Demand for Cycling Infrastructure: Building a Spatial Tool to Identify Gaps in Cycling Networks

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A Senior Honours Thesis Submitted in Partial Fulfillment of the

Degree of Batchelor of Environmental Studies

(Honours Geomatics)

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August 2020

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Abstract

Cycling as a mode of transportation has been shown to provide numerous benefits, whether economic, ecological, or health-related to both communities and individuals. Key to shifting transportation mode-share to more sustainable methods of travel such as cycling, is the infrastructure in place to support this travel. Current efforts to map relationships between cycling and the built environment have been focused primarily on existing cycling infrastructure, often using local transportation survey data that is not available in many cities and regions. The goal of this project was to develop a methodology to map the demand for cycling infrastructure in the Region of Waterloo independent of existing cycling facilities and without the use of uncommon survey data. Review of the literature found that the phenomenon of cycling infrastructure demand could be explained primarily by three factors: cyclist's perception of safety; proximity to destination hubs; and population density. Using empirical evidence and commonly available data, each of these factors were mapped across the region, and combined using four different weighting schemes, developed in collaboration with a member of CycleWR, a local cycling advocacy group. The metric provides value as an evidence-based tool with which local governments can be better informed about where demand exists for cycling facilities. Demand can be used alongside other metrics such as Winters *et al.*'s bikeability index to further provide insight into how demand differs from the existing built environment. The methods in this project can be easily adapted and applied to other regions.

1.0 Benefits of Cycling as a Mode of Transportation

Cycling as both a recreational and utilitarian mode of transportation is becoming more prevalent in Canada due to positive health, environmental, and economic benefits (Statistics Canada, 2017). As an active form of transportation, cycling contributes to the prevention of several chronic diseases, and is associated with a reduced risk of pre-mature death (Warburton, Nicol, & Bredin, 2006). As well, modelling of transportation mode-shares in Adelaide, Australia has shown that just a 10% change from vehicular travel to commuter cycling can prevent more than 300 deaths annually from reduced accident potential, increased commuter health, and the reduction of vehicular air pollutants (Xia *et al.*, 2015). Vehicular traffic produces roughly a quarter of greenhouse gases on Earth, making it a significant contributor to climate change. This model found that carbon dioxide (CO_2) emissions in the city could be reduced by 191,313 to 238,636 tons per year with 5% and 10% mode shifts to cycling respectively (Xia *et al.*, 2015). As well, cycling as a form of transportation is more cost-effective than vehicular or public transportation both in costs to the individual user and in the costs of infrastructure (Pucher & Dijkstra, 2000). Due to the combined adverse effects of vehicular transportation on health, safety, the environment, and infrastructure costs, research has found that cycling can produce substantial economic benefits. In the Netherlands for example, the benefits of cycling translate into an estimated return on investment of €19 billion per year, equivalent to approximately $26.4 billion CAD in 2015 (Fishman *et al.*, 2015).

1.1 Cycling Infrastructure's Role in Cycling Success

While cycling has these broad positive effects, special care must be taken at municipal and regional levels to ensure the successful adoption of cycling as an alternative mode of transportation. Numerous studies have concluded that cycling infrastructure, including designated bike paths, parking, and bike lanes, is necessary for the success of cycling initiatives (Hull & O'Holleran, 2014; Aultman-Hall, Hall, & Baetz, 1997; Dill, 2009). It is important to note that low-traffic and residential streets can be considered highly suitable for cycling without designated cycling facilities; however larger streets which allow for more direct travel are in higher need of infrastructure (Mekuria, Furth, & Nixon, 2012).

In the cities of Guelph, Ontario and Portland, Oregon, research into the role of infrastructure in cycling has shown that individuals who cycle as their regular form of transportation tend to divert little from major road-routes with bike lanes, and that a disproportionate share of cycling occurs on streets with cycling infrastructure (Aultman-Hall *et al.*, 1997; Dill, 2009). It has also been found that when planning the expansion of a cycling network in a region, it is most important to identify and focus on major routes and destinations where cycling is most feasible such as major business and community centres (Nuworsoo *et al.*, 2012). It is evident that regions wishing to increase transportation mode share of cycling have a demand for effectively planned and located infrastructure.

1.2 Connectivity and Safety of Cycling Infrastructure

An important aspect of cycling infrastructure is connectivity, which has been identified by numerous studies as a primary factor in influencing one's desire to cycle as an alternative mode of transportation (Lowry, Furth, & Hadden-Loh, 2016; Hull & O'Holleran, 2014; Aultman-Hall *et al.*, 1997; Mekuria, Appleyard, & Nixon, 2017). Connectivity in this context represents both the ability of a cycling network to connect destinations with relatively low-stress travel, and the consistency of facilities throughout a network. While normally conceptualized based on existing physical infrastructure, network connectivity can be measured in terms of levels of cyclist stress throughout a region's road network (Mekuria, Furth, & Nixon, 2012).

A common measure of cyclist stress categorizes roads into four increasing levels of traffic stress (LTS 1-4) based on characteristics such as road width, traffic speed, and the presence of cycling facilities. Key to this research is the idea that high stress pathways for cyclists can greatly limit connectivity from route origins and destinations, and that road facilities for cyclists are the most useful tool in reducing stress in such areas (Mekuria *et al.*, 2012).

However, care must be taken when designing and implementing on-road cycling infrastructure. Cyclists' perception of safety is a factor that ties into stress and is often identified in literature as a severe inhibitor of the success of cycling infrastructure (Hull & O'Holleran, 2014; Mekuria *et al.*, 2017). As opposed to facilities in countries such as Germany or the Netherlands, which are often well-planned and separated from traffic by physical barriers, North American facility standards lack separation. This results in lower perception of cyclist safety and lower rates in cycling adoption (Pucher & Dijkstra, 2000). To combat this, low-cost barriers are being tested to increase both perceived and actual cyclist safety. The Region of Waterloo for example, launched the *Separated Cycling Network Pilot Project* in 2017 with the aim to increase the sense of comfort and safety of cyclists (Keyworth, 2017).

While bike lanes on major roadways are a popular type of cycling facility, intersections have been shown to increase cyclist stress and lower their perception of safety (Lowry *et al.*, 2016, Caviedes & Figliozzi, 2018). As well, the choice of intersection facilities can significantly impact the compliance rates of both cyclists and drivers. Bike lanes that are continuous throughout an intersection have demonstrated nearly unanimous compliance, but other methods of intersection cycling facilities show a significant drop in both cyclist and driver compliance (Johnson *et al.*, 2010).

1.3 Ideal Characteristics for Cycling

It is important to note that ideal geographic characteristics of cities exist that lend to the success of cycling initiatives (e.g. flat terrain, compact land-use, mild climate), and that the effectiveness of alternative modes of transportation depend on how well a region is designed to support them (Nuworsoo *et al.*, 2012; Mekuria *et al.*, 2017). However, the absence of these efficiencies can be overcome by a local culture that supports cycling. Cities such as Amsterdam and Copenhagen are geographically large and have colder climates yet remain world leaders in cycling due to strong local cycling cultures (Nuworsoo *et al.*, 2012).

1.4 Representing Infrastructure Across a Region

Little research has been done in the realm of using GIS to identify gaps in existing cycling facilities. Larson, Patterson & El-Geneidy used non-commonly available survey data such as cyclist origin-destination (OD) matrices, demographics, and cyclist preferences to map gaps in Montreal's cycling network (2013). In the absence of such data, areas like the Region of Waterloo need methods that utilize existing and openly available geospatial data. As well, review of the literature has found a lack of methods for explaining and mapping the demand for cycling infrastructure. Found in the literature, however, were several methods for mapping how well existing infrastructure and other factors contribute to the cyclist experience. The literature that describes levels of traffic stress represented this phenomena discretely across road and cycling networks based on cyclist levels of comfort in an aim to identify areas of low-stress connectivity and the high-stress pathways that separate them (Mekuria *et al.*, 2012). Other research sought out to map an area's bikeability, an index that refers to the ability of a network to connect cyclists to important destinations across a region (e.g. Lowry *et al.,* 2012; Winters *et al.,* 2012). Such analyses provide useful tools to identify areas in a region that are the most conducive to travel by bicycle given existing cycling facilities, but do not identify areas where new infrastructure development should be focused.

It is the goal of this research to develop a novel methodology to map demand for cycling infrastructure continuously using data that is widely available. A demand metric would provide value in government decision-making regarding new cycling initiatives. As well, alongside proven methods for mapping bikeability, such tools could be used in conjunction to identify gaps in cycling infrastructure: discrepancies between the usefulness of existing infrastructure to cyclists, and the demand for cycling infrastructure, independent of existing conditions.

2.0 Methodology

The methods of this project involve mapping Winters *et al.*'s bikeability metric along with developing and mapping a novel metric to represent demand for cycling infrastructure. Differences between the two metrics will then be calculated and examined. Mean bikeability and demand scores by Census Tract (CT) will then be compared to cyclist commuter mode-share using the Pearson correlation coefficient to determine if a significant relationship exists. Finally, a website will be created to showcase the data and findings of this project. Figure 1 is a data flow diagram illustrating the general processes used.

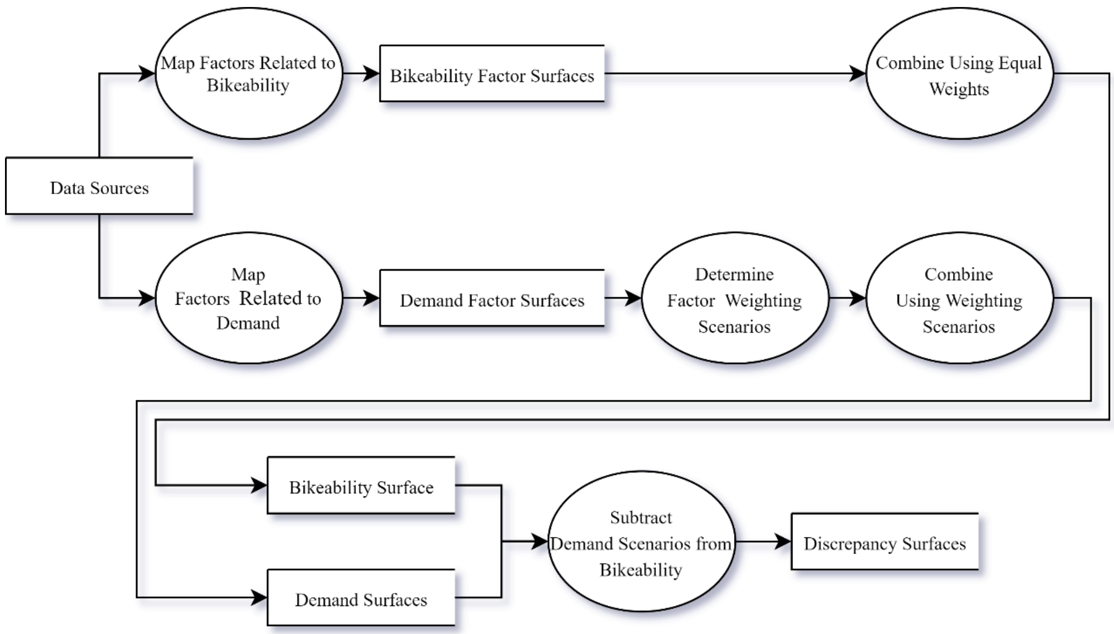

Figure 1. Data-flow-diagram of approach for mapping bikeability, demand, and discrepancies

2.1 Study Area

This project focuses on the Regional Municipality of Waterloo (RoW), a region in southwestern Ontario encompassing the cities Cambridge, Kitchener, and Waterloo, and the townships of North Dumfries, Wellesley, Wilmot, and Woolwich. Home to the University of Waterloo, Wilfred Laurier University, and Conestoga College, the region has a population of more than 530,000 (RoW, n.d.). Figure 2 illustrates the size and location of the municipalities within the Region of Waterloo.

