 3-way.

6.3.2.1.2 2040 Official Community Plan Scenario (S2)

The 2040 OCP scenario resulted in an improve i-THRIVE score for the urban centres. In particular, Capri-Landmark, South Pandosy, and Rutland achieved an i-THRIVE score of 62, 58, and 53%, respectively. The following will discuss individual i-THRIVE elements evaluation[1]:

Density: According to the city's OCP, The Capri-Landmark urban, South Pandosy, and Rutland centre are expected to grow by approximately 7800, 2000, and 3600 people by 2040. Given a forecasted average occupancy of 1.7 person per new household, it is expected that around 4500, 1200, and 2100 new units are needed to accommodate the growth in the the three neighbourhoods. Therefore, the residential unit densities for this scenario are assumed to be 84.5, 30.1, and 44, respectively. In addition, given the planned building heights map in the OCP, the non-residential FAR in the three urban centres are estimated to be 2.87, 6.02, and 2.71, respectively.

Service proximity: No significant zoning changes that would influence service proximity in the three urban centres.

Land-use mix: Based on the OCP, outdoor public spaces comprise approximately 5.3, 9.3, and 7.5% of the Capri-Landmark urban, South Pandosy, and Rutland total land. With regards to proximity to public schools, the Capri-Landmark is the only neighbourhood that did not meet this requirement in the 2016 scenario; however, the city is investigating the possibility of redeveloping the Parkinson recreational centre to add a new public school on the property.

[1] Note that not all i-THRIVE elements were addressed/affected by the changes proposed in the OCP, and thus the score for these elements were assumed to be similar to the 2016 scenario.

Finally, the OCP encourages active human-scale amenities on the ground floor of mixed-use buildings.

Street connectivity: No significant changes to the transportation network.

Road network and sidewalk characteristics: The city of Kelowna's Transportation Master Plan includes several objectives that aim to improve pedestrians and cyclists safety and convenience, including: expanding cycle track network on the city's active transportation corridors, implementing intersection treatments to improve cyclists and pedestrian safety (e.g. elephant feet and bike signals), and installing traffic calming features on local streets.

Functionality: Based on the Capri-Landmark urban centre map, 100% of the roads in the neighbourhood are categorized based on one function they fulfil. No similar plans were found for the South Pandosy and Rutland urban centres and thus their i-THRIVE score for this element was assumed to be similar to the 2016 scenario.

Predictability Not addressed in the OCP.

Homogeneity: The i-THRIVE evaluation for this element improved due to the city's plan to expand its protected bike facilities network.

Forgivingness: Not addressed in the OCP.

State awareness: The i-THRIVE evaluation for this element improved due to the city's plan to implement intersection treatments to improve cyclists and pedestrian safety, such as elephant feet and bike signals.

6.3.2.1.3 2040 SMARTer Growth Scenario (S3)

The 2040 SG scenario achieved the highest i-THRIVE score among for the urban centres. In particular, Capri-Landmark, South Pandosy, and Rutland achieved an i-THRIVE score of 96, 87, and 84%, respectively. The following will discuss individual i-THRIVE elements evaluation:

Density: The residential unit density for this analysis was assumed to be similar to the 2040 OCP scenario in order to be consistent with city's projected urban growth. However, the distribution of the residential density was different from the OCP since SMARTer Growth encourages higher density near the central arterial corridor to provide a greater proximity to services. For the FAR, the intensified mixed-use zones in the arterial corridor along with the high residential and employment densities ensures that the SG scenario will have a FAR value greater than 2.5.

Service proximity: In a SG neighbourhood, mixed, high residential and commercial land uses are located along calmed collectors and arterials. In addition, the SG design principles requires that each quadrant centre is within a maximum of 400m to the nearest collectors and/or arterial. This configuration allows residents to walk or bike to services in all four directions of the neighbourhood within five-minutes.

Land-use mix: The SG design principles facilitates a self-contained community with mixed land use that provides short commuting distances to work, school, or other services. In addition, SG provides at least 5% of the community land as outdoor public spaces since they provide the core of the AT off-road pathway network. In particular, the outdoor public spaces in the SG retrofit of the three urban centres account for approximately 5.7, 15.0, and 8.9% of the Capri-Landmark urban, South Pandosy, and Rutland total land. Moreover, 30% of street space that would normally be used in a traditional grid network is reclaimed and used in the SG for additional development, green space, and off-road AT networks. In addition, as discussed earlier, the variety of services the community provides and the mix of housing types allow the FG to easily achieve the heterogeneity of Land Use Mix element of the i-THRIVE.

Street connectivity: One of the key elements that make the SG unique is its high AT connectivity compared to vehicle connectivity via an off-road grid and calmed local roads. For the SG retrofits the Capri-Landmark, South Pandosy, and Rutland, the route directness ratio was calculated to be 0.81, 0.91, and 0.93, respectively.

Road network and sidewalk characteristics: The SG design principles assigns higher priority to AT users through AT cut-throughs, and off-street pedestrians and cyclist paths. In addition, the SG principles includes many traffic calming measures, such as roundabout, three-way intersection, and raised cross walks on major collectors to reduce the severity of collisions. Furthermore, all local roads have a posted speed of 15 km/hr. Moreover, the SG retrofits include sidewalks wider than 2.5 m, buffer strips, and side parking on major collector and arterial roads. For cyclists, facilities are provided according to the road classification that suits the road speed and volume as follow: 1) local roads with low speed and traffic will be designed to be pedestrian/cyclists priority streets, and 2) major collectors and arterials with moderate speed and high traffic volume have cycle tracks.

Functionality: The three SG retrofits follow a strict hierarchy street network system in which each road fulfils a single function only. For instance, local roads in the SG retrofits only provide accessibility to final destinations within neighborhoods. On the other hand, minor and major collectors distribute traffic between local and arterial roads.

Predictability: The SG principles encourage consistent and distinguishable road design features for each road classification. Thus, road users can easily predict the road class, speed, and availability of other types of road uses (e.g. pedestrians and cyclists). For example, local roads in an SG neighbourhood are narrow, two-way, with lower speed limits. On the other hand, arterial roads are wider with cycle tracks and wide sidewalks. Moreover, most of the intersections in an SG neighbourhood are either controlled by roundabouts or T-intersections.

Homogeneity: SG offers continuous grid networks of dedicated paths in the central green spaces to separate AT users from motorists. However, in cases where AT users and motorists are sharing the same space on local roads, the posted speed is reduced to 15 km/h. In addition, wide sidewalks and cycle tracks are provided on arterial roads where the traffic speed volume is high.

Forgivingness: The SG retrofits of the urban centres provide many forgiving features to reduce collisions, injury risk, and the risk of death such as t-intersections and roundabouts-controlled intersections and enforcing relatively low speed limits at all roads; 15 km/h on local roads and 50 km/h on arterial roads.

State awareness: The SG retrofits comply the user state awareness principle of the i-THRIVE by maintaining the task demand at a lower level than most of the road users' capabilities. For instance, the SG retrofits include t-intersections, roundabouts, off-road paths, and one-way couplets to reduce traffic conflict points between all the road users.

6.3.2.2 Air Quality

Traffic emissions in this research are assumed to be correlated with VKT only (i.e. speed, acceleration, and # of stops are not considered); thus, similar trends are expected for the various air pollutants (e.g. GHG, particulate matter, carbon monoxide). The results below show the GHG forecast for the three urban centres. GHG emissions were estimated for each road link for the 2016, 2040 OCP, and 2040 SG scenarios. Surprisingly, the SG retrofit resulted in 1.82, 1.80, and 0.44% increase in total GHG emissions compared to the 2040 OCP scenario in Capri-Landmark, South Pandosy, and Rutland, respectively. This increase can be attributed to the slight increase in trip lengths due to the discontinuous local vehicular network in the SG retrofits. In addition, some off-road driveways in gated communities and large residential developments were not modelled in the existing and 2040 OCP scenario; however, they were defined as local roads in the 2040 SG scenario. Moreover, if we expanded the scale of analysis from a neighborhood to a city-wide level, resulting emissions would reasonably be expected to show significant reductions across all road classes in the SMARTer Growth scenario.

Examining GHG emissions by road classification, Figure 6.6 shows that the Capri-Landmark SG retrofit significantly reduced emissions on local roads by 72% compared to the 2040 OCP scenario, while emissions on arterials and collectors increased by 14.6 and 30%, respectively. Similar trend but of reduced magnitude was observed in the Rutland urban centre, where emissions on local roads decreased by 3.6% while emissions on arterials and collectors increased by 2.6 and 4.9%, respectively. Interestingly, the results of the South Pandosy urban centre revealed an increase of emissions on local roads compared to 2040 OCP scenario. This counterintuitive result could be attributed discrepancies in road classification between the OCP and SG scenarios. In particular, some roads in the South Pandosy urban centre were not classified according to the function they serve; however, these roads were reclassified in the SG scenario.

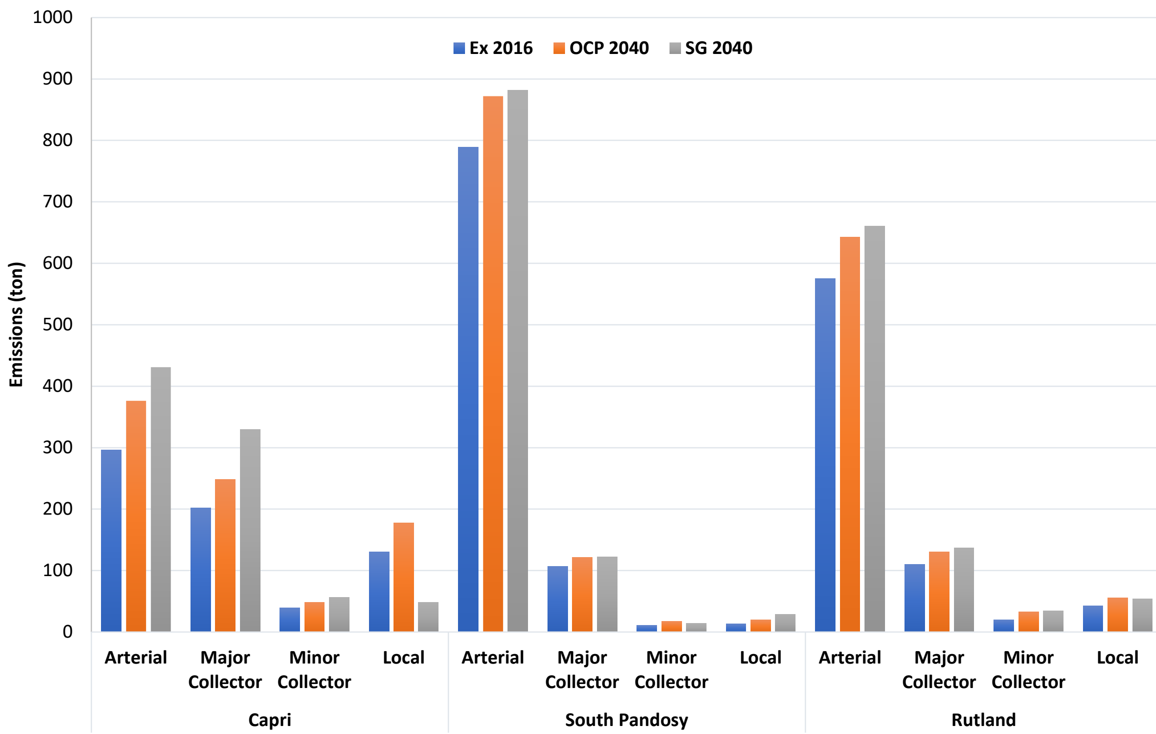


Figure 6.6: Traffic GHG emissions aggregated by road classification

This figure shows results at a neighborhood level. If we expanded the scale of analysis from a neighborhood to a city-wide level, resulting emissions would reasonably be expected to show significant reductions across all road classes in the SMARTer Growth scenario.

