Evaluating potential relationships between marginality and healthy food access in Guelph, Ontario through network analysis

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ABSTRACT

Marginalized groups are often restricted by food access in terms of wealth and transportation. As a result, they are prone to be in vicinity of cheap, fast-food dense areas, increasing risks to their health. Although there are studies that look at marginalization and food access, no studies address transportation modes while also considering the affordability and healthiness of food sources in study areas. Therefore, we classified food establishments around Guelph using different affordability (free, affordable, and costly) and health classes (healthy, moderately healthy, and unhealthy). Using only pedestrian and bus networks, we computed various service areas under the different affordable and health scenarios to derive a multitude of food accessibility scores. We classified Guelph dissemination areas as having access to healthy or moderately healthy foods and if not, as food deserts or swamps. Linear and geographically weighted regressions were used to analyze the relationships between marginalization and food accessibility under the different scenarios and transportation modes. We found that under all scenarios, food access was more restricted by walking in comparison to public transit and that the northwestern and southeastern parts of Guelph are consistently considered food deserts. However, our maps suggest people who have access to transportation have healthier options and people who do not are more vulnerable to unhealthy foods. The statistical analyses suggest that marginalization and food access are only weakly correlated. Our results illustrated positive relationships between marginalization and food access on the outskirts of Guelph but did not support any clustering of significant negative relationships. Ultimately, our study demonstrates the need for thorough examination of marginalization indices and food accessibility within the City of Guelph.

LIST OF ABBREVIATIONS

- DA – Dissemination Area
- FAP – Food Access Point
- GIS – Geographic Information Systems
- GWR – Geographically Weighted Regression
- SA – Service Area
- SAR – Service Area Ring

I. PROBLEM CONTEXT

The interaction between food and humans plays a huge role in determining health and food security (Luan et al., 2015). Food security can be defined as having access (both physically and financially) to enough food that is nutritious to meet dietary demands.

Food deserts are areas where localities are unable to access healthy foods due to a shortage of food stores nearby, whereas food swamps are areas that have limited access to healthy foods, but no limitations to unhealthy foods (Osorio et al., 2013). The existence of these deserts and swamps can be detrimental to neighbourhood health. For instance, both Cooksey-Stowers et al. (2017) and Ver Ploeg et al. (2009) found a strong correlation between food swamps and obesity cases in surrounding households. Moreover, Cooksey-Stowers et al. (2017) identified that low- to mid-income households and racial minorities lived near these fast-food dense areas, depicting how marginalized groups are more prone to obesity.

Examining relationships between marginalized groups and food access are essential. These groups are often restricted by food prices, but also by transportation access (Charreire et al., 2010). Larsen & Gililand (2008) identified food deserts by assuming people can only walk or use public transportation but failed to consider the health class of food access points (FAPs). In contrast, Van Ploeg et al. (2009) focused on supermarkets that provided healthy foods but evaluated accessibility only through personal vehicles and walkability. Cooksey-Stowers et al. (2017) and Luan et al. (2015) identified food swamps using unhealthy FAPs but neglected the need for transportation to get to these locations.

To our knowledge, no studies have evaluated food access while also considering the affordability and healthiness of FAPs in conjunction with affordable transportation modes. Hence, we emphasized affordability by assuming people only have access to walking or public transit. Furthermore, we ranked FAPs using three affordability classes (free, affordable, costly) because we recognized that not all marginalized groups will be able to shop at all food establishments. Lastly, we ranked FAPs using three health classes (healthy, moderately healthy, unhealthy) as we are aware that not all FAPs provide healthy options.

To achieve these goals, we applied geographic information systems (GIS) to locate different affordability and health classes of FAPs, while also incorporating the possible transportation routes people may take to get there. GIS allowed us to develop network analyst models that identified possible routes based on Guelph's public transit line and pedestrian walkways. We spatially identified areas within Guelph that had high access to specific FAPs using these routes. The purpose of our research was to determine the relationship between marginalized groups and food accessibility by developing three accessibility scores for each health class and comparing how these accessibility scores varied across affordability classes and transportation modes.

II. RESEARCH OBJECTIVES

1. To identify and determine possible FAPs and its corresponding affordability and health classes.
2. To develop a pedestrian and a multimodal public transit network analyst model to evaluate the level of accessibility to FAPs.
3. To create service areas (SAs) around each health class of FAPs to identify and locate any food deserts or food swamps in Guelph.
4. To evaluate how accessibility changes when run against two network models, three affordability classes and three health classes.
5. To conduct statistical analyses to determine whether marginalized groups have a strong relationship to varying classes of FAPs.