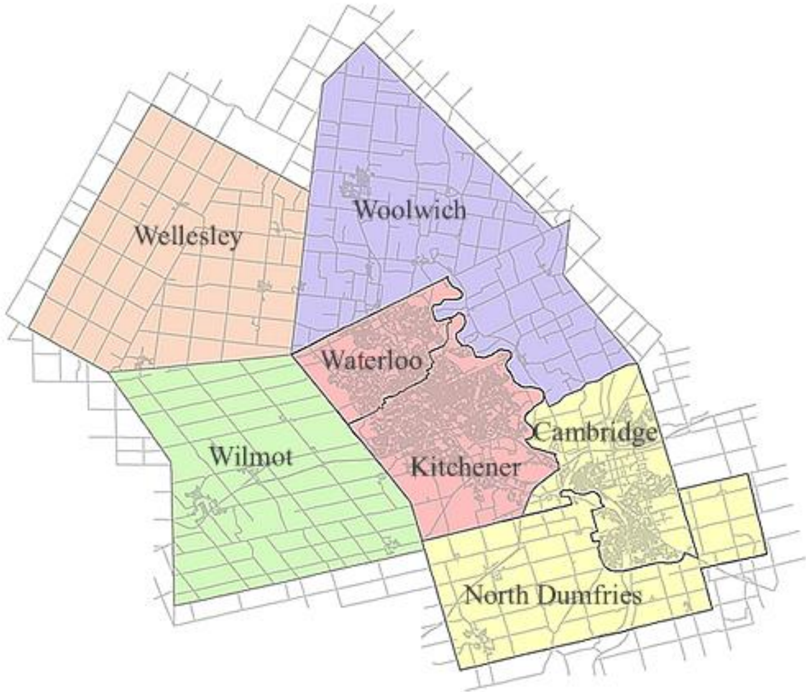

Figure 2. Municipalities in the Region of Waterloo (Dodsworth, 2008)

2.2 Bikeability

To achieve the goal of using demand alongside other metrics to identify discrepancies between demand for cycling infrastructure and the built environment, a bikeability metric must be chosen that uses commonly available geospatial data and that is based on research that is representative of the Region of Waterloo. For these reasons, this project will utilize Winters *et al.*'s bikeability index (2012). This index is based on opinion surveys, travel behaviour studies, and focus groups in the Metro Vancouver area, finding that bikeability can be described by the factors of bicycle route density, bicycle route separation, connectivity of bicycle-friendly streets, topography, and destination density. Descriptions of each of these factors are shown in table 1.

Table 1. Descriptions of factors relating to bikeability (Winters *et al.*, 2012)

Bikeability Factor	Description
Bicycle Route Density	Metres of bicycle routes within 400m of a cell
Bicycle Route Separation	Presence of a physically separated bicycle routes within 200m of a cell
Connectivity of Bicycle-Friendly Streets	Number of intersections within 400m of a cell where at least one connecting road is favourable for cycling (local road, off-street path, or designated cycling route)
Topography	Based on the slope of a cell
Destination Density	Number of bicycle-friendly destinations (parcels with land uses determined to encourage cycling) within 400m of a cell

The data needed to map these factors were collected through local regulating bodies' open data portals, including the Ontario Ministry of Natural Resources and Forestry (MNRF), the Region of Waterloo, City of Cambridge, City of Kitchener, and the City of Waterloo (MNRF, 2020; RoW, 2020a; RoW, 2020b; RoW, 2020c; City of Cambridge, 2019; City of Kitchener, 2020a; City of Kitchener 2020b; City of Waterloo, 2019; City of Waterloo, 2020). Such data included a Digital Elevation Model (DEM) of the province, a road-network for the entire region, and cycling infrastructure and trail data for the region and the three cities. For the destination density factor, land-use by parcel data was obtained from the University of Waterloo Library's Geospatial Centre (Teranet Incorporated, 2018).

Cycling route data from the Region of Waterloo and three cities were combined. As each governing body had different data conventions, layers representing trails were vetted to determine if they were suitable and intended for use by cyclists and merged with cycling infrastructure layers. As well, attributes of each layer were used to identify whether the section of cycling facilities were physically separated from road traffic. This was accomplished by creating an empty feature class in ArcGIS with fields to represent the data provider and road separability. Next, similar fields were added to the cycling infrastructure and trails layers, and each input dataset was appended to the new feature class using the Append tool in ArcGIS and assigning the new data provider and separability fields to their corresponding attributes.

Each factor was mapped continuously across the region following the methods outlined in the article *Mapping bikeability: a spatial tool to support sustainable travel* (Winters *et al*, 2012). All factors were mapped using 10m cells to provide a high-resolution surface, except for *Topography*, which utilized a 30m DEM input. Once a factor had undergone pre-processing, cells were assigned values from 1-10 as outlined in the paper, where 1 represents low bikeability, and 10 represents high bikeability. Commonly, the factors utilize 400m buffers, with which to reflect a rough distance that cyclists have been found to be willing to travel to reach cycling facilities (Winters *et al.*, 2010; Aultman-Hall *et al.*, 1997). The factor of *Bicycle Route Separation* utilizes a 200m buffer to represent just the presence of such facilities. Figure 3 outlines the methods and ArcGIS tools used to process each of bikeability's factors.

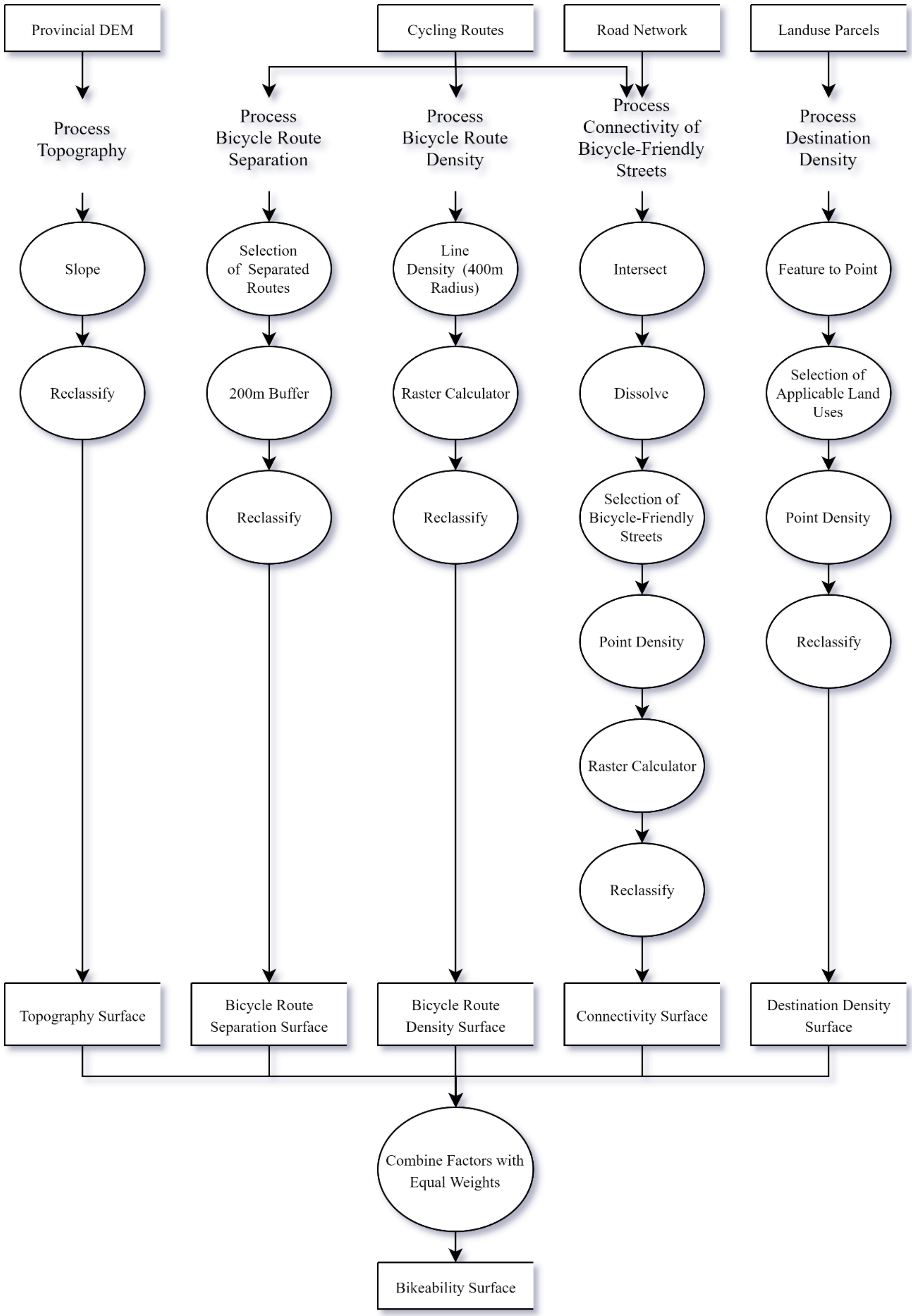

Figure 3. Data flow diagram for mapping bikeability

The factor of *Topography* was processed using the Slope tool in ArcGIS's Spatial Analyst toolbox, generating an output surface of percentage rise. Ranges of percentage rise were then assigned bikeability scores using the Reclassify tool.

Next, *Bicycle Route Separation* was generated by creating a new layer of just the physically separated bicycle routes and applying a 200m radius buffer to these pathways. The buffer feature was then converted to a raster dataset using the tool Feature to Raster. Bikeability scores are assigned using Reclassify simply as 1 for areas outside of the buffer and 10 for areas inside.

The factor of *Bicycle Route Density* was created by applying the Line Density tool to a layer of all bicycle routes in the region, using a 400m radius. This generated a surface wherein each cell represents the density of cycling facilities in units of m/m^2 within a 400m radius circle of the cell. Next, the units of the dataset were converted to 'meters of bicycle route' within the 400m buffer using the Raster Calculator tool and the equation $A_{400m}x$ where A_{400m} represents the area of a circle with a radius of 400m and x represents the value of the cell. Bikeability scores were then assigned using the Reclassify tool.

Destination Density was created in a similar fashion. First, land-use parcels in the region were converted to points using the Feature to Point tool. Next, points representing land-uses that were found to be potential destinations for cyclists in Winters *et al.*'s travel behaviour analysis were selected. Where their research identified the land-uses of neighbourhood commercial, education, entertainment, and office, the data for the Region of Waterloo contained only the applicable land uses *commercial* and *institutional*. A density surface was generated using the Point Density tool within a radius of 400m with the units ‘number of destination parcels per m^2’. The units were again converted using Raster Calculator to ‘number of destination parcels’ within the buffer and assigned bikeability scores using the Reclassify tool.

Finally, *Connectivity of Bicycle-Friendly Streets* was mapped. The layer of all bicycle routes in the region was combined with a street network layer. The original paper had used an ESRI script to generate a point file of all intersections, where each point contained the number of connecting roads, though the script is no longer available. Instead, the Intersect tool was used with a tolerance of 10m to create a point layer of all locations where streets or bicycling facilities intersected with one another, though this produced overlapping points, one for each line segment involved in an intersection. Overlapping points were dissolved based on matching latitude and longitude using the Dissolve tool, and the 'Count' summary statistic was added to show the number of road/cycling sections involved. Only intersections involving 3 or more road or bicycle route segments (at least T-junctions) were kept and selected by location with a 10m tolerance to 'bicycle friendly streets,' meaning local-roads or bicycle routes. As with *Destination Density*, the Point Density tool was then used with a buffer of 400m to generate a surface with the units ‘number of bicycle-friendly intersections per m^2’. Raster Calculator was then used to convert into units of 'number of bicycle-friendly intersections' within the 400m buffer, and bikeability scores were assigned using Reclassify.

Once all the factors were generated and assigned bikeability scores, they were combined using equal weightings using the Weighted Overlay tool. Such a weighting scheme was decided upon by Winters *et al.* based on earlier research. The combined bikeability across the Region, along with bikeabilities of each individual factor can be found in figure 7.

2.3 Demand for Cycling Infrastructure

As no index like Winters *et al.*'s bikeability exists for the demand for cycling infrastructure, this project proposes a novel methodology. Using Multi-Criteria Analysis (MCA) this project identified factors in the literature that were found to contribute to demand for cycling infrastructure, and combined them using weights determined through the Analytical Hierarchical Process (AHP) with the help of an expert on cycling in the region. Demand for cycling infrastructure is defined for the purposes of this project as the demand of the general population for cycling facilities in an area, independent of existing dedicated cycling infrastructure.

The factors contributing to this demand are a cyclist's perception of their safety, population density, and proximity to destination hubs. Higher population density has been found to be significantly associated with a higher likelihood of cycling (Winters *et al.*, 2010). Likewise, destination hubs, defined as cycling destinations that have been shown to be associated with higher levels of cycling, have been identified in the literature as significant contributors to increased demand. Surveys conducted in Vancouver and the US have found that nearly all cycling trips had destinations that could be categorized as shopping and running errands, social or recreational, or for education/religious reasons (Winters *et* *al*, 2010; McNeil, 2011). As well, two surveys, one international and the other in Portland, have found that cyclists are willing to travel at most 4km (2.48 miles) and 2.5 miles respectively to reach their destinations (Krizek *et al.*, 2009; Dill & Gliebe, 2008).

Perception of one's safety, however, is widely considered to be the dominant factor behind demand for dedicated cycling facilities (Hull & O'Holleran, 2014; Mekuria *et al.*, 2017). In New Zealand, for example, it was found that the lack of on-road safety measures such as dedicated cycling facilities are a significant deterrent to increased levels of cycling (Cleland & Walton, 2004). As well, the perception of cycling-accident potential has been found to play a significant factor in cycling travel demand (Ritveld & Daniel, 2004). One's perception of safety is not equal throughout a cycling network, however. The literature draws a distinction between perception of safety along road segments and at intersections. Intersections have been identified as being the location of most cyclist collisions and to cause an increase of stress to cyclists compared to road segments (Watchtel & Lewiston, 1994; Caviedes & Figliozzi, 2018; Lowry *et al.*, 2016). Due to the difference in one's perception of safety on road segments compared to intersections, this project will further delineate the factor of *Perception of Safety* into road segments and intersections.