Overall, these results demonstrate that the well-defined SG's street hierarchy did succeed in re-routing through traffic away from local/residential roads to arterials and collectors. In addition, the simulation results show that pedestrian traffic in the SG retrofits tend to be concentrated on local roads and off-road path, as illustrated in Figure 6.7, which means reduced air pollution exposure for more pedestrians.

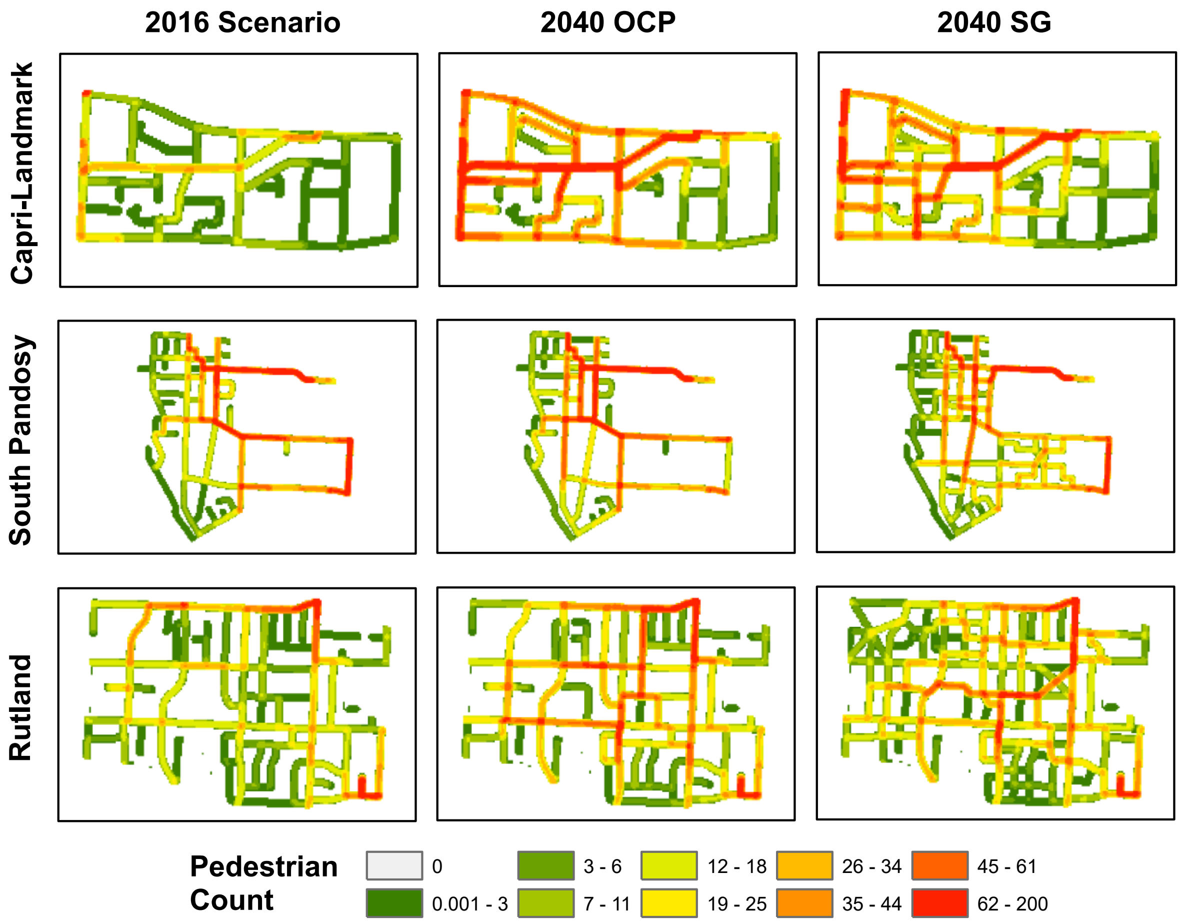


Figure 6.7: Pedestrian Traffic

6.3.2.3 Noise Pollution

Similar to traffic emissions, noise pollution was estimated for each road link and then aggregated by road classification. The results show that the SG retrofits have the lowest noise pollution on local roads. In particular, the Capri-Landmark, South Pandosy and Rutland retrofits achieved 11.8, 6.6, and 6.0% reduction in noise levels in local roads. The low noise pollution in the SG retrofits is due to low posted speed limit on local roads and the strict street hierarchy that preclude shortcutting through the residential core.

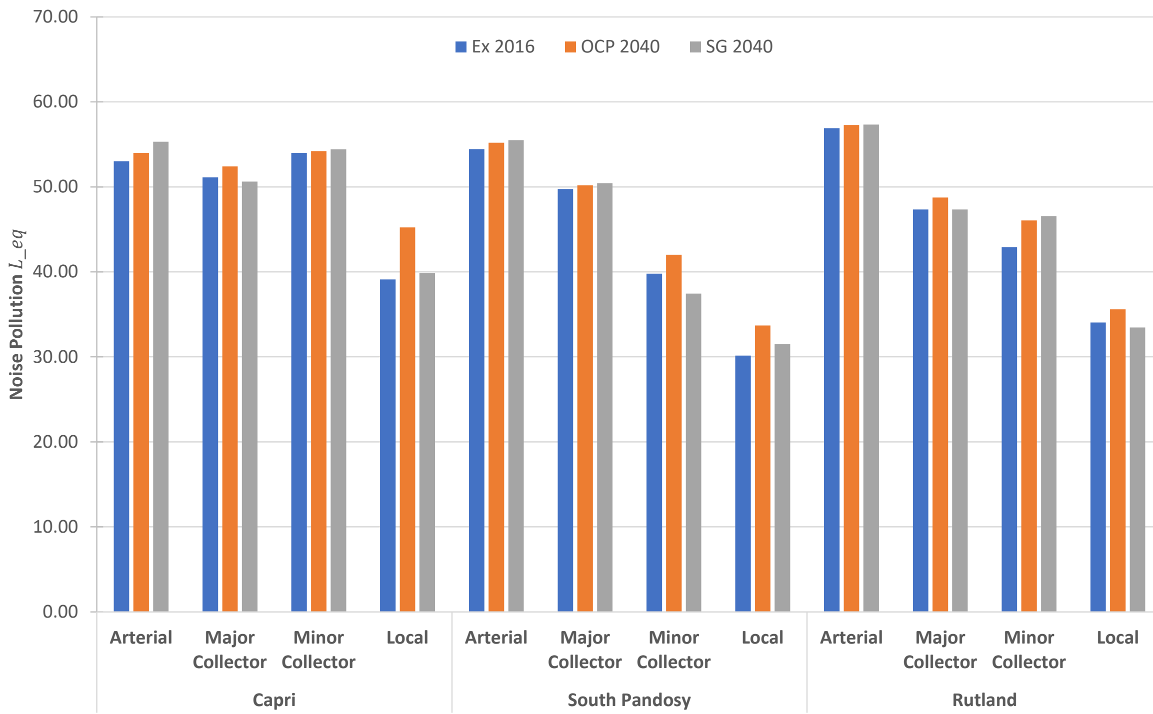


Figure 6.8: Traffic noise pollution aggregated by road classification

6.3.2.4 Walkability

A walkability surface was generated at the dissemination area level for each of the considered scenarios. First, the four walkability components (net residential density, retail floor area ratio, intersection density, and land use mix) were estimated at the dissemination area level. Second, the four components were normalized using z-score. Third, the walkability score was calculated by summing the z-value for each of the walkability components. Finally, the dissemination areas were grouped into deciles based on their walkability score, where the top deciles represent high walkability and the bottom deciles represent low walkability. Figure 6.9, Figure 6.10, and Figure 6.11 show Kelowna's walkability surface for the 2016, 2040 OCP, and 2040 SG scenarios, respectively. In addition, the figures include maps for each of the four walkability component surfaces, which enables analysts to understand what contributed to the final walkability score in each dissemination area and subsequently identify areas for improvement.

For the 2016 scenario, the walkability index scores ranged from -4.49 to 10.77. The South Pandosy urban centre was classified in the highest walkability decile, while the Capri-Landmark and Rutland were classified in the second highest decile. Specifically, the capri-Landmark had high scores for residential density and FAR, moderately high score for intersection density, but scored moderately in land use mix. The South Pandosy urban centre scored high in terms of residential density, FAR, and Land use mix; however, it scored poorly in intersection density, which suggests that it would benefit greatly from improving its walking network via the SG principles. Finally, Rutland had high scores for residential density and land use mix and moderately high scores for FAR and intersection density.

For the 2040 OCP scenario, the walkability index scores ranged from -4.33 to 16.93. In this scenario, the three urban centres achieved the highest walkability decile, which could be attributed to the significant projected growth in population.

Finally, the 2040 SG scenario's walkability index scores ranged from -4.32 to 16.41. This scenario achieved the most significant increase in walkability for the three urban centres. This increase can be attributed to the significant increase in population, similar to the OCP scenario, and intersection density. The latter is attributed to the SG's highly connected walking grid network of an on-road and off-road paths that allow convenient walking and cycling across the neighbourhood in less than 5 min.