III. STUDY AREA

The project focused on the City of Guelph and its dissemination areas (DAs) (Figure 1). The city is in Southwestern Ontario, just outside of the Greater Toronto Area. With a population of 131,794 as of 2016, Guelph has 200 DAs covering a total area of 87.22 km^2 (Statistics Canada, 2017b). As of 2016, most Guelph households are above the low-income cut-off range and approximately 15.8% of Guelph's total population are visible minorities (City of Guelph, 2020). Moreover, Statistics Canada (2017a) has identified somewhere between 11 to 12 limited service eating places (i.e. fast-food establishments) per 10 000 individuals in Guelph.

Food insecurity is a prevalent problem in Guelph with 1 in 6 families being food insecure (Guelph, 2018). The City of Guelph has households with varying incomes, visible minorities, and a surplus of fast-food establishments, and thus it is important to spatially assess if specific marginalized groups are found within food swamps or food deserts.

This analysis supported Chalmer's Community Services Centre's goals of helping any vulnerable areas found. Chalmer's are an emergency food provider of healthy and nutritious food in Guelph and these results can be used to determine if and where there is a need for another emergency food provider.

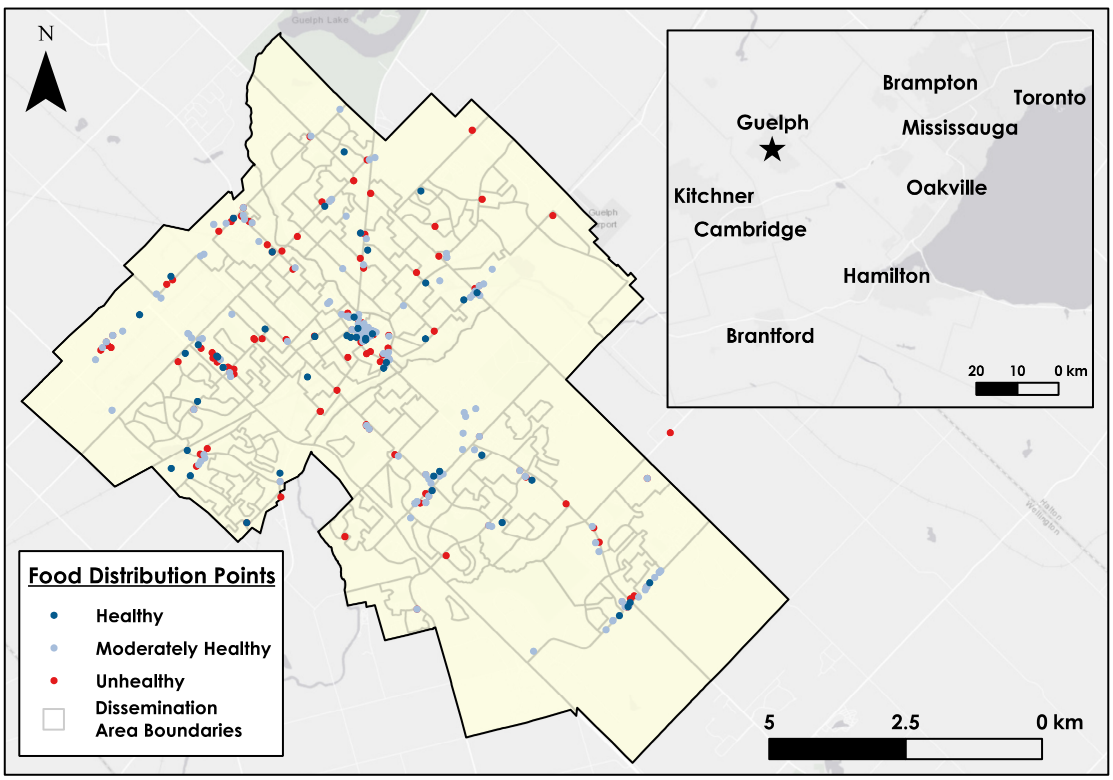

Figure 1. Map of the City of Guelph showing the locations of the dissemination areas and locations of some food establishments. The coordinate system is NAD_1983_UTM_Zone_ 17N (Statistics Canada, 2016a; 2016b; Google, 2020).

IV. RESEARCH APPROACH

1. Identification, Classification & Geocoding of Food Sources

We identified approximately 450 FAPs within Guelph. We used Google Scholar and the University of Guelph's Omni portal to identify the FAPs incorporated into our analysis (Table 1). To determine exact names and locations of food establishments, we relied on Google Maps and created a .csv file compiling the addresses.