2.3.1 Analytical Hierarchical Process (AHP)

With the factors effecting demand for cycling infrastructure determined, this project utilized methods for AHP described by Saaty, along with an expert on cycling in the Region to determine relative weights of these factors (Saaty, 1980). Among other methods for weighing criteria such as weighted linear combination (WLC), the Delphi method, and ordered weighted averaging (OWA), AHP was chosen for its widespread use in spatial analysis and its ability to ensure the consistency of comparisons between factors (Hosseinali & Alesheikh, 2008; Odu, 2019; Ouma & Tateishi, 2014; Rikalovic *et al.*, 2014). An equal weighting-scheme like what was used in Winters *et al.*'s bikeability metric was not chosen due to the larger emphasis of perception of safety in the literature.

In the field of spatial analysis and Geographic Information Systems (GIS), AHP is of the most utilized and effective methods for determining criteria weights in MCA (e.g. Hosseinali & Alesheikh, 2008; Ouma & Tateishi, 2014; Rikalovic *et al.*, 2014;). As well, AHP takes a mathematical approach to determining weights to ensure consistency and reduce bias. An expert or stakeholder makes a series of pair-wise comparisons between the criteria involved in the analysis. For each comparison, a number from 1-9 is chosen, corresponding to the relative importance of one criterion compared to the other as shown in table 2.

Table 2. The fundamental scale (Saaty, 1987)

Intensity of importance on an absolute scale	Definition	Description
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement strongly favor one activity over the other
5	Essential or strong importance	Experience and judgement strongly favor one activity over the other
7	Very strong importance	An activity is strongly favoured, and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgements	When compromise is needed
Reciprocals of above	If activity *i* has one of the above numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	
Ratios	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

These values are entered into an n x n comparison matrix, where n represents the number of criteria. As this analysis is comparing three factors, three total comparison were made and entered into a 3x3 matrix. The element (i, j) of the matrix represents the relative importance of the criterion for row i compared to the criterion for column j. If criterion i is found to be more important than criterion j, the number from the comparison is entered for element (i, j), elsewise the reciprocal of the value is used. As a criterion holds no difference in importance compared to itself, the diagonal of the matrix is filled with values of 1. Once the area of the matrix below the diagonal is filled with comparison values, the area above the diagonal can be filled with the reciprocals of the corresponding values in the lower half.

Values in each column of the comparison matrix are then totalled. A *normalized matrix* is created by the quotient of each value in the comparison matrix by its column's total. Percentage weights are then derived from the standardized matrix by dividing the sum of each standardized column by the number of criteria being examined.

AHP then allows for the consistency of the stakeholder's comparisons to be calculated as what is called the *consistency ratio* (*CR*). Here, consistency means that if criterion A is said to be more important than criterion B, and B more important than criterion C, logically C should have a lower relative importance than both A and B. The *CR* is a way of ensuring that pairwise comparisons are logically consistent enough to be used. *CR* values of at most 0.10 (10%) are consistent enough to be used in analysis, as perfectly consistent comparisons are unlikely when using a scale from 1-9 (Saaty, 1980). If such a

CR value is not met, the comparisons are recompleted until consistent enough. *CR* is calculated as the ratio between the *consistency index* (*CI*) and a *random index* (*RI*). *CI* is meant to represent the consistency of comparisons made, and is calculated using the following equation, where λ_{max} represents the largest eigenvalue in the matrix:

$$CI = (\lambda_{max} - n)/(n - 1)$$

RI is a value corresponding to the number of comparisons, obtained by Saaty by averaging the *CI*s of a randomly generated reciprocal matrix (Saaty, 1980). Table 3 shows *RI* values corresponding to different numbers of comparisons .

Table 3. Random index (*RI*) values and corresponding numbers of comparisons N

N	1	2	3	4	5	6
Random Index (*RI*)	0	0	0.58	0.90	1.12	1.24

In collaboration with David Trueman, member of the CycleWR Steering Committee, member of the board of directors for Waterloo Cycling Club, and chair of the Transportation Sector Committee of ClimateActionWR, pair-wise comparisons between the three factors were made, as well as a comparison between how much roads and intersection play into one's perception of safety. Two attempts were made at comparing the factors before a suitable *CR* value was met. The comparison and normalized matrices for the first attempt are shown in tables 4 and 5.

Table 4. Comparison matrix for attempt 1 of AHP

Comparison Matrix			
Criteria	**Population Density**	**Destination Hubs**	**Perception of Safety**
Population Density	1	1/5	1/7
Destination Hubs	5	1	1/7
Perception of Safety	7	7	1
Total	13	8.2	1.285714

Table 5. Normalized matrix for attempt 1 of AHP

Normalized Matrix				
Criteria	**Population Density**	**Destination Hubs**	**Perception of Safety**	**Weight**
Population Density	0.07692308	0.02439024	0.111111	7.08%
Destination Hubs	0.38461538	0.12195122	0.111111	20.59%
Perception of Safety	0.53846154	0.85365854	0.777778	72.33%
Total	1	1	1	100%

The first attempt of AHP resulted in a *CR* value of 0.27, higher than the allowable threshold of 0.10. This may have been caused by the same relative importance put on *Perception of Safety* compared to the other factors, while *Proximity to Destination Hubs* was given a much higher relative importance over *Population Density*. A second attempt was conducted, this time producing similar weightings but with a much lower *CR* value. Tables 6 and 7 show the comparison and normalized matrices of the second attempt.

Table 6. Comparison matrix for attempt 2 of AHP

Comparison Matrix			
Criteria	**Population Density**	**Destination Hubs**	**Perception of Safety**
Population Density	1	1/3	1/7
Destination Hubs	3	1	1/5
Perception of Safety	7	5	1
Total	11	6.333333	1.342857

Table 7. Normalized matrix for attempt 2 of AHP

Normalized Matrix				
Criteria	**Population Density**	**Destination Hubs**	**Perception of Safety**	**Weight**
Population Density	0.09090909	0.05263158	0.106383	8.33%
Destination Hubs	0.27272727	0.15789474	0.148936	19.32%
Perception of Safety	0.63636364	0.78947368	0.744681	72.35%
Total	1	1	1	100%

The second attempt at AHP produced a *CR* value of 0.06. Both the importance of *Perception of Safety* over *Proximity to Destination Hubs* and *Proximity to Destination Hubs* over *Population Density* were lessened in this attempt, addressing the issues present in the first. As the *CR* value is below 0.10, this attempt has an acceptable level of consistency. *RI*, *CI*, and *CR* values for both attempts are shown in table 8.

Table 8. Consistency Values for both AHP attempts

Attempt	***RI***	***CI***	***CR***
1	0.58	0.156683	0.270143
2	0.58	0.032909	0.056740

The final step in this process in to determine the relative importance of road segments and intersections pertaining to the *Perception of Safety* factor. As this involves a single comparison, inconsistencies will not be present as they were when making three comparisons. The comparison and normalized matrices comparing roads and intersections are shown in tables 9 and 10.

Table 9. Comparison matrix of intersections & roads for *Perception of Safety*

Comparison Matrix		
Criteria	**Intersections**	**Roads**
Intersections	1	2
Roads	1/2	1
Total	1.5	3

Table 10. Normalized matrix of intersections & roads for *Perception of Safety*

Normalized Matrix			
Criteria	**Intersections**	**Roads**	**Weight**
Intersections	0.66666667	0.66666667	66.67%
Roads	0.33333333	0.33333333	33.33%
Total	1	1	100.00%

This process resulted in the relative weights of 8.33% for *Population Density*, 19.32% for *Proximity to Destination Hubs*, and 72.35% for *Perception of Safety*. This emphasis on the relative importance of *Perception of Safety* reflects the importance found in the literature. Within the *Perception of Safety* factor, *Intersections* were found to hold a weight of 66.67%, and *Roads* were found to hold a weight of 33.33%. This emphasis on intersections over road segments also reflects concerns raised in the literature.

2.3.2 Other Weighting Schemes

As demand can vary between existing and prospective cyclists, this project proposes three additional weighting schemes to reflect this diversity. Roger Geller, Bicycle Coordinator of the Portland Office of Transportation, developed a classification scheme of four different types of cyclists based on a survey of Portland residents' attitudes towards cycling facilities in the region (Geller, 2009). Based on their level of confidence in cycling, Geller assigned the population into the categories of 'Strong & Fearless', 'Enthused & Confident', 'Interested but Concerned', and 'No Way No How'. This project adopted all categories except for 'No Way No How' as that is meant to represent the population that has no interest in cycling. Figure 4 shows the approximate size of the population that each category is meant to represent. It is important to note that of the categories this project will use, 'Interested but Concerned' roughly represents the majority. From here on out, the AHP weighting will be referred to as the 'Expert' weighting, and the other scenarios will be referred to by their category's name.

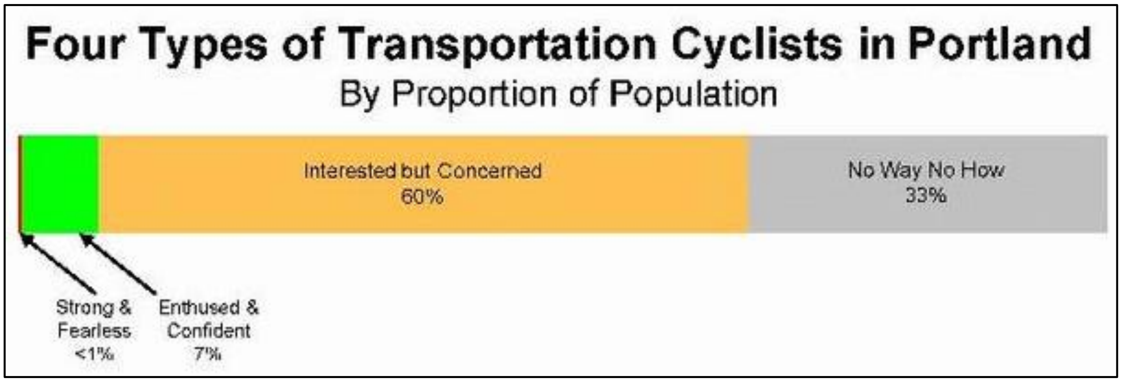

Figure 4. Classification of cyclists in Portland (Geller, 2009)

As these categories represent differences in a cyclist's confidence in their safety, new weighting schemes using the categories will only effect the size of the *Perception of Safety* factor and the size of the other two weights relative to one another are maintained from the ‘Expert’ weighting. Using Geller's descriptions of each category of cyclists, *Perception of Safety* weights were chosen and verified by David Trueman as being representative of each population. The other two factor weights were calculated using the same proportion to one another as in the AHP weighting. Factor weights for all weighting scenarios are outlined in table 11.

Table 11. Factor weights for the demand for cycling infrastructure scenarios

Scenario	Population Density (%)	Proximity to Destination Hubs (%)	Perception of Safety (%)
Strong & Fearless	20.19	46.81	33
Enthused & Confident	10.24	23.76	66
Interested but Concerned	6.03	13.97	80
Expert AHP Weighting	8.33	19.32	72.35

2.3.3 Mapping the Factors

In addition to the data collected to map bikeability, population by Dissemination Area (DA) data from the 2016 Canadian census for the region was obtained from the University of Waterloo Library's Geospatial Centre (Statistics Canada, 2016). To be comparable to bikeability, the demand for cycling infrastructure metric must be on the same scale. As with bikeability, each factor was mapped across the region and standardized to values ranging from 1 to 10, where 1 represents low demand and 10 represents high demand. To provide a high-resolution product, 10m cells are used for demand as they were for bikeability. Descriptions of what each of the factor surfaces represent are found in table 12.

Table 12. Description of factors relating to the demand for cycling infrastructure

Demand Factor	Description
Perception of Safety	Level of cyclist stress due to road and intersection conditions within 200m of roads and intersections
Proximity to Destination Hubs	Relative distance of a cell from the nearest bicycle-friendly destination (parcels with land uses determined to encourage cycling) within 2.5 miles
Population Density	Relative population density in a cell, based on population by Dissemination Area (DA)

Figure 5 presents the overall process to map demand for cycling infrastructure and each of its factors. Processes in the diagram use the names of the specific ArcGIS tools that were used at each stage.