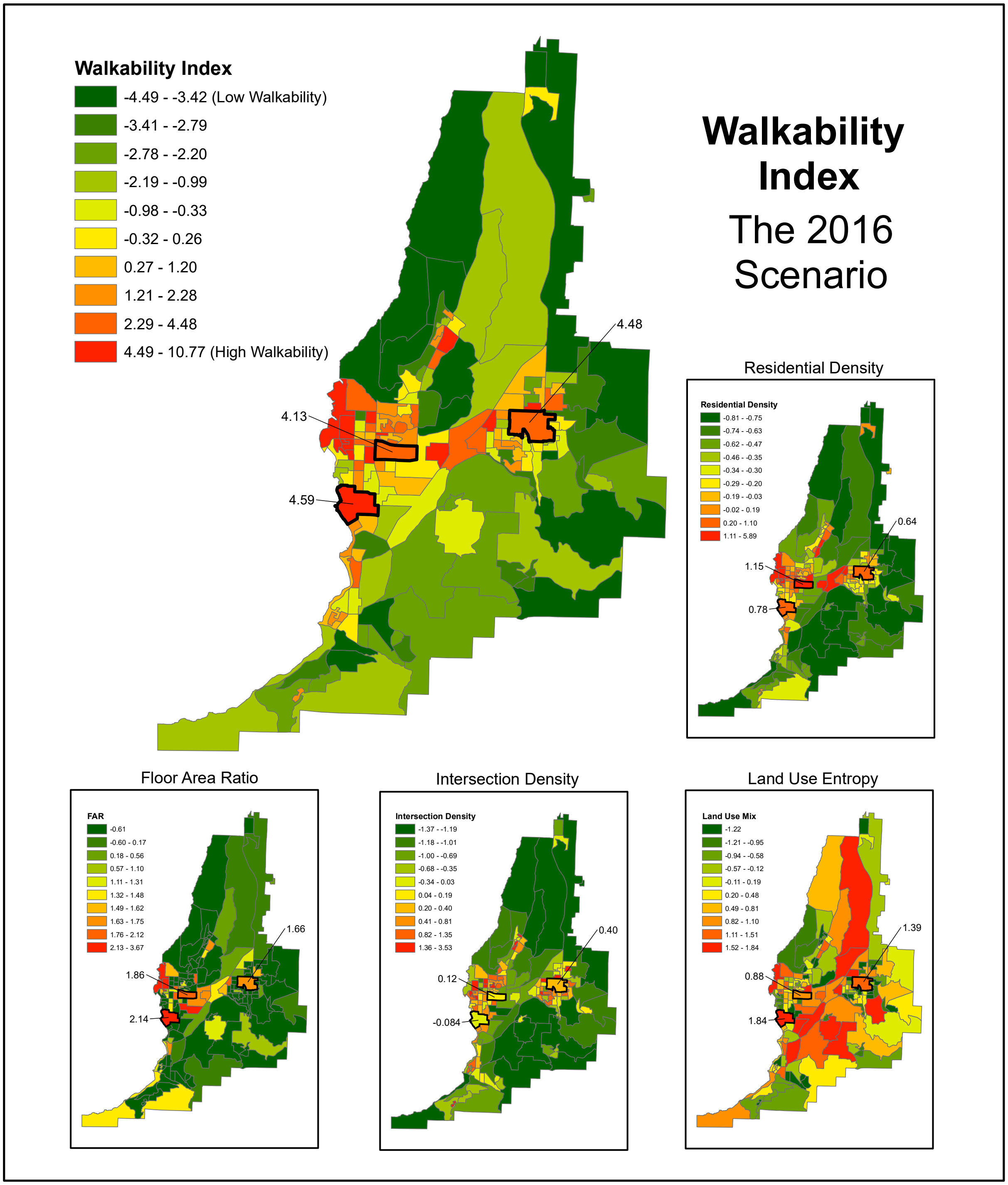


Figure 6.9: Walkability index for the 2016 scenario

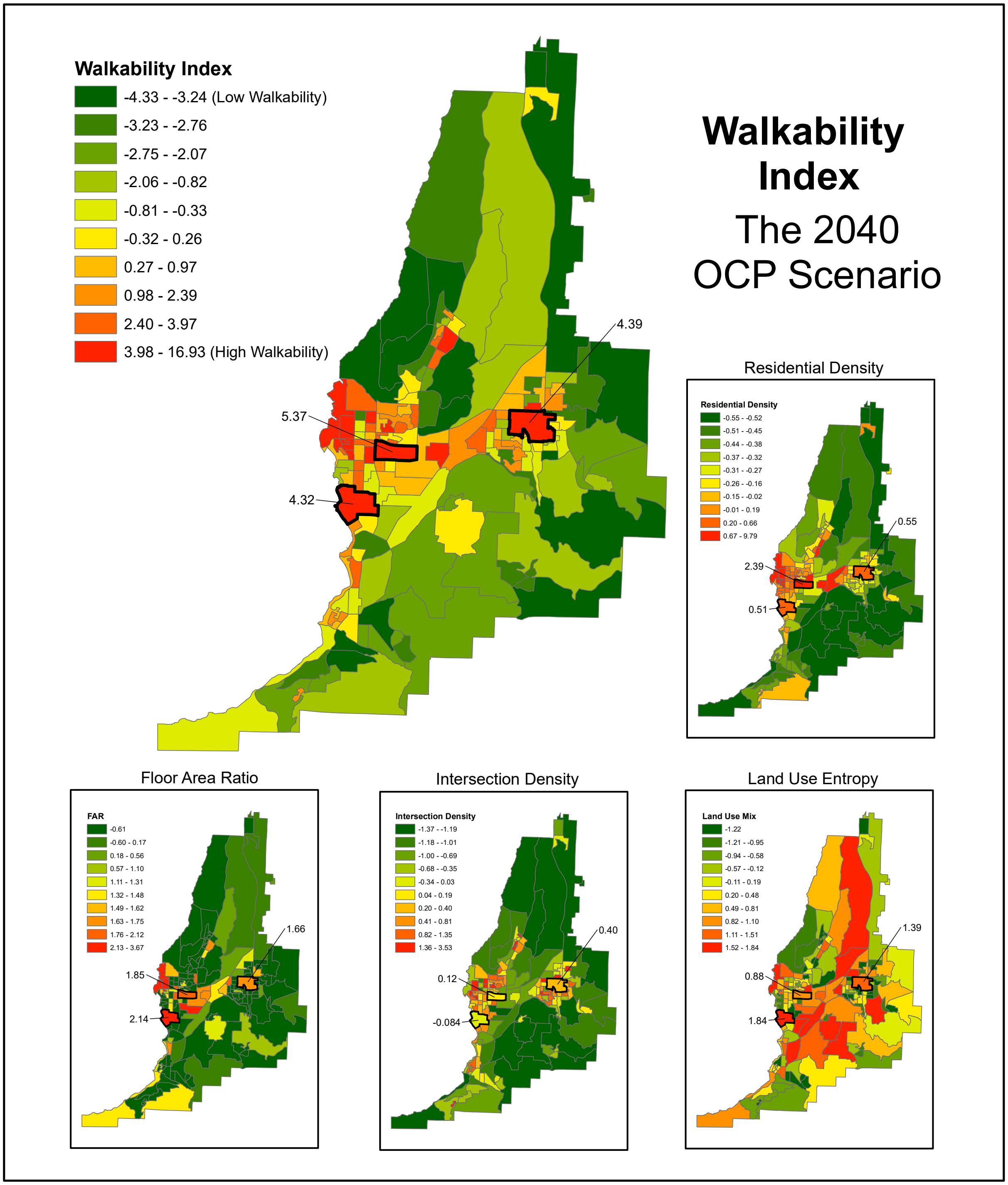


Figure 6.10: Walkability index for the 2040 OCP scenario

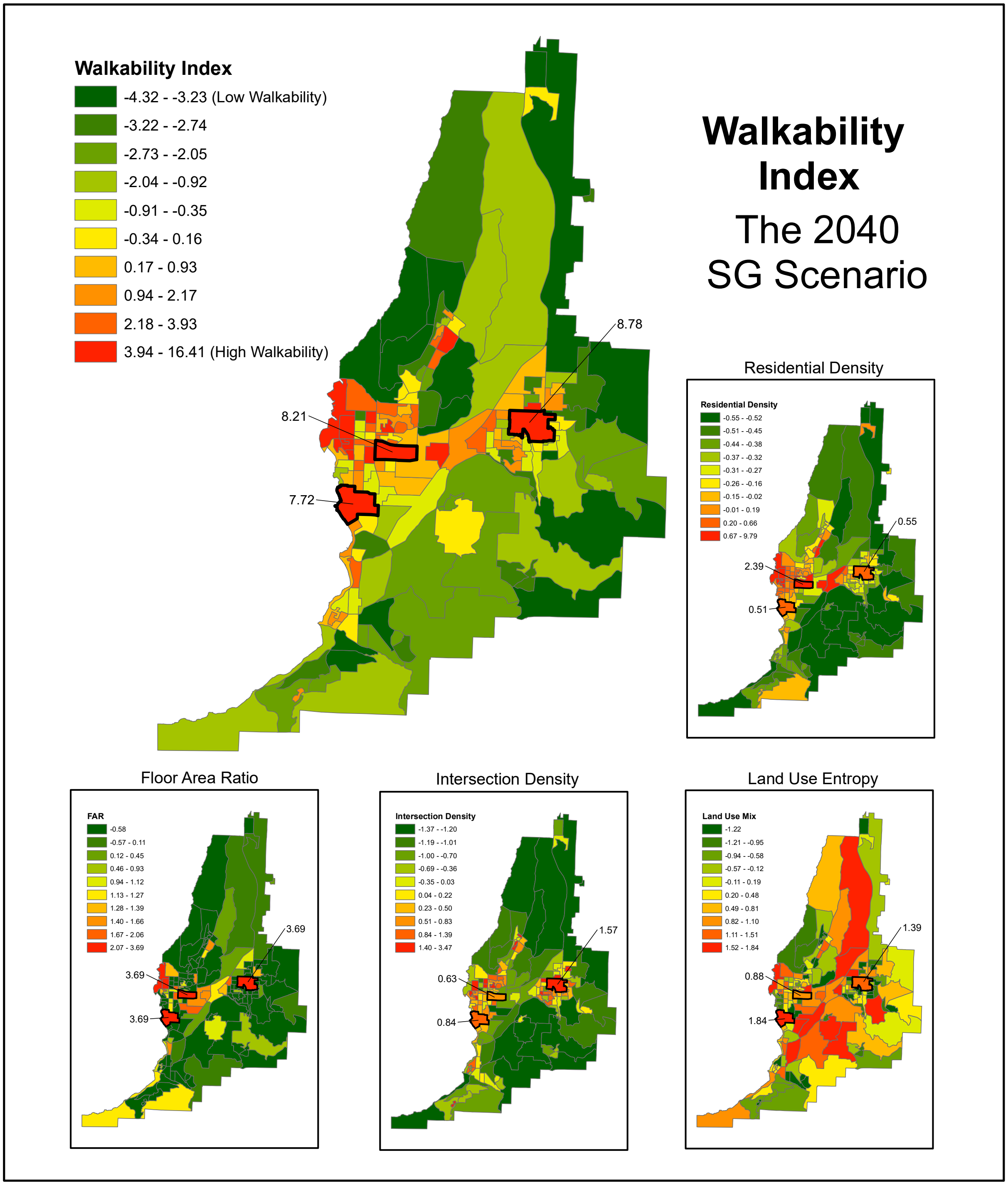


Figure 6.11: Walkability index for the 2040 SG scenario

6.3.2.5 Bikeability

A bikeability surface of 10m grid-cell raster for each of the considered scenarios. First, a raster data was generated for each of the bikeability components (cycling route density, cycling route separation level, connectivity of cycling friendly streets, topography, destination density), as described in section 2.6.5. Second, each surface was reclassified into deciles and recoded from 1 to 10, with the 1st decile assigned a value of 1 and the 10th decile assigned a value of 10. Third, the five surfaces were combined to generate the bikeability score for each 10m cell. Finally, the urban centre's bikeability score was generated by aggregating the cells values that are located within them. Figure 6.12, Figure 6.13, and Figure 6.14 show Kelowna's bikeability surface for the 2016, 2040 OCP, and 2040 SG scenarios, respectively.

For the 2016 scenario, the three urban centres scored well on topography, due to their flat slopes. In addition, they scored well on connectivity of cycling friendly streets and potential destination density for the 2016 scenario, which is expected due to their relatively high employment and retail area. On the other hand, the bikeability evaluation revealed a lack of dedicated cycling routes in the Capri-Landmark and Rutland urban centres as well as a lack of the availability of separated bike infrastructure in all three urban centres.

The 2040 OCP scenario did improve the bikeability score of the Capri-landmark and Rutland urban centres. Surprisingly, there was a slight decrease in the bikeability score of the South Pandosy. This rather contradictory result could be attributed to the low investment rate in new cycling infrastructure in the South Pandosy urban centre compared to the rest of the city. Keep in mind that the bikeability index score for a zone is a function of its performance relative to the performance of the other zones in the study area.

Finally, the 2040 SG scenario achieved the most significant increase in bikeability for the three urban centres. This increase could be attributed to two factors. First, the SG's continuous grid network of off-road paths and cycle tracks (physically separated) to provide full walk/bike connectivity. Second, the intensified mixed land uses, commercial, and services along collector the arterial corridors in a SG neighbourhood.

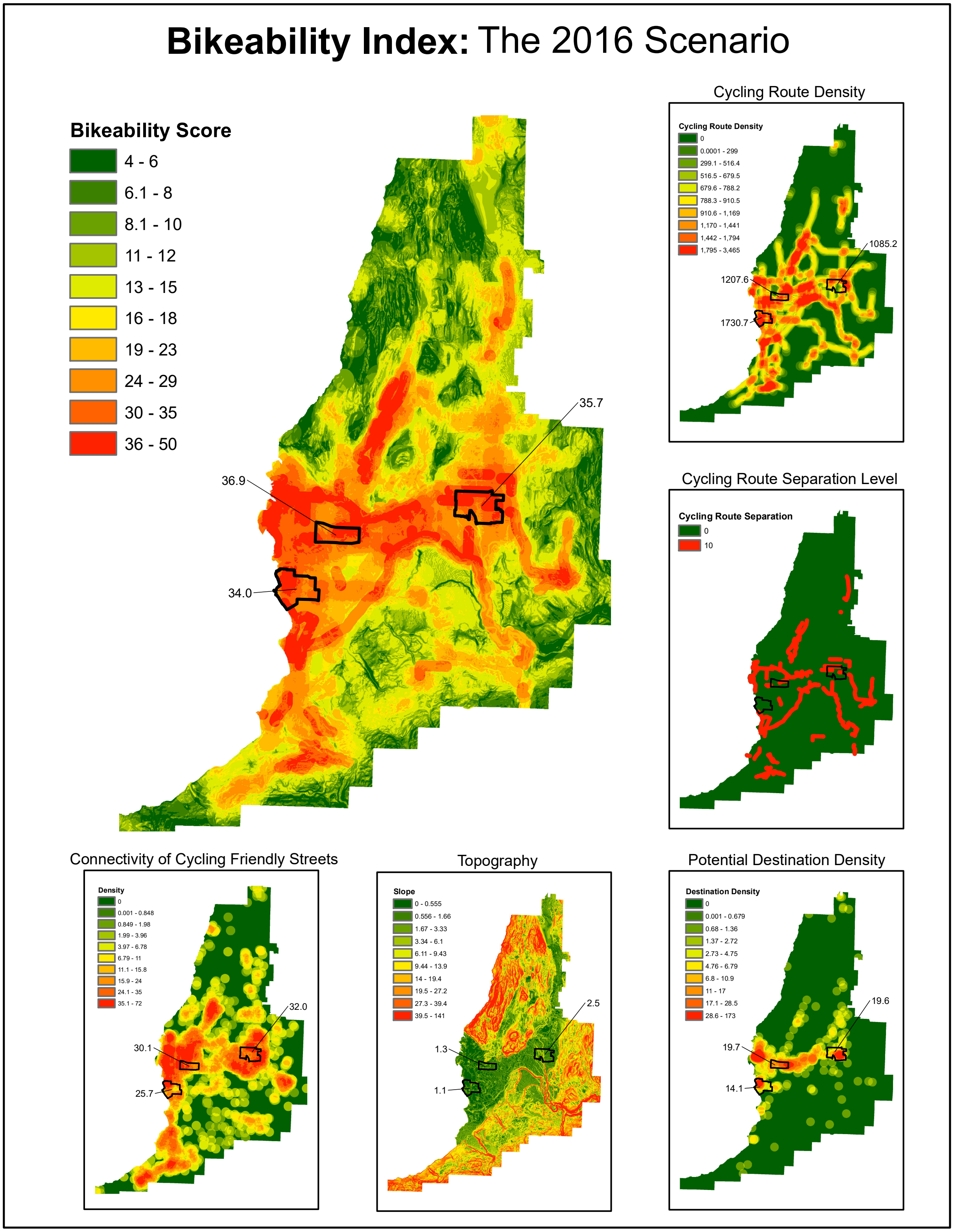


Figure 6.12: Bikeability index for the 2016 scenario

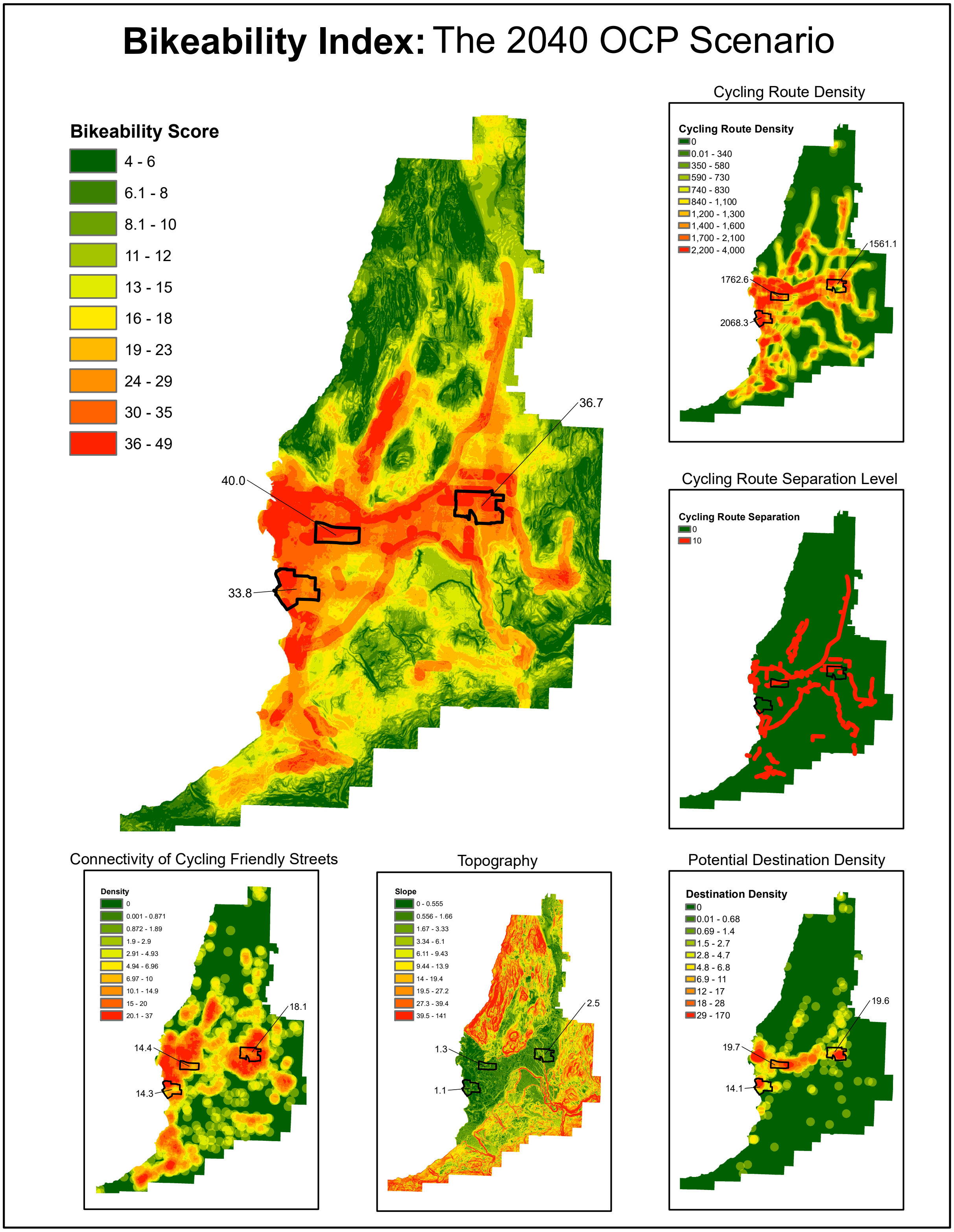


Figure 6.13: Bikeability index for the 2040 OCP scenario

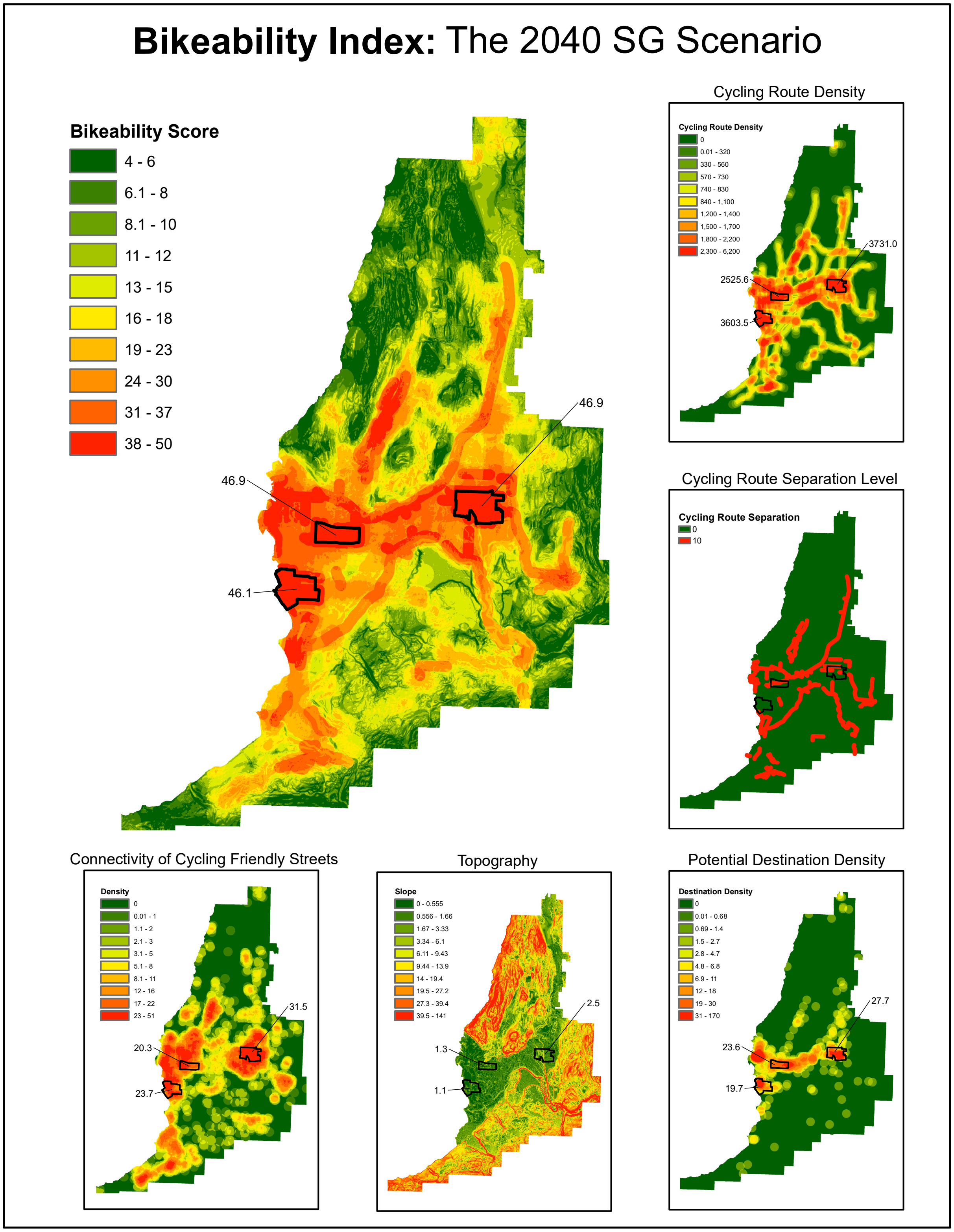


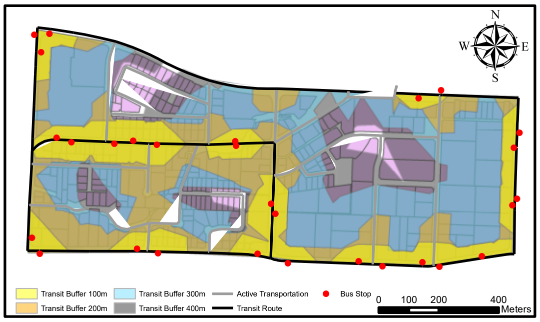
Figure 6.14: Bikeability index for the 2040 SG scenario

6.3.2.6 Transitability

Figure 6.15 shows the stop coverage ratio index (SCRI) for the 2016 and 2040 SG scenarios using 100-400m buffer distances; the 2040 OCP transit network was assumed to be similar to the 2016 scenario. The figure shows that all three urban centres achieved a high SCRI score in the 2016 Scenario, which indicates a high transit accessibility. In particular, the Capri-Landmark resulted in the highest value of 95.6% for the 400m buffer distance, while the South Pandosy resulted in the lowest value of 84.4%. These results demonstrate how well the three urban centres are supported from a transit perspective.

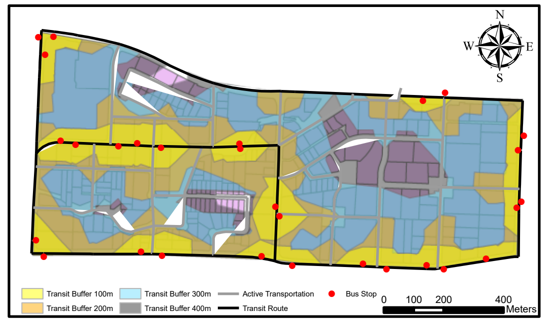
Nevertheless, the 2040 SG scenario resulted in a significant increase in the SCRI value, especially for the 300m buffer in South Pandosy and Rutland. For instance, the 300m SCRI value increased by 7, 36, and 19% in Capri-Landmark, South Pandosy, and Rutland. This increase in the SCRI value is attributed to the highly connected walkable network in the SG retrofits.

Capri-Landmark 2016 Scenario



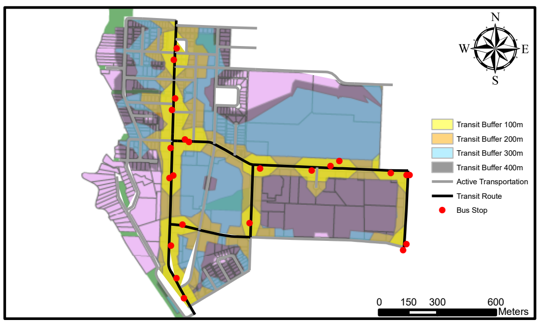
Buffer Distance	100m	200m	300m	400m
SCRI	21.3%	43.0%	81.2%	95.6%

Capri-Landmark 2040 SG Scenario



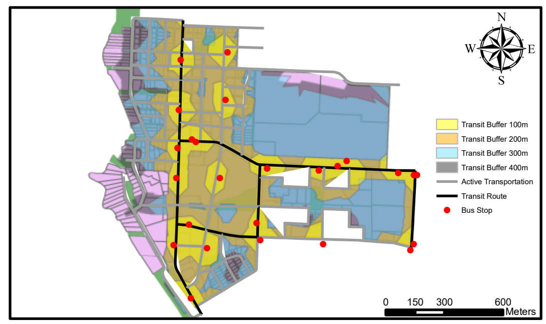
Buffer Distance	100m	200m	300m	400m
SCRI	21.4%	46.4%	87.0%	98.7%

South Pandosy 2016 Scenario



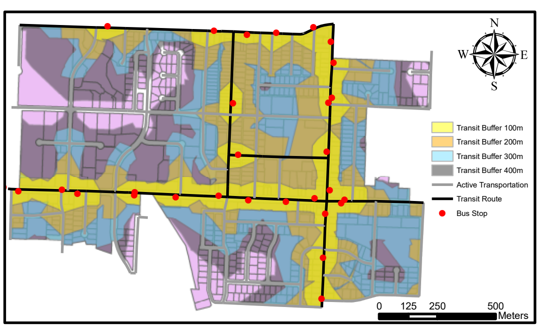
Buffer Distance	100m	200m	300m	400m
SCRI	15.1%	30.2%	60.4%	84.4%

South Pandosy 2040 SG Scenario



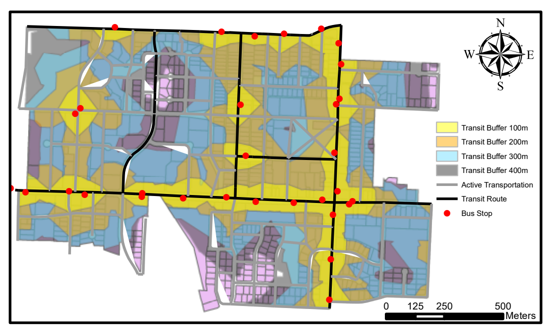
Buffer Distance	100m	200m	300m	400m
SCRI	19.7%	47.8%	82.3%	90.1%

Rutland 2016 Scenario



Buffer Distance	100m	200m	300m	400m
SCRI	19.4%	42.7%	68.9%	88.3%

Rutland 2040 SG Scenario



Buffer Distance	100m	200m	300m	400m
SCRI	20.5%	48.8%	82.0%	94.9%

Figure 6.15: The SCRI score for the study area

6.3.2.7 Playability

As discussed in section 2.6.7, playability in this research was evaluated subjectively based on the following elements: 1) close proximity to destinations, 2) walkability, 3) traffic safety, and