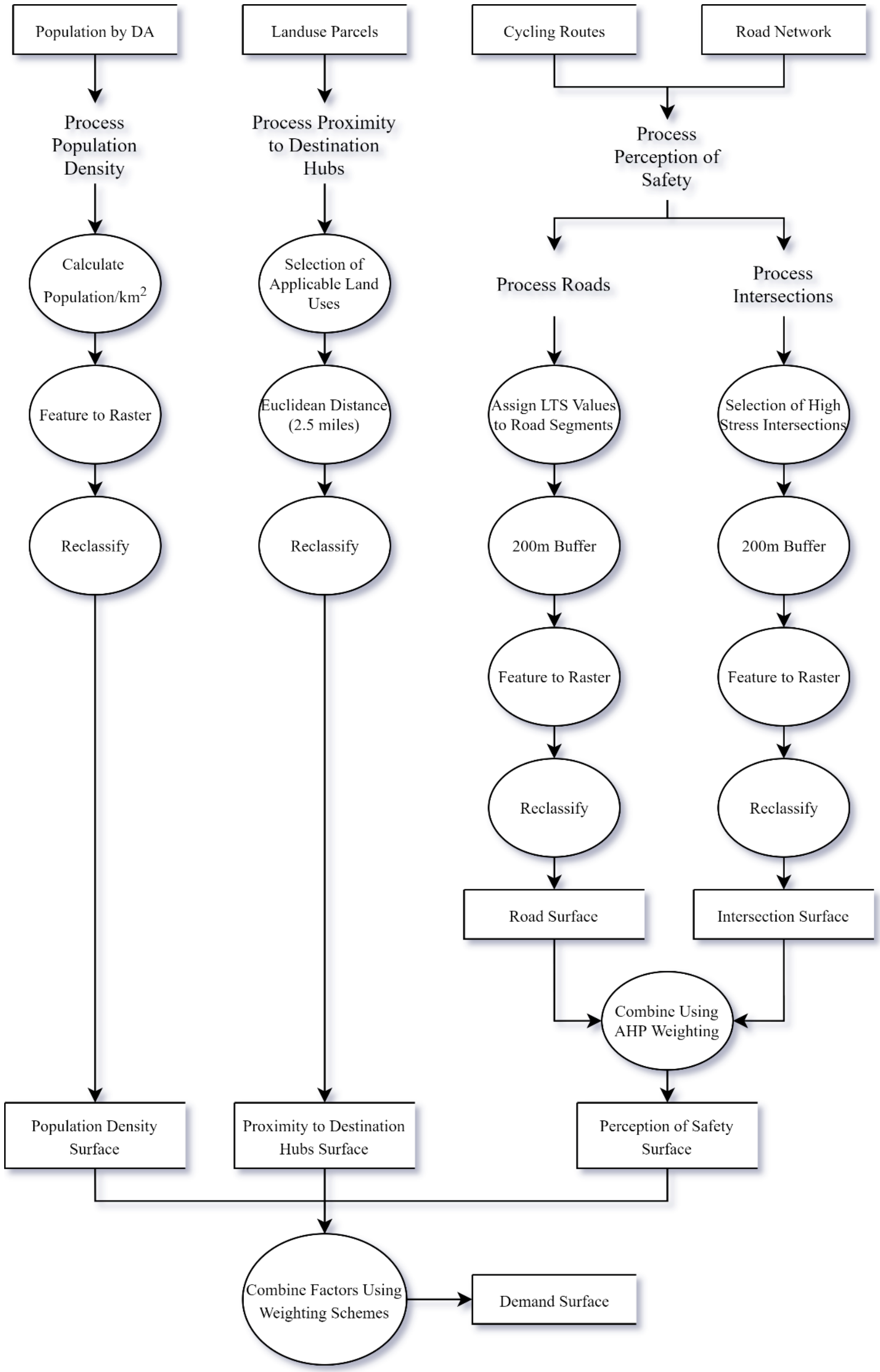

Figure 5. Data flow diagram for mapping demand for cycling infrastructure

The *Population Density* factor was generated by first calculating population per km^2 in each DA using the census data. Next, outlying DA's with very highly skewed population densities were identified and ignored before determining ranges for demand scores. As the literature did not suggest that *Population Density* contributed to demand at only certain thresholds or at a particular rate, demand values were assigned as outlined in table 13, using a Quantile classification scheme in ArcGIS where the maximum non-outlying population density was 72,311. The DA data was then converted to a raster file using the Feature to Raster tool in ArcGIS and reclassified using the Reclassify tool.

Table 13. Assignment of demand scores for population density

Density (pop/km^2)	Demand Score
0-7200	1
7200-14400	2
14400-21600	3
21600-28800	4
28800-36000	5
36000-43200	6
43200-50400	7
50400-57600	8
57600-64800	9
64800+	10

Proximity to Destination Hubs was mapped using the land-use by parcel data. This factor is generated based on the literature from Krizek *et al.* and Dill & Gliebe that identifies roughly 2.5 miles as being the distance ordinary cyclists are willing to travel to destinations (2009; 2008). Again, as the literature does not suggest a specific relationship between distance and demand, demand scores were generated in equally distanced classes. As with bikeability, parcels with commercial and institutional land-uses were converted into points. The Euclidean Distance tool was then used to create a raster of the region where each cell has a value representing its distance from the closest destination point and reclassified using the Reclassify tool according to table 14.

Table 14. Assignment of demand scores for proximity to destination hubs

Distance (mi)	Distance (m)	Demand Score
0-0.25	0-402.336	1
0.25-0.5	402.336-804.672	2
0.5-0.75	804.672-1207.008	3
0.75-1.0	1207.008-1609.344	4
1.0-1.25	1609.344-2011.68	5
1.25-1.5	2011.68-2414.016	6
1.5-1.75	2414.016-2816.352	7
1.75-2.0	2816.352-3218.688	8
2.0-2.25	3218.688-3621.024	9
2.25-2.5	3621.024-4023.36	10

Finally, the factor of *Perception of Safety* was created using road network data along with the intersection layer (at least T-junctions) created when mapping bikeability. Using these data, demand scores for road segments were assigned based on LTS, where higher levels of traffic stress contribute to higher levels of demand for cycling infrastructure. Mekuria *et al.*'s research outlines characteristics for segments of roads that contribute to higher levels of stress for cyclists (2012). As this index is meant to represent demand independent of existing infrastructure, roads were assigned LTS values based on traffic stress on roads with mixed cycling and vehicular traffic. As with the *Bicycle Route Separation* factor in bikeability, a 200m buffer was then applied to the road segments to represent their presence (Winters *et al.*, 2012). The buffer feature was then converted to a raster surface with the tool Feature to Raster, using the highest LTS value where multiple buffers overlapped, and assigned demand values using Reclassify according to table 15. Figure 6 outlines the criteria requirements for LTS levels, as developed by Mekuria *et al.* (2012).

Table 4. Criteria for Level of Traffic Stress in Mixed Traffic

Speed Limit	Street Width: 2-3 lanes	4-5 lanes	6+ lanes
Up to 25 mph	LTS 1[a] or 2[a]	LTS 3	LTS 4
30 mph	LTS 2[a] or 3[a]	LTS 4	LTS 4
35+ mph	LTS 4	LTS 4	LTS 4

Note: [a] Use lower value for streets without marked centerlines or classified as residential and with fewer than 3 lanes; use higher value otherwise.

Figure 6. Criteria for LTS assignment of road segments in mixed traffic (Mekuria *et al.*, 2012)

Table 15. Assignment of LTS values to demand scores

LTS	Demand Score
N/A	1
1	3
2	6
3	8
4	10

Due to the lack of research in the literature regarding characteristics of intersections that contribute to stress, a simpler classification was made. All intersections involving at least one or more road segments classified as Arterial, Collector, or Private were selected. A 200m buffer was applied, again to represent the presence of such intersections. The buffer feature was converted into a raster surface using Feature to Raster and reclassified to demand as 10 in the buffers around these intersections, and 1 in their absence. The remaining road classifications of Local, Highway/Freeway, Alleyway/Lane, and Cul-de-Sac were excluded due to the lack of stress on cyclists as found in the literature.

Finally, the *Roads* and *Intersections* raster surfaces were combined using the weights 33.33% and 66.67% identified through the AHP process to form the surface for the

Perception of Safety criteria. The three factors were then combined with the Weighted Overlay tool according to the four classification schemes outlined in table 11.

2.4 Evaluating the Metrics

Unlike the US, Canada does not conduct a nation-wide travel behaviour survey. Instead, some useful information can be found in the Canadian census. The 2016 Canadian census provides data on the main mode of commuting to and from work for the working population aged 15 and over (Statistics Canada, 2016). Counts of cycling responses for commuters can be used alongside total responses in a census geography area to determine the percentage of commuter cycling mode-share in that area. These data are flawed in that they do not capture most of the population (only ~25% of responses) and do not account for multi-modal trips or trip destinations. This project extracted both percent cycling mode-shares for Census Tracts (CTs) in the region from 2016 census data, as well as average bikeability and 'Expert' demand weighting scenario values for said CTs. In the study area, 110 CTs were available, however data for the township of Wellesley and a couple CTs in Kitchener and Waterloo were not available. For those 110 CTs, Pearson correlation coefficients were calculated to describe the relationship between commuter cycling mode-share and mean bikeability and demand scores.

2.5 Website

In order to increase its use as a tool for decision making, a website was created to allow users to further explore bikeability and demand for cycling infrastructure in the region, along with the factors that each metric is built upon. The maps allow users to toggle layers on and off, and pan to areas of interest in the region.

The website was built using HTML5, CSS, and Bootstrap 3.4.1, and is hosted with GitHub Pages at nathantorrence.github.io. Web maps on this site were created using Mapbox GL JS, a JavaScript library that uses WebGL to render interactive maps (Mapbox, n.d.). For each of the maps, layers are loaded from PNG files in a directory on GitHub with their colours pre-rendered. Legends are added into a 'console' HTML element using CSS to create a colour-ramp using the exact colour values used in the PNG images. When the map is loaded, layers meant to be shown initially are set as visible, and a menu is initialized with the names of all the map's layers. Users can toggle layers on and off using the menu.

Two of the web maps provide further functionality using Mapbox GL JS. The first of these maps allows users to swipe between two loaded layers (bikeability and the 'Expert' demand scenario) using a vertical slider. This is accomplished by loading two separate maps in the same HTML container and using the mapbox-gl-compare functions to synchronize the two maps and initialize the slider in the centre of the map container. The second map allows users to 'fly' to example areas for comparing the differences between the bikeability and demand metrics. This is achieved using the flyTo function and specifying the coordinates of the example location, the desired scale, and the speed of the animation. Up to date versions of the HTML, CSS, and JavaScript code used to create the website can be found at github.com/NathanTorrence/NathanTorrence.github.io.