4) residential density. First, numerous research has found that playability is positively associated with having accessible child-friendly destinations such as schools, parks and play spaces. For the 2016 scenario, all three urban centres score high on this element as 100% of the population live within a 400m buffer to a park and around 80, 100, and 88% are within an 800m radius buffer of a school. Similarly, a high proximity to child-friendly destinations is expected for the 2040 OCP and SG scenario, especially for the later scenario as all residents are expected to live within one-minute walk of a park without crossing ay streets.

Second, playability was found to be positively associated with high walkable neighbourhoods. The walkability of each urban centre was discussed in section 6.3.4 in which it was demonstrated that the 2040 SG scenario achieved the highest walkability score, followed by the 2040 OCP scenario and finally the 2016 scenario.

Third, higher perception of traffic safety is associated with higher playabilities for girls. Previous research has predicted that the SG design would significantly improve road safety, with over 60% fewer crashes compared to the traditional grid and cul-de-sac pattern neighbourhood designs (sun and Lovegrove, 2013). In addition, the SG design controls the speed (15 km/h) and volume of traffic on local roads maintains low traffic volume on local roads even in its highest density scenario. Therefore, the 2040 SG scenario is expected to score higher on this element that the 2016 and 2040 OCP scenarios.

Finally, playability is positively associated low residential density. This association could be explained by other features that usually accompany high density such as higher traffic volume and speed and lack of sufficient play and public spaces. The SG design by definition provides traffic calmed with self-enforcing infrastructure that ensures low vehicular speeds in the neighbourhood core. These traffic calming measures include but are not limited to 15 km/h maximum design speed, roundabouts/traffic circles, three-way intersections, discontinuous internal vehicle grid (culs-de-sac), and continuous internal walking and cycling network. All these features are expected to mitigate the negative effects of high residential density in the 2040 SG scenario.

6.3.2.8 Social Interactions

A social interaction opportunity in this research is defined as two walking/cycling agents passing each other. The simulation only counts and logs the location of the first interaction between two agents, such that if agents pass each other at another time step, it would not be counted. The simulation results show that the 2040 OCP scenario is likely to facilitate 34, 25, and 6% more social interaction opportunities than the 2040 SG scenario in the Capri-landmark, South Pandosy, and Rutland urban centres. A possible explanation is that pedestrian traffic in the 2040 OCP scenario is likely to be concentrated on collectors due to the lack of alternative routes, as shown in Figure 6.16. Whereas the SG retrofits provide more reasonable alternative routes for pedestrian traffic is distributed evenly along the walking network.

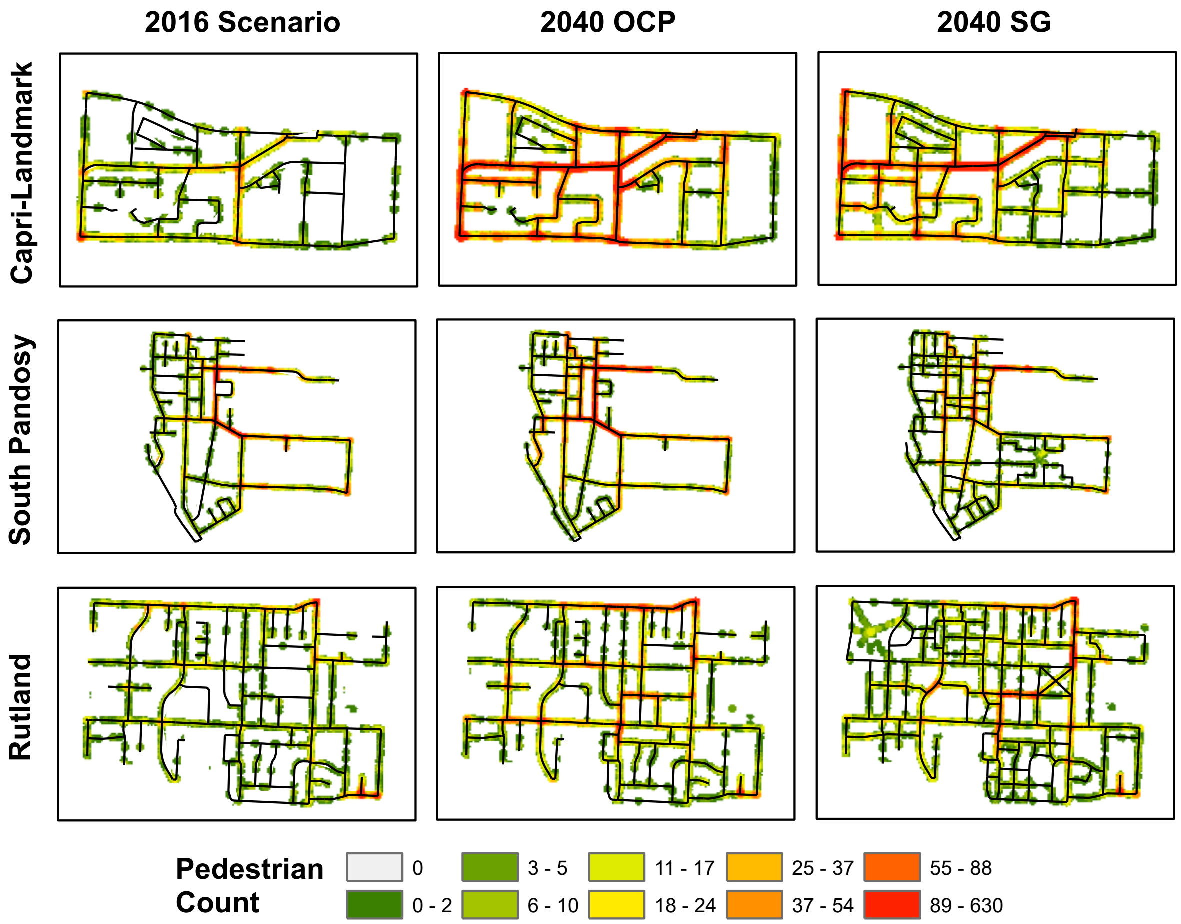


Figure 6.16: Social interaction special pattern

In addition, Figure 6.17 illustrates the number of social interactions aggregated by road classification. The figure revealed that the SG retrofits resulted in more social interaction opportunities on local roads and off-road paths, compared to the 2040 OCP scenario. This finding reflects that the SG design principles might facilitate fewer, but higher quality social interaction opportunities. In addition, it suggests that SG increases natural surveillance on local roads, which contributes to an increase in perception of safety and personal security.

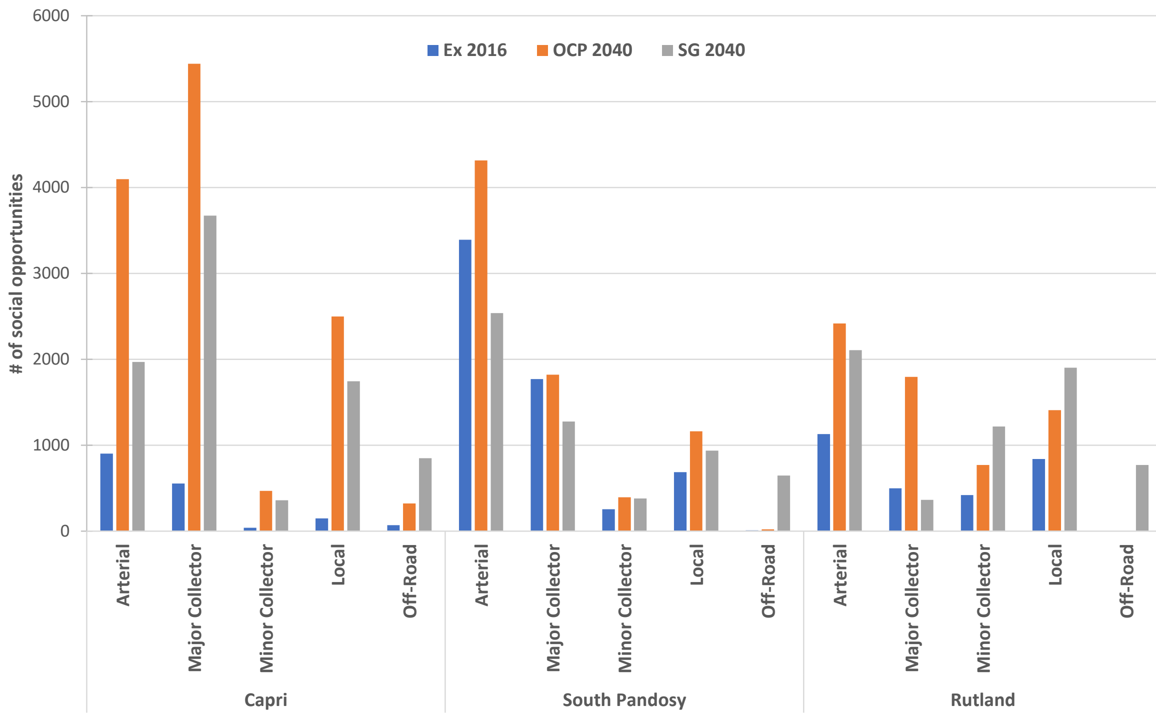


Figure 6.17: Number of social interactions aggregated by road classification

Chapter 7 Conclusions & Recommendations

7.1 Overview

This chapter summarizes the dissertation along with the research conclusions. Section 7.2 gives a summary of the research objectives. Section 7.3 presents a summary of the dissertation. Finally, Section 7.4 discusses the research conclusions.

7.2 Research Objectives

The objectives of this research have been to:

1. Develop a state-of-the-art agent-based travel behaviour framework to provide a comprehensive evaluation of the influence of neighbourhood design on travel behaviour;

2. Propose a suite of tools that can be used to evaluate the influence of the SMARTer neighbourhood design on community quality of life; and

3. Demonstrate the developed framework and the suite of evaluation tools via an application to assess the sustainability benefits of the SMARTer Growth design in the city Kelowna

7.3 Research Summary

Auto-dependency has caused many public health challenges for North American citizens including the increase in physical inactivity rates, road collisions, Greenhouse Gas (GHG) emissions, and our ability to sustain a desired Quality of Life (QoL). Consequently, there has been a growing interest in addressing these challenges by promoting more sustainable neighbourhood designs that reduce automobile dependency and encourage people to use more sustainable modes of transportation.

Given the limited impact of neighbourhood designs in promoting more livable and sustainable communities, researchers from the University of British Columbia and the Canada Mortgage and Housing Corporation developed the SMARTer Growth (SG) neighbourhood design principles. SG (aka Fused Grid) is an alternative neighbourhood model that combines the easy orientation and connectivity of the traditional grid pattern with the land-use efficiency and quietness of the contemporary cul-de-sac pattern. Its objective is to provide a balance between walkability and traffic flow while optimizing the use of land for infrastructure, increasing social interactions, encouraging AT modes, and improving neighbourhood safety.

Nevertheless, there is a relatively small body of literature relating to the performance of SG neighbourhood design. Most of these studies were limited to evaluating the performance of the transportation network layout component of the SG design; hence, the former name of Fused Grid. However, the performance of a neighbourhood design and its resultant travel behaviour are results of a complex interaction between many factors including transportation network layout, personal preferences, socio-economic status, land use, behavioural aspects, and operating conditions, perceived safety, and social interactions. As a result, evaluating a neighbourhood design in terms of each one of these performance measures individually, without accounting for their cumulative interactions, does not draw the full picture of its performance. Thus it has been rebranded as SMARTer Growth Neighborhood design in recognition of the need for a system-based approach to its design and evaluation.

Beyond travel behaviour, neighbourhood design influences our QoL in two ways. First, it directly influences our travel behaviour which in turn influences some quality of life indicators such as air pollution and traffic safety. Second, neighbourhood design indirectly influences other aspects of human behaviour that are related to quality of life such as social interactions and child development. However, no study has been able to draw on any systematic research into evaluating the impact of the SG principles on community QoL.

To address these gaps, this research proposed a systematic evaluation process. First, it developed an agent-based travel behaviour model, using Repast, to provide a comprehensive evaluation of the influence of neighbourhood design at a fine spatial resolution (i.e. parcel level) on travel behaviour. The model simulates agents' daily trip activities and it employs a framework that integrates Random Utility Maximization-based modelling with reinforcement learning concepts to account for the bounded rationality and knowledge learning process. Moreover, the developed agent-based model utilizes the Diffusion of Innovations Theory to account for the impact of social interactions by simulating how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. In addition, the model accounts for the iterative feedback process between agents' actions and the environment. It also adds a time dimension to the modal shift process which could be used to indicate the relative duration it would take to reap the full benefits of various proposed scenarios.

To complement this mode choice model, this thesis proposed a suite of proven empirical tools that could be utilized by community planners and engineers to objectively evaluate key factors of a neighbourhood's design using previously researched quality of life metrics. While most of these were pre-existent, this thesis applied them in the first systematic analysis to evaluate the QoL of a neighbourhood, including: 1) i-THRIVE, 2) air quality, 3) noise pollution, 4) walkability, 5) bikeability, 6) Transitability, 7) playability, and 8) Social Interactions.

To demonstrate the developed agent-based model and QoL suite of tools, three urban centres in Kelowna, BC were examined in this research: Capri-Landmark, South Pandosy, and Rutland. These urban centres have been selected as a study area for two main reasons: 1) the city has mandated to accommodate 26% of its future growth in them and 2) the selected urban centres represent various levels of land use mix.

Four primary data sources were utilized for the development and calibration of the agent-based model and QoL evaluation, including: 1) the 2014 Okanagan Travel Survey (OTS), 2) Statistics Canada 2016 Census Profiles, 3) transportation networks, and 4) land use information. First, the OTS is a household-based travel survey for the residents of the Regional District of Central Okanagan (RDCO) and the City of Vernon. The OTS data includes both socioeconomic and demographic characteristics as well as information on travel patterns. Second, socio-economic marginal distributions of the population in Kelowna were extracted at the dissemination area level from Statistics Canada 2016 Census Profiles files using the Canadian Census Analyser tool. Third, transportation networks data was obtained from the City of Kelowna's open data portal and the General Transit Feed Specification (GTFS) dataset for Kelowna. Finally, land use data for the study area in 2014 were obtained from the city of Kelowna. The data was compiled at the parcel level using various sources including Census Canada profiles, BC Assessment, Canada Business Points, and the Central Okanagan School District's enrollment counts.

Using the previously mentioned datasets, agents were generated for the city of Kelowna using the following four steps 1) generation of agents at the dissemination area level using an iterative proportional updating algorithm 2) random allocation of the synthesized households at the parcel level, 3) assignment of the synthetic agents to workplace dissemination area, and 4) random assignment of the synthetic agents to workplace parcel. The population synthesis results yielded a high level of goodness of fit, with a statistic $\overline{\psi}$ value of 0.037 (a value of zero indicates a perfect fit). Moreover, the results revealed 64% and 92% of the dissemination areas have standardized absolute error values of less than 5% and 10%, respectively, which is consistent with accepted research tolerances. The next step in the population synthesis process was to assign workplace dissemination areas to the synthesized agents using a multinomial logit attraction-end choice model, which had an adjusted ρ^2 value of 0.438. The resultant attraction-end choice model parameter estimate indicated that individuals in the higher income groups were less sensitive to travel impedance than those in the lower-income groups, which is consistent with previous research. Similarly, the number of vehicles per person in a household were found to be associated with a reduced sensitivity to travel impedance.