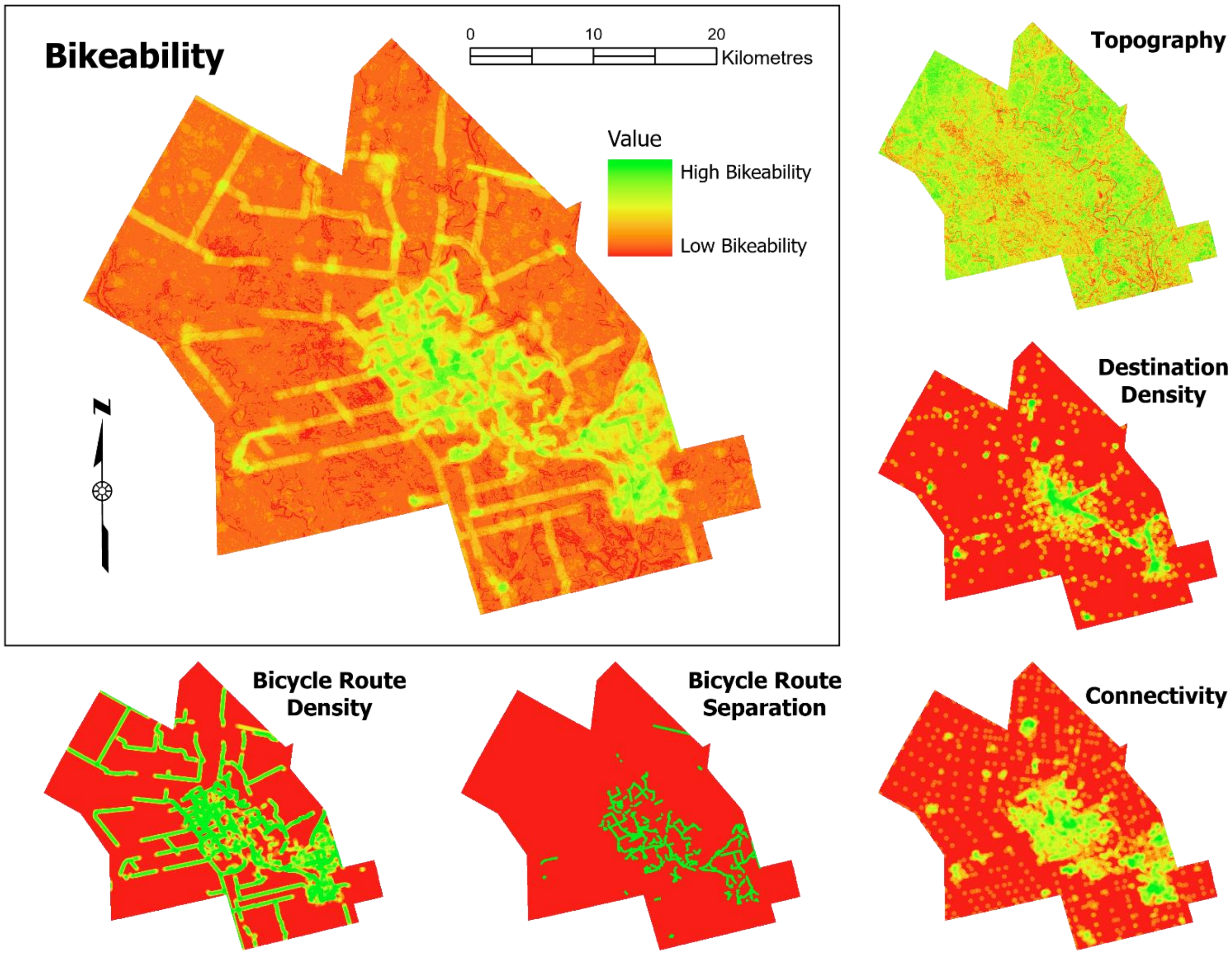

Figure 7. Bikeability and related factors across the region

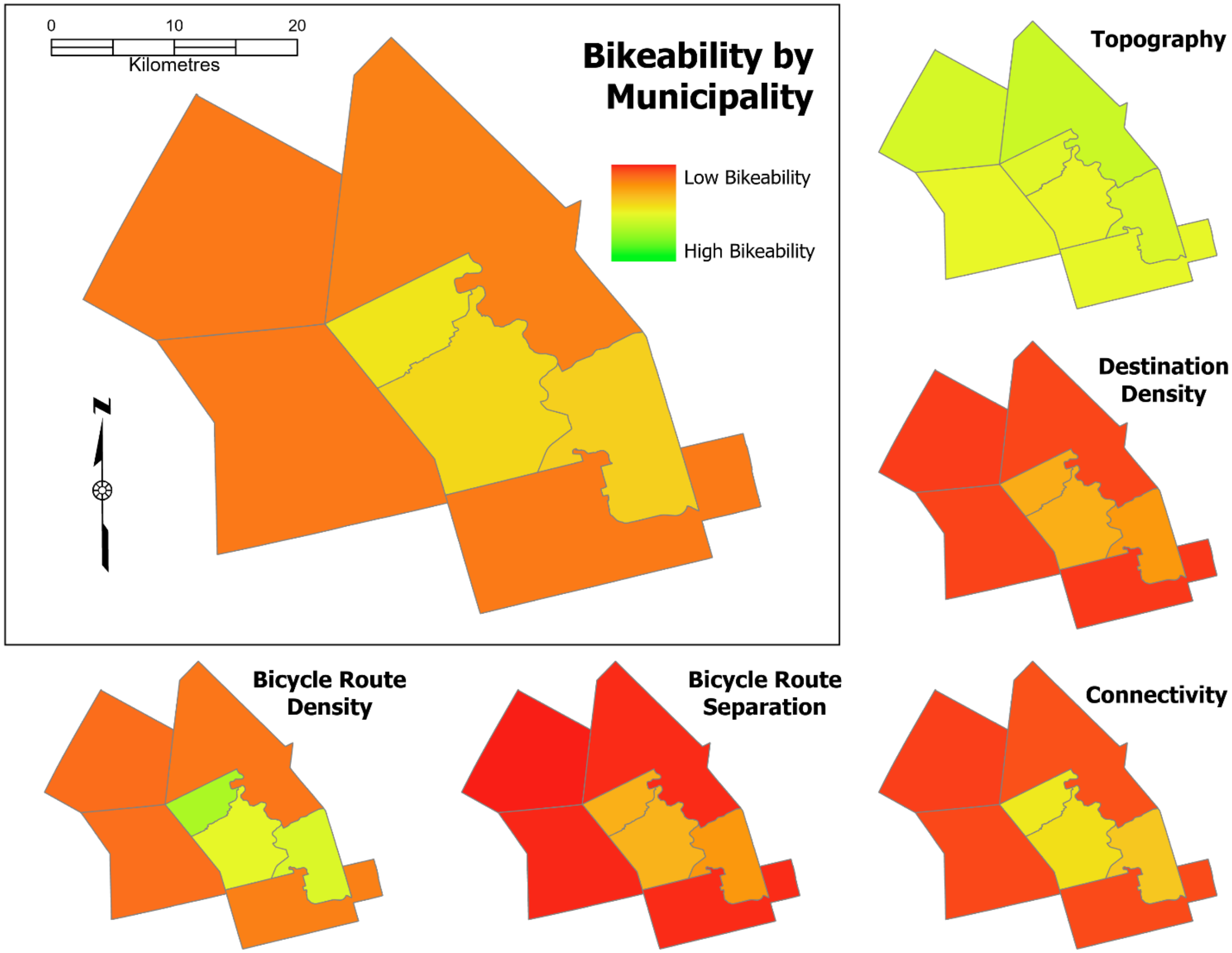

Figure 8. Mean bikeability and related factors by municipality

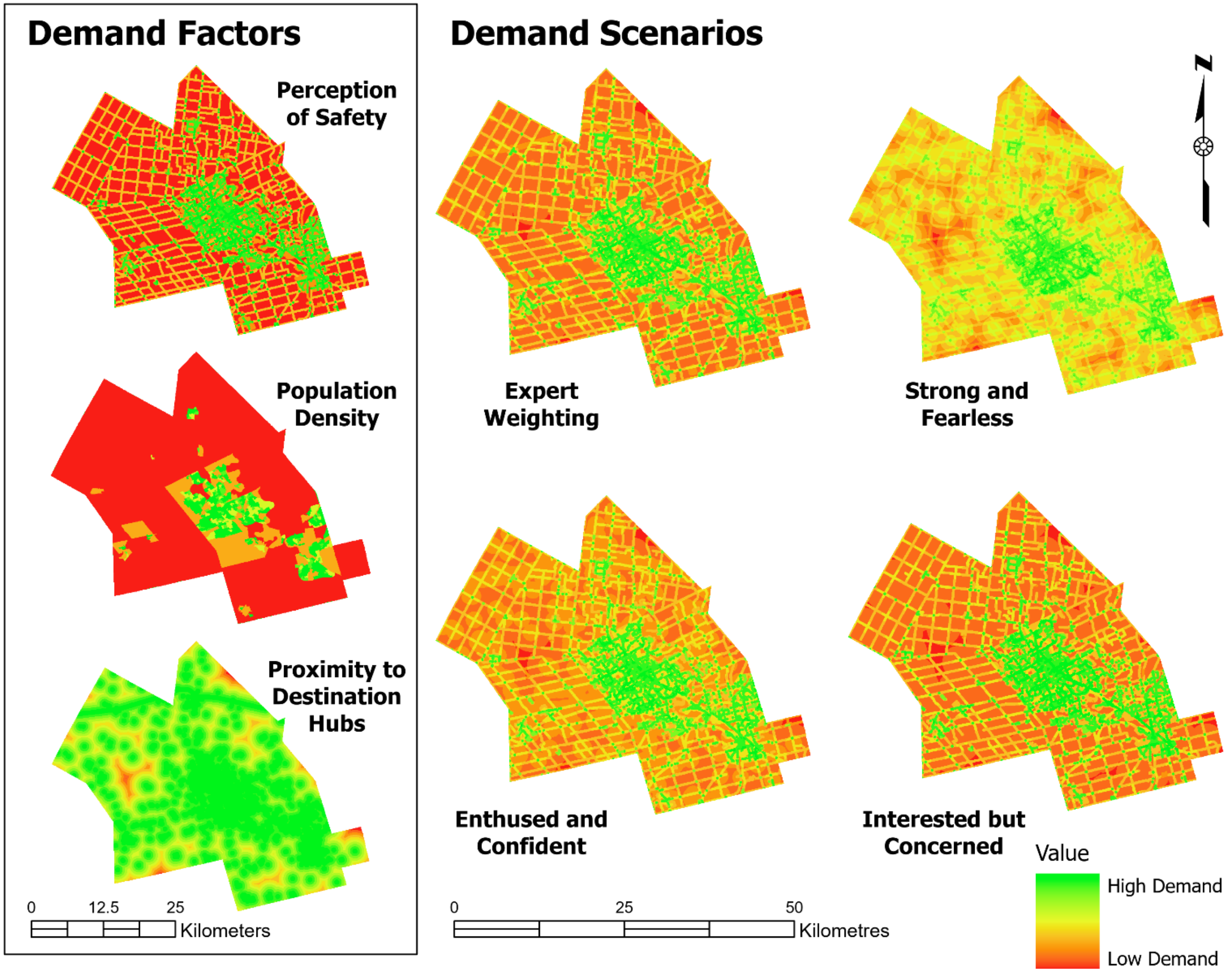

Figure 9. Demand for cycling infrastructure scenarios and related factors across the region

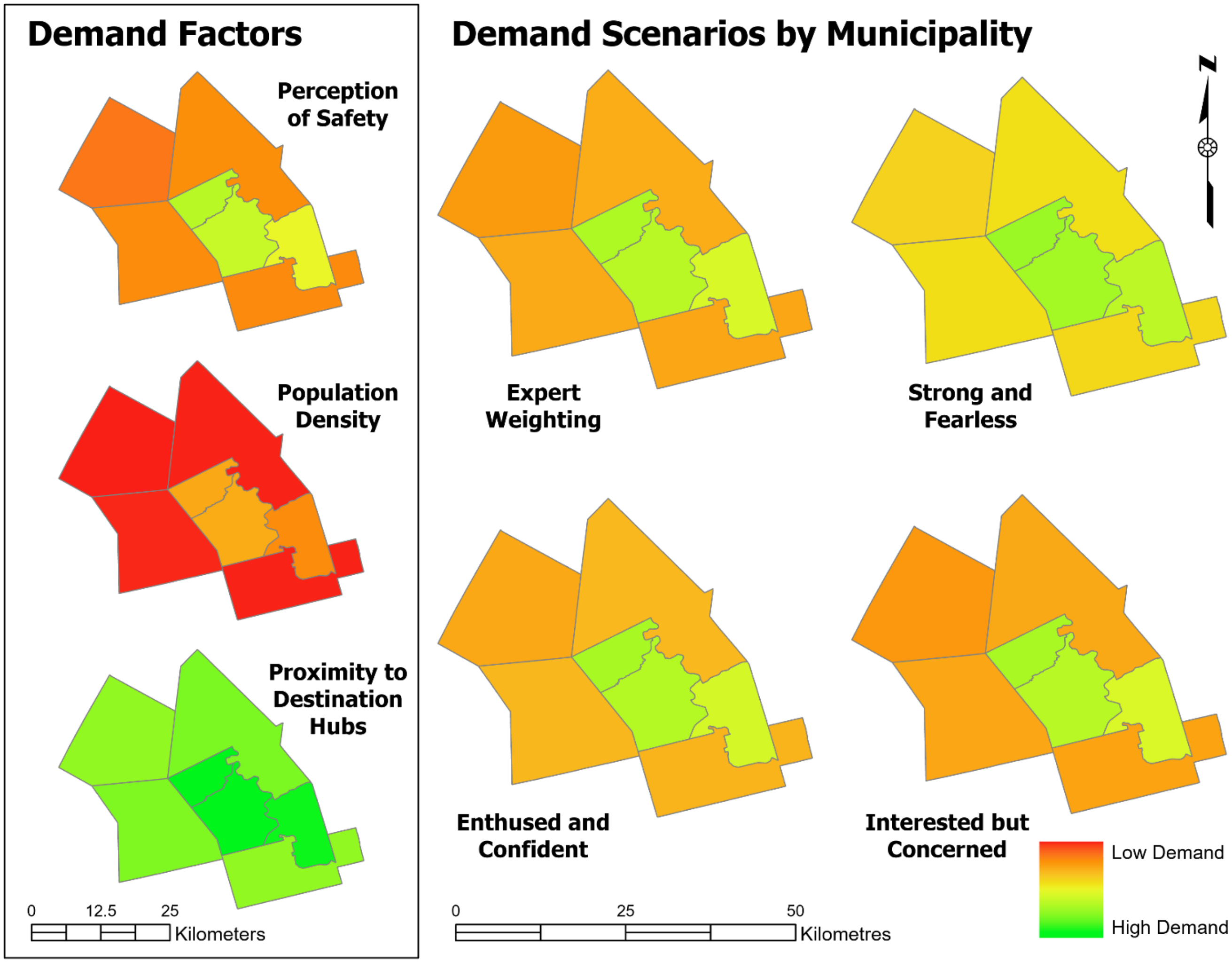

Figure 10. Mean demand for cycling infrastructure scenarios and related factors by municipality