In addition, a multinomial logit model for morning home-to-work mode choice decisions was developed for the city of Kelowna, BC. The model accounted for socioeconomic characteristics, level of service attributes, and built-environment measures. The built-environment measures were quantified at various buffer distances for all trips' origins and destinations. The model yielded an adjusted ρ^2 value of 0.663, which is consistent with recognized goodness-of-fits found in the literature. The model parameter estimate indicate the following: 1) females are more sensitive to the increase in cycling distance than males, 2) the availability of high and medium frequency bus stops within 800m and 500m, respectively, of trip origins has a positive association with transit use, 3) the availability of green spaces and is positively associated with the cycling mode.

A preliminary case study was conducted to examine the influence of several land use and transportation demand management policies on transportation travel behaviour, including increased activity density and/or non-motorized to vehicle route directness ratio, and transportation demand management (TDM) strategies. The case study was carried out using an initial model of the agent-based simulation that was applied to the Capri-Landmark urban centre. The results showed that retrofitting non-motorized networks have more impact on modal shift than retrofitting road networks. In addition, the results highlighted the significance of land use policies and maintaining users' familiarity with the offered service on active transportation modal share. Finally, the results revealed an increase in auto modal share when retrofitting the road network only, which is contrary to expectations. In addition, agents with knowledge decay displayed a significant increase in driving probability in all the proposed scenarios.

This agent-based model and accompanying suite of tools was applied to evaluate the impact of the SG neighbourhood design on mode choice behaviour and community QoL, in three major urban centres in Kelowna, BC, including: Capri-Landmark, South Pandosy, and Rutland. Three scenarios were examined for each of the urban centre as follows: 1) 2016 transportation and land use systems, 2) 2040 projected transportation and land use systems based on city of Kelowna's endorsed Official Community Plan, which represents business as usual scenario, and 3) 2040 projected transportation and land use systems based on the previously noted, UBCO-developed SG neighborhood design principles.

Compared to the existing and 2040 official community plan scenarios, the results of the mode choice modelling show promise, as retrofitting the three urban centres using the SG principles resulted in significant modal shift towards active transportation. away from auto use. In addition, the results show that the Capri-landmark exhibited the highest potential for modal shift towards non-motorized modes in both the 2040 OCP and SG scenarios. With the SG results in (brackets), the 2040 OCP (SG) scenario resulted in 12% (22%) decrease in auto use, 70% (92%) increase in walking, and 17% (74%) increase in cycling, respectively.

Finally, eight indicators were utilized in this research to evaluate the QoL outcomes of the existing, 2040 OCP, and 2040 SG scenarios, as follows:

1. The i-THRIVE evaluation of the urban centres resulted in the 2040 SG scenario achieving the highest score. With the SG results in (brackets), the i-THRIVE scores of the 2040 OCP (SG) scenario are 62% (96%) in Capri-Landmark, 58% (87%) in South Pandosy, and 53% (84%) in Rutland, respectively.

2. Traffic air and noise pollution were estimated on each road link in the study areas. The results demonstrated that the 2040 SG scenario re-routed through-traffic away from local/residential roads to arterials and collectors, which resulted in a significant decrease in pollution on local roads, compared to the 2040 OCP scenario. In addition, the simulation results showed that pedestrian traffic in the SG retrofits tend to be concentrated on local roads and off-road path which means reduced air pollution exposure for more pedestrians.

3. Walkability, bikeability, and transitability surfaces were generated at the dissemination area levels for each of the considered scenarios. The results showed that the 2040 SG scenario achieved the most significant improvement in the three indices, which could be attributed to two factors: 1) the SG's continuous grid network of off-road paths and cycle tracks to provide full walk/bike connectivity and 2) the intensified mixed land uses, commercial, and services along collector the arterial corridors in a SG neighbourhood.

4. Playability was evaluated subjectively based on elements that have been identified earlier in the literature review. The results show that the 2040 SG scenario is expected to achieve high playability due to 1) high close proximity to child destinations as all residents will be live within one-minute walk of a park without crossing any streets, 2) high walkability, 3) improved road safety, and 4) low traffic volumes at load roads even at the highest density scenario. On the other hand, the 2040 OCP scenario is expected to achieve lower playability relative to the SG scenario due to high traffic volume on local roads lesser road safety.

5. Social interaction opportunities were quantified in each scenario by counting the first encounter between two walking/cycling agents. The results show that 2040 OCP scenario is expected to facilitate more overall social interaction opportunities than the 2040 SG scenario. However, the SG is judged to promote a higher QoL as it is expected to facilitate higher quality interactions, whereby more social interaction opportunities would occur on local roads and off-road paths, which contributes to an increase in natural surveillance and higher perception of safety and personal security.

7.4 Conclusions & Policy Implications

Based on the development and calibration of the agent-based simulation and the results obtained from the case studies presented in this research, the following conclusions and policy implications can be drawn:

- **Linear utility functions work best to predict AT mode choice:** Considering numerous studies suggesting non-linear relationship between non-motorized modes and their predictors, several non-linear forms for walking and cycling utilities were examined including exponential, logarithmic and quadrant functions. However, the results indicated that a linear utility function for walking and cycling modes provides better goodness-of-fit for the mode choice model.

- **Compact development promotes gender equity:** The modelling results of the morning home-to-work mode choice model revealed that females are more sensitive to the increase in cycling distance than males, which indicates a potential gender gap in opportunities available for females to be more physically active. This gap can be filled by land use policies that aim at limiting urban sprawl and supporting higher densities and mixed land use (i.e. SMARTer Growth).

- **People will walk farther to use higher frequency transit service:** The availability of medium and high frequency bus stops within 500m and 800m, respectively, of trip origins is positively associated with an increase in the likelihood of using transit. These results indicate that people are willing to walk longer distances to reach bus stops with high frequency service than previously assumed.

- **Commuters are better informed of their mode choices:** The calibration process of the proportions of the information provision categories using a genetic algorithm revealed the following information provision proportions: 32% partial information, 18% partial information with knowledge decay, and 50% perfect information. The proportion of commuters with perfect information is higher than that of previously reported in the literature, which could be attributed to people's improved technology platforms to access real-time vehicular traffic and transit service information.

- **AT network improvements are the better investment:** Retrofitting the non-motorized network scenario resulted in higher modal shift towards non-motorized modes compared to retrofitting the road network only scenario. This implies that infrastructure investments related to providing more accessibility for non-motorized users might have more impact on decreasing auto use compared to restricting vehicular network connectivity.

- **Go after the low hanging fruit first to increase AT use:** The previous finding also suggests that applying SG to a neighborhood with more opportunities to increase non-motorized connectivity (e.g. cul-de-sac) will have more impact than applying it to a neighborhood with already high non-motorized and vehicular connectivity (e.g. grid pattern).

- **Integrated land use planning is critical to the AT shift:** The overall modal share results for various scenarios indicate that land use policies have a more significant impact on modal shift towards active transportation modes compared to retrofitting the transportation network. This finding highlights the importance of the integration of transportation and land use planning in reducing auto-dependency.

- **Road network changes alone will fail:** The results of the preliminary analysis revealed an increase in auto modal share when retrofitting the road network only, which is contrary to expectations. In addition, agents with knowledge decay displayed a significant increase in driving probability in all the proposed scenarios. These results suggest that altering the behaviour of individuals with rooted driving culture requires significant changes to the transportation and land use systems in order to be successful.

- **TDM programs help to introduce AT choices:** The forecasted modal shift for the TDM policy scenarios demonstrated the significance of familiarity and awareness on active transportation modal share. Municipalities and transit agencies can benefit from implementing programs (e.g. temporary free transit service, bike to work week, and transit marketing campaigns) that aim to entice the public to try active transportation modes and thus gain familiarity with the offered service.

- **SG better than OCP, especially for Capri-landmark:** Retrofitting the Capri-Landmark, South Pandosy, and Rutland urban centres using the SG design principles resulted in significant modal shift towards transit and non-motorized modes and a reduction in auto for morning home-to-work trips. In addition, the results show that the Capri-landmark exhibited the highest potential for modal shift towards non-motorized modes, followed by Rutland and South Pandosy.

- **SG promotes overall QoL:** The community QoL evaluation of the three urban centres shows that applying the SG design principles improves walkability, bikeability, and playability, and decreases air and noise pollution on local roads.

- **SG promotes higher quality social interactions and perceived safety:** The agent-based simulation results showed that pedestrian traffic in the SG retrofits tend to be concentrated on local roads and off-road path which means reduced air and noise pollution exposure for more pedestrians and an increase in natural surveillance, which could contribute to an increase in perception of safety and personal security.

7.5 Contributions of this Research

There were four major contributions of this dissertation, as follows:

This research set out to fill a key knowledge gap related to putting the SMARTer Growth neighbourhood design into practices in Canada by providing a better understanding of the influence of neighbourhood design as a system on travel behaviour. The literature review has shown that previous agent-based models lack the consideration of one or a combination of the following: end-to-end travel demand, psychological factors such as habit formation, social interactions and their influence on travel behaviour, considering walking and cycling as separate modes of transportation, the effect of micro-scale built environment measures. To address this knowledge gap, **the first significant contribution** of this research is the development of a novel agent-based travel behaviour model, using Repast, to provide a comprehensive evaluation of the influence of neighbourhood design at a fine spatial resolution (i.e. parcel level) on travel behaviour. The developed model integrates the traditional Random Utility Maximization (RUM)-based modelling technique with reinforcement learning concepts to account for the bounded rationality of human beings and knowledge learning process. Moreover, the developed agent-based model utilizes the Diffusion of Innovations Theory to account for the impact of social interactions by simulating how agents share their knowledge and propagate information about their preferred travel mode across family members and co-workers. In addition, the model accounts for the iterative feedback process between agents' actions and the environment. It also adds a time dimension to the modal shift process which could be used to indicate the relative duration it would take to reap the full benefits of various proposed scenarios.

A second significant contribution of this research has emerged from the work related to the first objective which is that this research offers new insights into the influence of information provision and of habit formation on commuting behaviour. For example, the calibration process of the proportions of the information provision categories revealed a proportion of commuters with perfect information that is higher than that of previously reported in the literature. This finding indicates that commuters are becoming more informed of their mode choices and changes in the transport system. In addition, an experimentation of the agent-based simulation showed that increasing driving travel time by 19% resulted in a slight increase in auto modal share. Similarly, agents with knowledge decay displayed a significant increase in driving probability in all the proposed scenarios. These results suggest that altering the behaviour of individuals with rooted driving culture requires significant changes to the transportation and land use systems to be successful. Finally, the simulation results demonstrated the importance of maintaining users' familiarity of the with the offer service through programs such as temporary free transit service, bike to work weak, and transit marketing campaigns.

A second objective of this research was to fill the knowledge gap related to evaluating the influence of the SG neighbourhood design on community quality of life. This has led to a

third significant contribution on that this dissertation identified a reliable suite of empirical tools that could be utilized by community planners and engineers to objectively evaluate key factors of a neighbourhood's design and their influence on a community quality of life. In particular, eight tools and indicators were utilized in this research to evaluate the QoL of a neighbourhood, including: 1) i-THRIVE, 2) air quality, 3) noise pollution, 4) walkability, 5) bikeability, 6) Transitability, 7) playability, and 8) Social Interactions. This is a significant contribution as it addresses the need of small and medium municipalities for a practical tool that uses open source data to explore alternative transportation and land use scenarios and subsequently identify best policies to meet/sustain their communities' desired quality of life. The proposed suite of tools was demonstrated in an application to three urban centres in Kelowna, BC to explore the influence of various policy scenarios on quality of life.