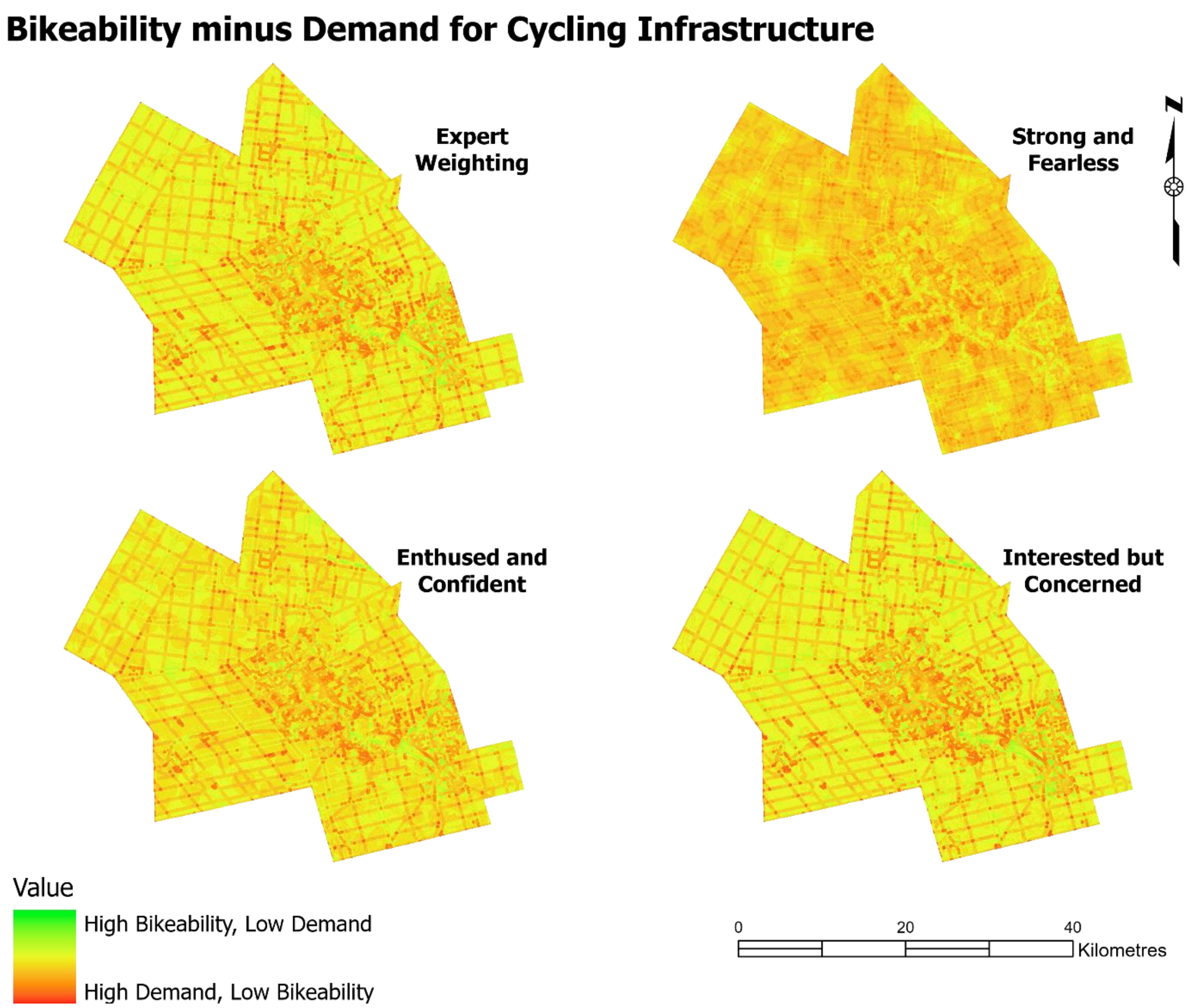

Figure 11. Bikeability subtracted from demand for cycling infrastructure across the region

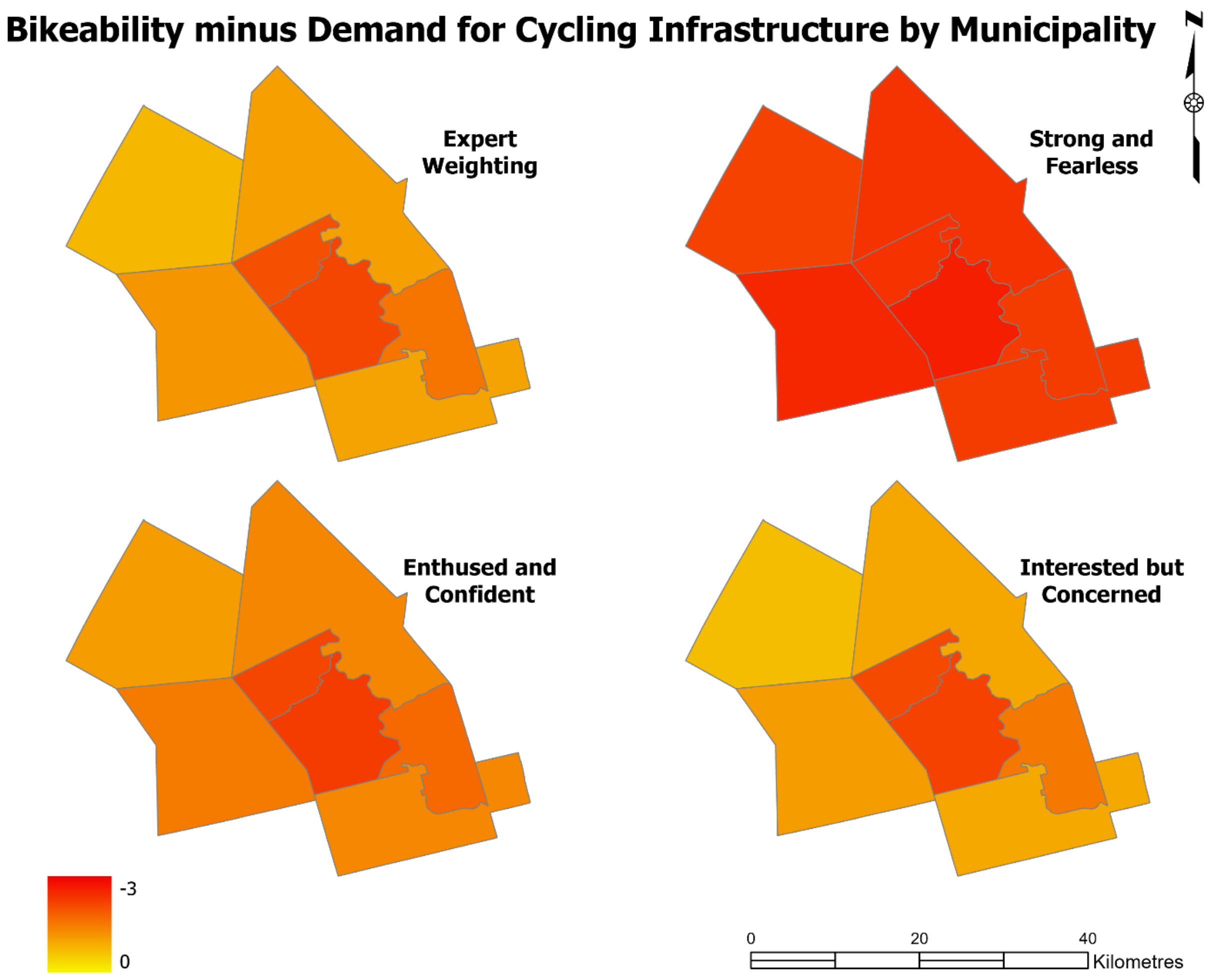

Figure 12. Bikeability subtracted from demand for cycling infrastructure scenarios, averaged by municipality

3.0 Results

Figures 7 and 9 illustrate continuous bikeability and demand scores respectively across the Region of Waterloo. High values of each metric are displayed in green, and low values are displayed in shades of orange and red. Predictably, the four bikeability factors in figure 7 that relate to infrastructure have large concentrations of high-scoring areas clustered around the populated centres of Cambridge, Kitchener, and Waterloo. This results in a final bikeability surface that has very high scores only within those cities.

A similar effect is seen in all scenarios in figure 9. The metric is meant to reflect the overall demand from a population for cycling infrastructure, and as such considers factors that are tied heavily to human settlements in the region. Each of the weighting scenarios shows high demand concentrations in urban areas, due to the generally high weightings of the *Perception of Safety* factor which utilizes existing road infrastructure data.

Figures 8 and 10 show the mean values of bikeability and demand for each municipality in the region and the exact averages are displayed in table 16. For bikeability, very similar scores are seen in two distinct groups of municipalities; the cities in the region share similar scores with one another, as do the townships.

Table 16. Mean bikeability and demand values by municipality

Municipality	Mean Bikeability	Mean Demand (Expert)	Mean Demand (SnF)	Mean Demand (EnC)	Mean Demand (IbC)	Range of Demand
Cambridge	4.415078	5.975893	6.668468	6.132813	5.93331	0.735158
Kitchener	4.628023	6.774579	7.247605	6.898055	6.815812	0.473026
North Dumfries	2.350021	3.353251	4.623627	3.683479	3.29693	1.326697
Waterloo	5.023872	7.051298	7.415023	7.169695	7.128994	0.363725
Wellesley	2.312502	3.067068	4.506266	3.409912	2.999062	1.507204
Wilmot	2.29655	3.458106	4.816498	3.799777	3.375729	1.440769
Woolwich	2.49089	3.536315	4.870824	3.839889	3.448363	1.422461

The demand scenarios show similar findings as bikeability across the municipalities. This is to be expected as the more densely populated areas have higher concentrations of the factors contributing to demand. Table 16 shows the amount demand values varied across the four weighting scenarios for each municipality. Here, the smallest ranges are seen in the cities, and larger ranges are seen in the townships. This is largely caused by the increased effect of *Proximity to Destination Hubs* in the 'Strong and Fearless' scenario in filling out lower-bikeability areas with its larger reach. The small ranges in Cambridge, Kitchener and Waterloo however suggest that demand for cycling infrastructure may be more robust in these areas. As roughly 60% of the population is considered part of the 'Interested but Concerned' group, which shares very similar scores with the ‘Expert’ weighting, these demand surfaces should be considered more representative of the general population in the Region of Waterloo (Geller, 2009).

Demand scores were subtracted from bikeability scores and are illustrated in figures 11 and 12 to show the direct differences between the surfaces and average differences by municipality. As the two indices are inherently different, this is meant as an exploratory approach to visualize general areas where large differences between the surfaces occur, rather than to derive significant findings. As demand for cycling infrastructure scores were generally higher than bikeability, all average discrepancies by municipality fell in the range of roughly -0.69 to -2.62.

Mean values for bikeability and demand for cycling infrastructure were compared to cycling-to-work mode shares at the CT level. Cyclist commuter mode-shares ranged from 0% to roughly 11.7%, with 55 of the 110 CTs reporting a 0% cycling mode-share. Significant, though relatively low correlations were found between cycling mode-share and the factors of bikeability ($r = 0.25, p < 0.01$) and demand for cycling infrastructure ($r = 0.22, p < 0.05$). These relationships suggest that the share of cyclists commuting to work in a CT may increase as mean bikeability and demand scores increase. Scatterplots of percentage cycling mode-share versus mean bikeability and demand are illustrated in figures 13 and 14.

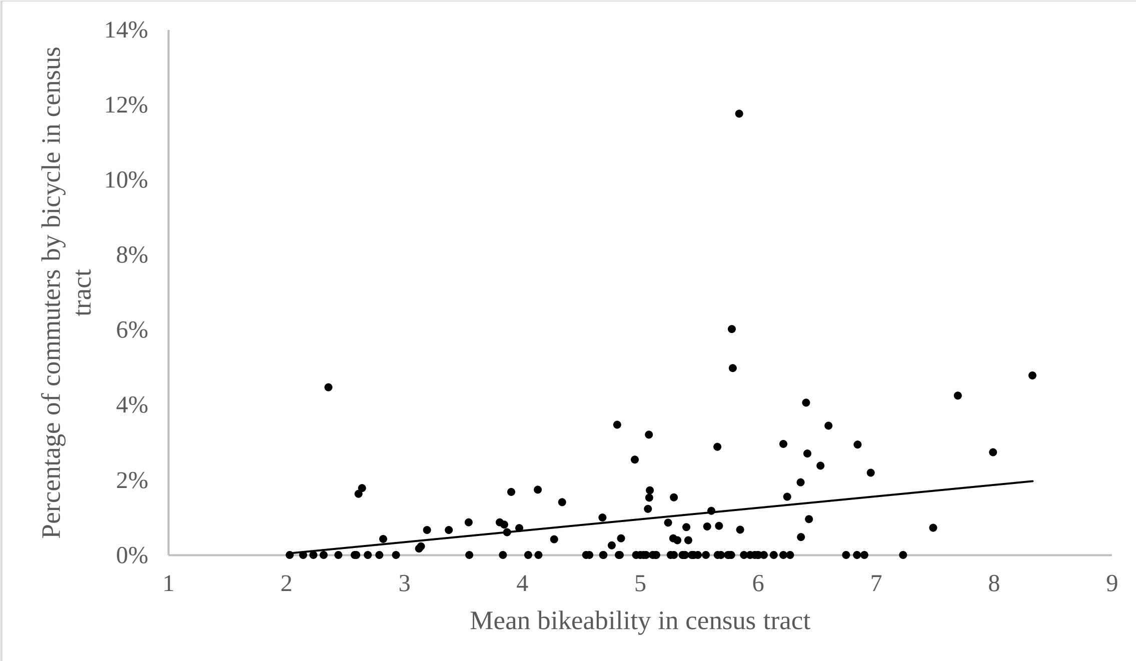

Figure 13. Mean cycling commuter mode-share versus mean bikeability by census tract