The third research objective of this research was to utilize the agent-based framework and the suite of evaluation tools to assess the sustainability benefits of the SMARTer Growth design as a system in the city Kelowna. Most of previous studies address individual aspects of the SMARTer Growth's performance such as safety, traffic performance, and walkability. Moreover, the research to date has mainly studied the SMARTer Growth as a street network layout, neglecting its system-based approach that involves many components other than simply a road network layout, including human-scale block sizes, active transport, intersection design, green spaces layout, and land use distribution. As such, **the fourth significant contribution** of this research is that it is the first attempt to evaluate the impact of the full-fledged SMARTer Growth design principles on travel behaviour and community quality of life. This contribution also addresses the city of Kelowna's need for a robust evaluation tool that aids its effort to update the city's Official Community Plan (OCP). In addition, the presented case study, that is related to this contribution, provides a critical building block in the city's objective to develop detailed urban centre plans that outlines the long-term transportation and land use policies for each of the urban centres in the city of Kelowna.

7.6 Limitations & Future Research

This section presents some limitations and recommendations for future research that have been identified during this study, as follows:

- This research evaluated the impact of the SMARTer Growth design principles on weekday morning home-to-work trips due to their permanence, non-discretionary nature, and resemblance of long-term decisions. A previous investigation by the author on the influence of the street connectivity component of the SMARTer Growth on travel behaviour revealed a minor modal shift for non-work trips, compared to work trips. This minor effect was attributed to the lack of consideration of other elements of the SMARTer Growth design including high density and mixed land use, aesthetically pleasing due to green open spaces, and increased neighbourhood safety. Therefore, a further study could utilize the developed agent-based framework to assess the effect of the full-fledged SG design travel behaviour for non-work trips. In addition, examining if there is any variation in the influence of SMARTer Growth design on travel behaviour between weekday and weekends would be a fruitful area for further research.
- Modeling only morning commuting trips, rather than 24-hour activities, constitute a major limitation of the QoL evaluation of the SMARTer Growth design in this research. Morning commuting trips represent a relatively small number of trips out of people's daily activities.

In addition, a person's behaviour varies between commuting trips and non-commuting trips. For instance, a commuter could be using transit in the morning but drive long distances in the evening for non-work trips. Therefore, the results of the QoL evaluation of the SMARTer Growth design based on modeling only morning commute trips should be confirmed using an all-day modeling analysis in future research. The agent-based model developed in this research can simulate multiple trips for each agent; however, it lacks an activity scheduling module. A natural progression therefore would be to add an activity scheduling microsimulation module to generate an agent's 24 -hour activity schedule.

- Due to data availability, the proportions of information provision categories in the synthetic population were calibrated by simulating the period 2014-2016, which reflects a shift in travel behaviour over a short-range period of two years. However, the agent-based framework developed in this research was designed to assess the long-term impact of transportation and land use policies on travel behaviour. Therefore, a natural progression of this work is to validate/re-calibrate the proportions of information provision categories using the 2021 census data once they become available. In addition, the use of genetic algorithm for model calibration was due to its easy implementation and relatively good performance; however, the author acknowledges that other advanced optimization algorithms might provide better performance and efficient computation, and should be checked in future research.
- The current implementation of the agent-based simulation assigns agents randomly to a social influence group and an information provision category. Future research would benefit from developing a systematic procedure to dynamically assign agents to each of

these groups based on empirical data, which potentially would provide insights on the link between transportation users' socio-economic characteristics and how they share their knowledge, propagate information, and learn from their experience. It is also worth exploring whether agents are expected to change their information provision/social interaction groups over time during a simulation run. In addition, further research could explore incorporating the influence of social interactions from transportation perspective using theories that are more related to travel behaviour.

- The assumption that the step size parameter (i.e. how much do agents learn from previous experience) and the temperature parameter (i.e. how much are agents willing to explore new alternatives) are inversely proportional to the choice probability of the recent dominating mode has not been validated. A natural progression of this work is to calibrate these parameters using longitudinal travel data. The data should be collected over the course of new land use and transportation policies implementation as well as post-implementation. In addition, the time between each two waves of data should be as short as practical (e.g. three or six months). Similar to the proportions of information provision categories, the step size and temperature parameters could be calibrated using a genetic algorithm.

- The current implementation of the agent-based simulation utilized a transit routing solution that was developed on the based of graph theory and utilizes a simple Dijkstra algorithm to compute agents' door-to-door transit path. Some of the limitations of this algorithm is that it does not account for waiting and transfer nor transit vehicle capacity constraint. Additionally, the algorithm does not simulate public transit vehicles in mixed traffic, with cars, to account for the interaction between both modes. This limitation could be addressed by developing an in-house Repast implementation of a public transit shortest path algorithm that accounts for the aforementioned factors and utilizes Open Street Map (OSM) and General Transit Feed Specification (GTFS) data to allow for universal implementation of the algorithm. Alternatively, future research could explore integrating the developed agent-based framework with a third-party timetable-based transit routing algorithm. Similarly, the current implementation of the traffic assignment algorithm requires further refinements to appropriately capture traffic flow while accounting for network equilibrium. This limitation could be addressed by integrating the developed agent-based framework with an established traffic assignment module, such as EMME. Doing this would also help to ascertain the expectation that emissions and noise at a city-wide scale of analysis would show more significant benefits from a SMARTer Growth design.

- This research proposed a reliable suite of empirical tools that can be utilized to evaluate the influence of neighbourhood design on community quality of life. However, a major limitation is that it did not offer a methodological framework to combine all of the proposed metrics into an overall normalized index/score for use across different cultures and locales. One way to calculate an overall score could be to assign a weight to each of the proposed quality of life metrics. The weights could be estimated using the Analytic hierarchy process

(AHP) based on inputs from expert panels of stakeholders, such as: residents, decision-makers, urban planners, and/or transportation engineers.

- The simulation performance in terms of runtime needs improvement. The simulation was run on desktop computers with Intel i7-6700 CPU @ 3.40GHz and 32 GB RAM. The one-day run-time for the city of Kelowna case study, which has 60,000 agents and 19,000 transportation links, averaged 110 minutes. This poor performance has caused delays in the calibration process of the model, which took around two months to complete. The model performance also limited the use of a larger dataset for the calibration process; only 30% of the dataset was used for calibration. Repast Simphony, the version used in this research, does not provide automatic parallelisation of the simulation code; hence, the developed agent-based model runs on a single thread. Therefore, future research should explore parallelizing the developed model using Java's Thread Pools. Alternatively, the model could be translated to C++ in order to utilize Repast for High Performance computing, which is designed for use on large computing clusters and supercomputers.

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Appendix A: Urban Quality of Life Indicators

Table A.1 Urban Quality of life Indicators

Model	Domain	Indicators
Dutch	Health	• Environmental quality/ physical living • Microclimate (heat stress) • Movement stimulation (walking and cycling) • Collisions • Amenity Value
	Climate resistance	• Rainwater management • Green • Biodiversity
	Mobility	• Active transportation • Shared mobility • Connectivity with public transit • Sustainable transportation
	Circularity	• Circular demolition • Circular design • Material Passport
	Energy	• Indoor climate • Green energy • Heat network
	Social economy	• Healthy Urban Living • Local activity • Cooperation • Sharing
Serag El Din et al. (2013)	Environmental	• Biodiversity • Energy saving • Green spaces • Waste management
	Physical	• Compact, mix land use neighbourhood • Close proximity to services • Eco-buildings and housings • Well-structured building layout • Well-defined street hierarchy

Model	Domain	Indicators
		• Maintenance management
	Mobility	• Alternative modes of transportation • Close proximity to transit and activities • High walking network connectivity • Pedestrian-friendly streets
	Social	• Gender Equity and social justice • Safe environment • Mix housing types • Public spaces • Social interactions • Traffic safety
	Psychological	• Preserving heritage and historic sites • Privacy • Pleasing environment
	Economical	• Job accessibility • Affordable housing
	Political	• Integrated urban governance • Public consultation • Long-term community plan
Bonaiuto et al. (2006)	Architectural/ town-planning features	• Building density • Building aesthetics • Building volume • Internal practicability • External connections • Green areas
	Socio relationship	• Security and tolerance • Discretion and civility • Sociability and cordiality
	Functionality	• School services • Social-care services • Sport services • Socio-cultural activities • Commercial services

Model	Domain	Indicators
		• Transport services
	Contextual	• Relaxing vs. Distressing • Stimulating vs. Boring • Environmental health • Upkeep and care
	Neighbourhood Attachment	• Neighbourhood Attachment

Appendix B: i-THRIVE Evaluation Summary

Table B.1 A detailed summary of the i-THRIVE evaluation for each of the urban centres

Element	Metric	Max	Capri			South Pandosy			Rutland		
			S1	S2	S3	S1	S2	S3	S1	S2	S3
Density	Residential density	**10**	0	10	10	0	0	0	0	1	1
	Non-residential Floor Area Ratio	**10**	0	10	10	2	10	10	0	10	10
Service proximity	Proximity to services	**15**	10	10	15	10	10	15	10	10	15
	Proximity to transit	**10**	10	10	10	10	10	10	10	10	10
	Proximity to employment	**10**	10	10	10	10	10	10	10	10	10
Land-use mix	Heterogeneity of LU mix	**10**	3	10	10	8	10	10	6	10	6
	Heterogeneity of building mix	**10**	4	8	10	4	8	10	4	8	10
	Mixed housing types	**5**	0	3	5	0	0	5	0	0	5
Street connectivity	Street connectivity	**10**	1	1	10	1	1	3	1	1	3
Road network and sidewalk characteristics	Traffic calming	**10**	1	1	10	1	1	10	1	1	10
	Speed control/pedestrian priority	**10**	0	0	10	0	0	10	0	0	10
	Sidewalks and buffer strips	**5**	0	1	5	0	1	5	0	1	5
	Cycle friendly design	**10**	4	9	10	3	8	10	4	9	10
	Lighting	**5**	5	5	5	5	5	5	5	5	5
Parking	Unbundled & Shared parking	**10**	7	7	10	7	7	10	7	7	10
	Parking price and restrictions	**10**	0	0	10	6	6	10	0	0	10
	Parking location and alleys	**10**	2	2	10	2	2	10	2	2	10
Aesthetics and human scale	Building height to street width ratio	**7**	3	7	7	1	7	7	1	7	7
	Setbacks and street walls	**8**	6	6	8	8	8	8	6	6	8
	Tree placement and characteristics	**10**	10	10	10	10	10	10	10	10	10
Functionality	Functional Classification	**7**	3	7	7	0	1	7	3	1	7
	Access Management on collector roads	**5**	3	3	3	0	0	3	3	3	3

Predictability	Distinguishable design characteristics	**12**	0	0	8	0	0	8	0	0	8
Homogeneity	Road Users Homogeneity	**12**	0	9	9	0	3	12	0	3	9
Forgivingness	Forgivingness	**12**	0	0	12	0	0	12	0	0	12
State Awareness	Reducing motorists task demand	**6**	0	0	6	6	6	6	0	0	6
	Reducing cyclists task demand	**6**	0	6	6	0	6	6	0	6	6