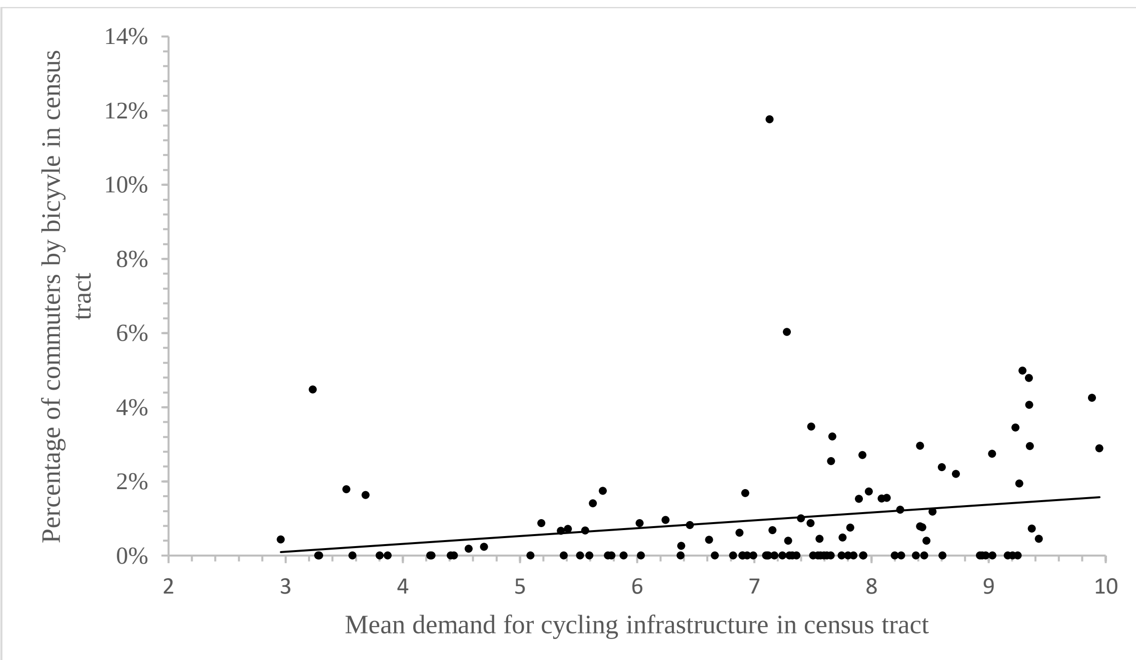

Figure 14. Mean cycling commuter mode-share versus mean demand by census tract

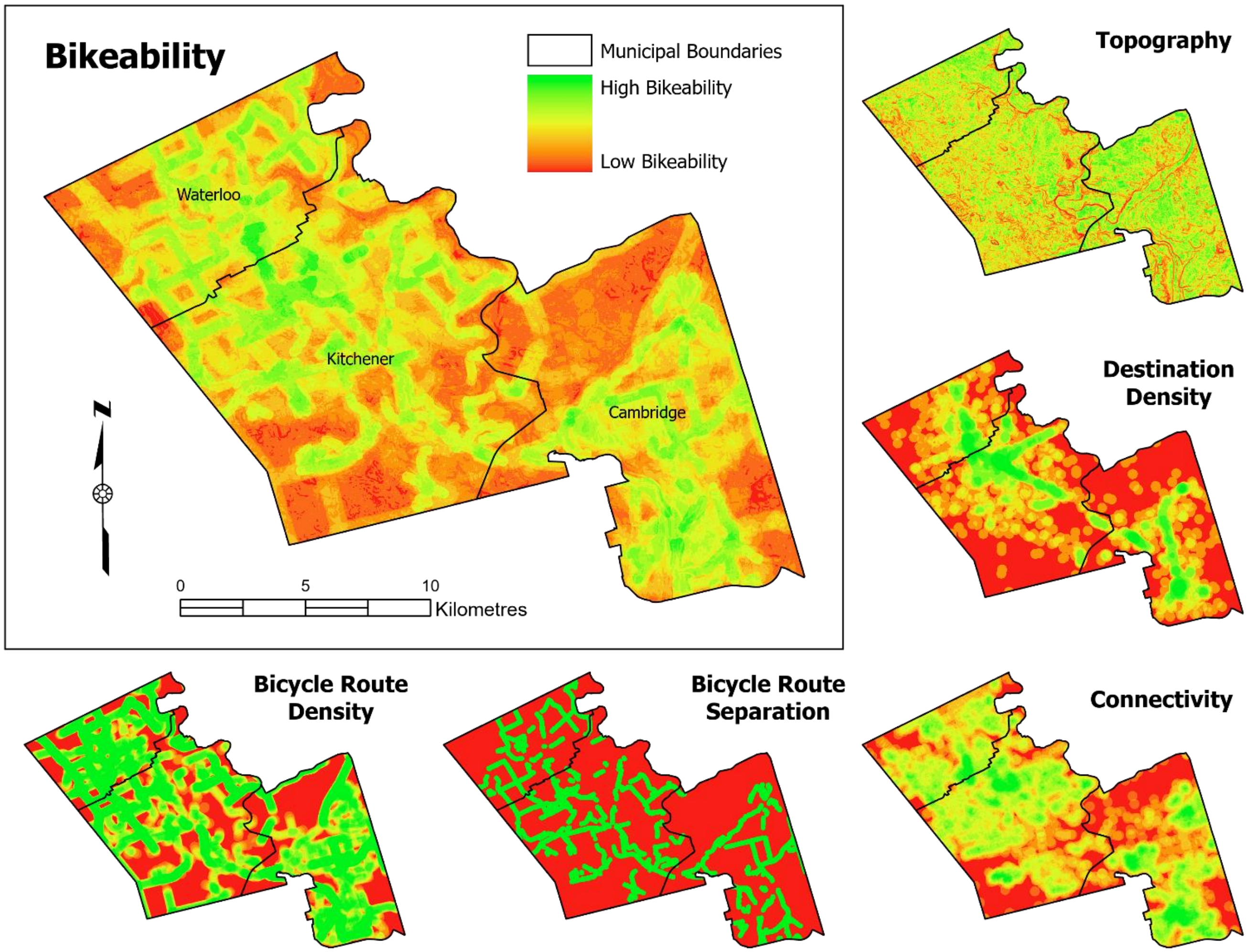

Figure 15. Bikeability and related factors in Cambridge, Kitchener, and Waterloo

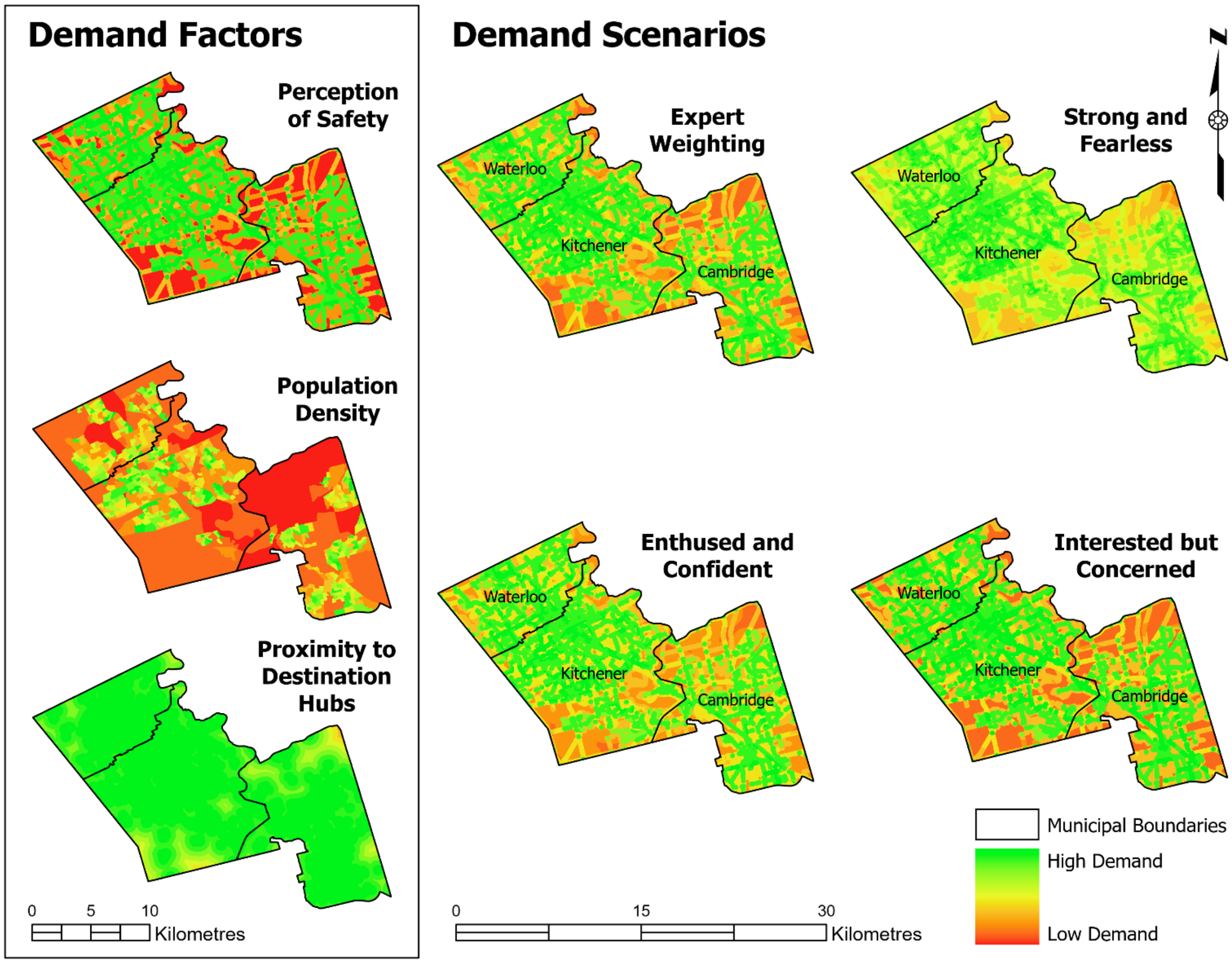

Figure 16. Demand for cycling infrastructure and related factors in Cambridge, Kitchener, and Waterloo

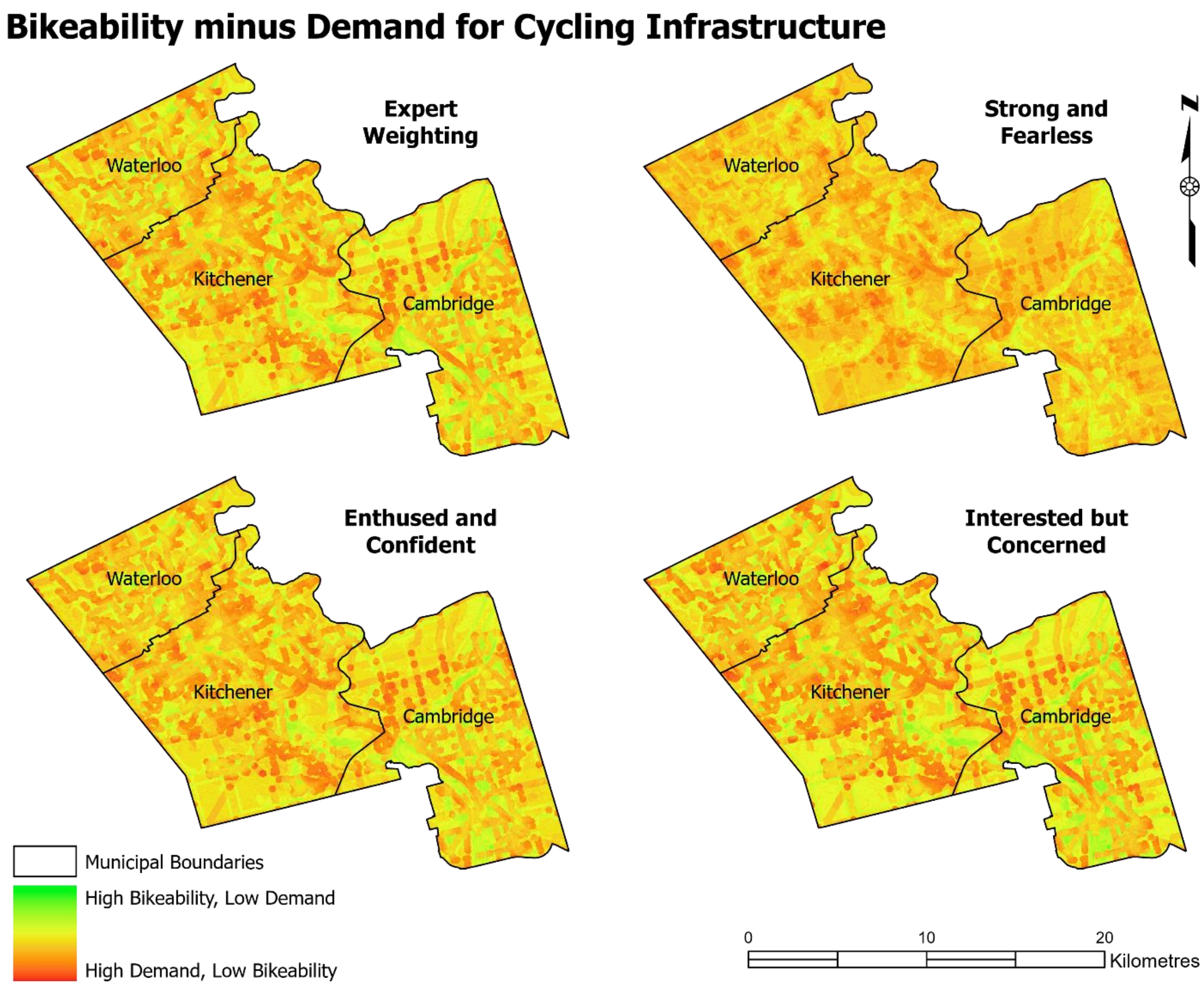

Figure 17. Bikeability minus demand for cycling infrastructure in Cambridge, Kitchener, and Waterloo

It is necessary as well to focus on areas where cycling infrastructure will have a larger impact. Figure 15 shows bikeability scores mapped across the cities in the region: Cambridge, Kitchener, and Waterloo. It is in these areas where the majority of the region's population reside, and where bikeability and its factors are most concentrated. There are, however, some areas such as northern Cambridge and southern Kitchener that are scarcely populated and where little infrastructure, be it bike routes, destinations, or bicycle-friendly streets are located.

Figure 16 focuses on demand scores across the cities. Here, both the factors of *Perception of Safety* and *Proximity to Destination Hubs* exhibit very high demand scores across the three cities. *Population Density,* however, has a wider range of scores in the region and delineates where the cities' populations reside. Because of the concentrations of high demand in these areas, the four weighting scenarios appear more uniform here than they do across the entire region. The starkest differences between weighting scenarios are seen in the less populated areas in Kitchener and Cambridge, where the 'Strong & Fearless' and 'Enthused & Confident' scenarios show higher demand than the 'Expert' and 'Interested but Concerned' groups.

Figure 17 presents the differences between bikeability and the demand scenarios in the cities. There are many areas in the cities where demand dominates bikeability, represented in red. For most of the demand scenarios, demand and bikeability are similar in parts of the cities' populated centres and around the less-populated parts of Kitchener and

Cambridge. Areas where bikeability seems to overcome demand, represented in green, happen to be along the Grand River and in areas where large parks are present.

4.0 Discussion

This project created data products to better inform cyclists and local governing bodies of the bikeability and demand for cycling infrastructure across the Region of Waterloo. The demand for cycling infrastructure metric was developed to fill a gap in the existing literature to not only develop a novel methodology to map demand across an area, but to do so using data available to most local governments. These indices were used collectively to provide further utility to identify areas with high discrepancies between how well an area is suited to cycling (bikeability) and the level of demand for cycling infrastructure independent of existing facilities.

Mean differences between the two indices were seen in higher proportions in the cities in all but the 'Strong & Fearless' scenario, which may be explained by the higher proportion of populated land in the cities compared to the surrounding townships. As well, the surfaces showing localized differences between the indices showed a large difference in all the townships in the form of rural roads and their intersections. Such a large discrepancy suggests the need for further investigation into cycling on rural roads, a subject that is scarcely explored in the literature. Research conducted in rural communities in Nebraska found that similar roadways to those in the Region of Waterloo are less compatible for cyclists than urban roads and require careful consideration for bicycle travel and infrastructure implementation (Jones & Carlson, 2003). Addressing these differences is important in improving cyclists' and potential cyclists' safety and comfort levels on the road. The discrepancies seen on roads and intersections in the region suggest that there may be further work to be done in the region to address the safety concerns of cyclists.

The most emphasis in mapping demand for cycling infrastructure should come from the ‘Expert’ and ‘Interested but Concerned’ weighting scenarios. While the population categories are based off survey responses in Portland, the ‘Interested but Concerned’ group is meant to represent a large segment of the population as well as represent potential new cyclists (Geller, 2009). This scenario and the ‘Expert’ weighting are similar as they represent the same goal: attracting new cyclists. By addressing the predominant concern of this population: safety, the Region of Waterloo may find success in increasing cycling mode-share and reaping the economic, health, and environmental benefits (Hull & O’Holleran, 2014; Mekuria *et al.,* 2017; Fishman *et al.*, 2015; Warburton *et al.*, 2006; Xia *et al.*, 2015).

Relating back directly to Winters *et al.*'s bikeability work, their analysis also compared average bikeability to cycling mode-share at the CT level. In the Metro Vancouver area, these variables were found to have a stronger relationship ($r = 0.42$, $p < 0.001$) than seen in the Region of Waterloo ($r = 0.25$, $p < 0.01$) (Winters *et al.*, 2012). Several of factors may have contributed to this difference including local cycling cultures, differences in climate, and differences in the overall spread of population between the two regions (Nuworsoo *et al.,* 2012). Analyzing this relationship provides insight into the degree that good cycling conditions feed into the rate cycling is used for utilitarian travel. The purpose in analyzing cycling mode-share and demand for cycling infrastructure is to identify if there is a link between existing populations of commuting cyclists and the existence of demand. As the mode-share data does not account for trip paths or destinations, this relationship describes only the demand for cycling infrastructure around a commuter's place of residence.

Mapping discrepancies between the two indices may provide utility as a method for identifying gaps in existing infrastructure. Other methods in the literature that aim to identify gaps in cycling infrastructure such those conducted in Montreal by Larson *et al.*, rely on the existence and availability of location-specific travel behaviour surveys and collision data (2011). Conversely, the methods outlined here use more universally available data and includes the creation of two datasets that provide utility in additional ways.

Moreover, there are several other ways that Larson *et al*.'s methods for identifying gaps in cycling networks differ from this project's methods. First, the factors used were largely different. Larsen *et al.*'s work used the factors of observed cycling trips, potential cycling trips, priority segments (identified from survey responses), and cycling collisions (2011). The last of these factors ties heavily into the *Perception of Safety* factor used to map demand, though it is based only on recorded cyclist collisions rather than the safety conditions of roads themselves. The rest of the factors differ from those used in bikeability and demand for cycling infrastructure. As well, Larsen et al.'s methods assumed an equal weighting scheme, where the demand metric in this project used multiple non-equal schemes. The surfaces generated by both methods are somewhat different as well. Larsen *et al.* assign cells a "Prioritization Index" value from 0 to 1, where high values represent more appropriate sites for infrastructure investment, whereas the discrepancy surfaces produced using bikeability and demand include values ranging from -9 to 9, where values can represent demand being overly met (9), demand being met (0), and demand not being met (-9). The resolutions of the surfaces are significantly different as well, with Larsen *et al.* using a 300m cell grid, and this project using a 30m spatial resolution.

These differences are important because they can impact how the surfaces are interpreted. The aggregation of data to a 300m resolution grid results in some data loss, but also provides the user more direct areas of focus for further investigation. The 30m grid used in this project provides high resolution data, but the results are cloudier and more difficult to interpret. The high-resolution of the discrepancy surface also results in emphasis being given to intersections over stretches of roads, where infrastructure is easier to implement. It must be noted that because these surfaces are built on fundamentally different data, theoretical findings in the same study area would likely differ but could provide useful insight in future research.

5.0 Conclusions

The development of a metric to map demand for cycling infrastructure across the Region of Waterloo provides a novel insight into areas in which local governments can focus further expansion of their cycling networks. The demand for cycling infrastructure metric was developed as an evidence-based tool that uses commonly available data and presents the phenomenon in an easy to interpret way. Alongside existing metrics such as Winters *et al.*'s bikeability, further understanding can be made into the degree that the region's demand is being met by existing cycling facilities (2012).

This tool has several potential functions including research, decision-making, and cycling advocacy. This tool can be used in further research to analyze how demand varies between cities and regions, to analyze the spatial relationships between demand for cycling infrastructure and other phenomena, or to further flesh out methods for how demand can be represented across space. Decision makers in local governments can use this tool to identify areas where demand is not being met, along with doing further location-specific research for future cycling infrastructure projects, and areas such as small towns without many cycling facilities can use it to identify areas where cycling investments would be most wanted. Similarly, cycling groups can use this evidence-based tool to advocate for the expansion and further development of their community's cycling network.

5.1 Limitations

In the process of collecting data for bikeability and demand, some datasets such as bicycle routes had to be collected from multiple data providers (Region of Waterloo, City of Cambridge, City of Kitchener, and the City of Waterloo) and merged into a single file. Each jurisdiction's dataset had different ways of identifying on- and off-road facilities, whether facilities were physically separated from traffic, and classifications of trails. For example, trails in Kitchener that are suitable for cycling are designated as 'primary multi-use pathways', whereas all 'multi-use' trails in the City of Waterloo were planned to support cycling (MMM Group & Ecoplans Ltd., 2012; IBI Group, 2011). This difference between data providers may have also manifested as variance in accuracy, completeness, and error in attribute information.

In the process of mapping bikeability, some assumptions and adaptations had to be made. The methodology was developed to be representative of the Metro Vancouver region, an area with different climate, topography, and a likely different cycling culture than the Region of Waterloo (Winters *et al.*, 2012). As well, parcels in the study area had fewer land-uses than available in the original paper. The original land-use parcels used to map *Destination Density* (neighbourhood commercial, education, entertainment, and office) were swapped for similar land-use categories available for the Region of Waterloo (commercial and institutional).

While the demand for cycling infrastructure metric was designed to have values on the same scale as bikeability, directly comparing the two indices should be a visualization tool only and does not yet provide conclusive results. Demand for cycling infrastructure tends to yield higher values across the study area compared to bikeability, resulting in the maps of mean differences having only negative values. Differences may have arisen due to different buffer sizes used between bikeability and demand, and the more wide-spread nature of demand's predominant *Perception of Safety* factor.

Areas in figure 17 that show a high bikeability and low demand in the cities tend to be along the Grand River and around parks, exemplifying an issue with the demand metric. As the factors of demand for cycling infrastructure consider elements including road networks, population, and non-recreational destinations, the metric fails to recognize parks that fall too far away from these areas. As well, if changes were to be made to make demand and bikeability more comparable, the values in the discrepancy maps will shift and suggest somewhat different results.

It is important to recognize the differences between the cities and townships within the Region of Waterloo. Especially when aggregating mean values of the indices by jurisdiction, one cannot directly compare values between similar cities or townships. Each area has different demographics, population densities, and proportions of urban and rural land, and as such, a comparison between mean bikeabilities in the City of Waterloo and the City of Kitchener, for example, would not yield useful findings. Comparisons between a city and a township would produce even less value as more stark differences would be present.

Additionally, the surfaces of the differences between bikeability and demand may benefit from a reduced spatial resolution from its 30m cells to reduce bias in the data. Larsen *et al.*'s research for example found that 300m was optimal for their study area based on the cycling network density in Montreal (2011). As well, other fields of study such as meteorology down-sample climate data to reduce bias introduced in interpolation (Hijmans *et al.*, 2005).

5.2 Next Steps

Demand for cycling infrastructure still has room for improvement and can benefit from further research and development. Most importantly, for it to be used in conjunction with bikeability to identify ‘gaps’ in cycling networks, further work must be done to both equalize the distributions of the two metrics’ values and to flesh out demand’s shortcomings. As mentioned in the limitations, demand does not take large park areas, which are typically good candidates for cycling facilities, into consideration. As such, further research is needed to identify the relationship between recreational land-uses such as parks, and demand for cycling infrastructure. Weightings would have to be performed once again taking this additional factor into account. Demand may also benefit by focusing on smaller, more consistently populated areas, such as the municipalities of Cambridge, Kitchener, and Waterloo. A smaller study area such as this may increase the ability to effectively align bikeability and demand scores. If the goal of this alignment were to transform the scores of demand to better match the distribution of bikeability’s scores, a smaller area would allow for a transformation that better represents the values present in the cities where infrastructure development is most needed.

The surfaces generated through this project also can be used in several ways for cycling policy development in the region. Firstly, the tool is useful for quick visualization of where demand is present and could potentially be used in the process of prioritizing areas to expand cycling networks within the region. If some of the issues mentioned previously are fixed, and demand is used alongside bikeability, this tool can be used to easily and effectively identify limitations in the cycling network. This tool can be used to both identify areas for further development, after which analysis of the specific areas can be undertaken, as well as help justify and confirm areas selected through other means. In addition, the simple methodology and ease of interpretation of the surfaces can provide further utility in public consultation and justification for new cycling infrastructure projects. The visualizations of demand, bikeability, and the differences between them can be used to inform stakeholders of the current and potential conditions of the cycling network.

6.0 Acknowledgements

I would like to acknowledge David Trueman and Emily Slofstra of CycleWR's Steering Committee, for their help in conceptualizing and shaping this project. David played a vitally important role in the project, both in the development of weights for the 'Expert' demand weighting scenario and in validating the other demand scenarios. I would also like to acknowledge the University of Waterloo's Geospatial Centre for providing vital data for this project.

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