Each FAP was labelled with a health class (healthy, moderately healthy, or unhealthy) and with an affordability class (free, affordable, or costly). Health classes were determined by evaluating if the products or meals supplied by these establishments matched up with Canada's Food Guide and the 2019 nutritional food basket (Government of Canada, 2021; 2019) (Table 2). Affordability classes were determined by using price ratings ($, $$ or $$$+), where $ is affordable and $$+ are costly, on Google Maps, Yelp and Facebook, or as a last resort, blogs. Following classification, we used ArcMap's geocoding function to create and map these FAPs across Guelph.

Table 1. Types of food sources included in analysis.

Food Source	Source
Emergency Food Source Supplier	Olatundun - Chalmer's Executive Director, Personal Communication (2021)
Grocery Stores	Morland et al. (2002); Caspi et al. (2015)
Convenience Stores	Morland et al. (2002); Caspi et al. (2015)
Specialty Food Stores (i.e. meat markets, fish markets)	Morland et al. (2002)
Fast-Food Establishments	Morland et al. (2002)
Sit-down Restaurants/Cafes	Morland et al. (2002)
Carryout Eating Places (i.e. bagel shops, desert parlors)	Morland et al. (2002)
Other (i.e. dollar stores and pharmacies)	Caspi et al. (2015)

Table 2. Rules followed to classify food sources as a health class.

Health Class	Food Products Offered	Meals Offered
Healthy	Establishment provided all products: • Fresh produce • Canned vegetables/fruits • Canned proteins (beans, tuna) • Fresh protein (ex. Meat, fish, eggs) • Fresh Dairy • Whole Grain foods	Meals contain options with: • Fresh produce • Whole grain foods • Healthy proteins (ex. lean meats) Meals are only considered healthy if meals can be designed to have: • Little to no added sodium • Little to no added sugars • Little to no added saturated fats

Health Class	Food Products Offered	Meals Offered
Moderately Healthy	Establishment provided some of the items listed above, but not all.	Meals offered have the options of fresh produce but have options of additives such as dressings that are unhealthy.
Unhealthy	Establishment provided no items listed above. All products are highly processed.	Meals offered cannot be designed to provide healthier options (i.e. deep fried meals, overly processed meals like deserts).

2. Data Required

For the analysis, we required the datasets outlined in Table 3

Table 3. Table lists the datasets required to carry out our analysis. Characteristics of each dataset are also listed (i.e. scale, year produced) along with simple description and data processing steps.

Dataset name	Source	Year	Scale	Description/Preprocessing
Guelph Sidewalks	City of Guelph	2016a	Regional	Guelph sidewalks were used to locate roads associated with sidewalks.
Marginalized groups	Public Health Ontario	2016	Not spatial data	This excel file provided values representing marginalization per a dissemination area in Canada.
Census boundary	Statistics Canada	2016a	Canada Wide	The census boundaries were used to extract Guelph's boundaries.
Guelph Dissemination Areas	Statistics Canada	2016b	Canada wide	The dissemination dataset can be clipped to only show dissemination areas in the City of Guelph.
Guelph Transit GTFS data	City of Guelph	2020	Regional	The GTFS data (txt files) were transformed into bus routes and schedules in ArcMap to develop the multimodal public transit network.
Geocoded food locations	Google maps	2021	Regional	These FAPs were used to create SAs around in Guelph to determine DAs as food swamps and/or deserts.
Guelph trails	City of Guelph	2016b	Regional	The trails can be used in the network models as pedestrians may take

				these trails as part of their route. This is connected manually to the roads we will use for both models.
National Road network NRN Ontario	Government of Canada	2015	Province Wide	The roads network will be clipped to Guelph and used as a base for our network models.

3. Network Analyst Models

We developed individual networks that represent two modes of transportation - a pedestrian network for walking, and a multimodal network for a combination of public transportation and walking (Figure 2). To derive places where pedestrians can walk, we extracted walkable roads where roads either a) had a speed limit less than or equal to 40km/h since speeds between 30-50 km/hr are moderately safe for pedestrians to walk on (Budzynski et al., 2017) or b) were near sidewalks. We also manually connected any walking trails to the extracted road network for pedestrian use. These roads were used to create the pedestrian model.

The multimodal network incorporated walkable roads, trails, and bus routes. Bus routes were derived from General Transit Feed Specification (GTFS) data, which are a set of .txt files that can be transformed into bus routes and schedules using network analyst tools in ArcPro. The GTFS data allowed us to incorporate bus schedules into our analysis, which considered transfer times and in-between waiting times.

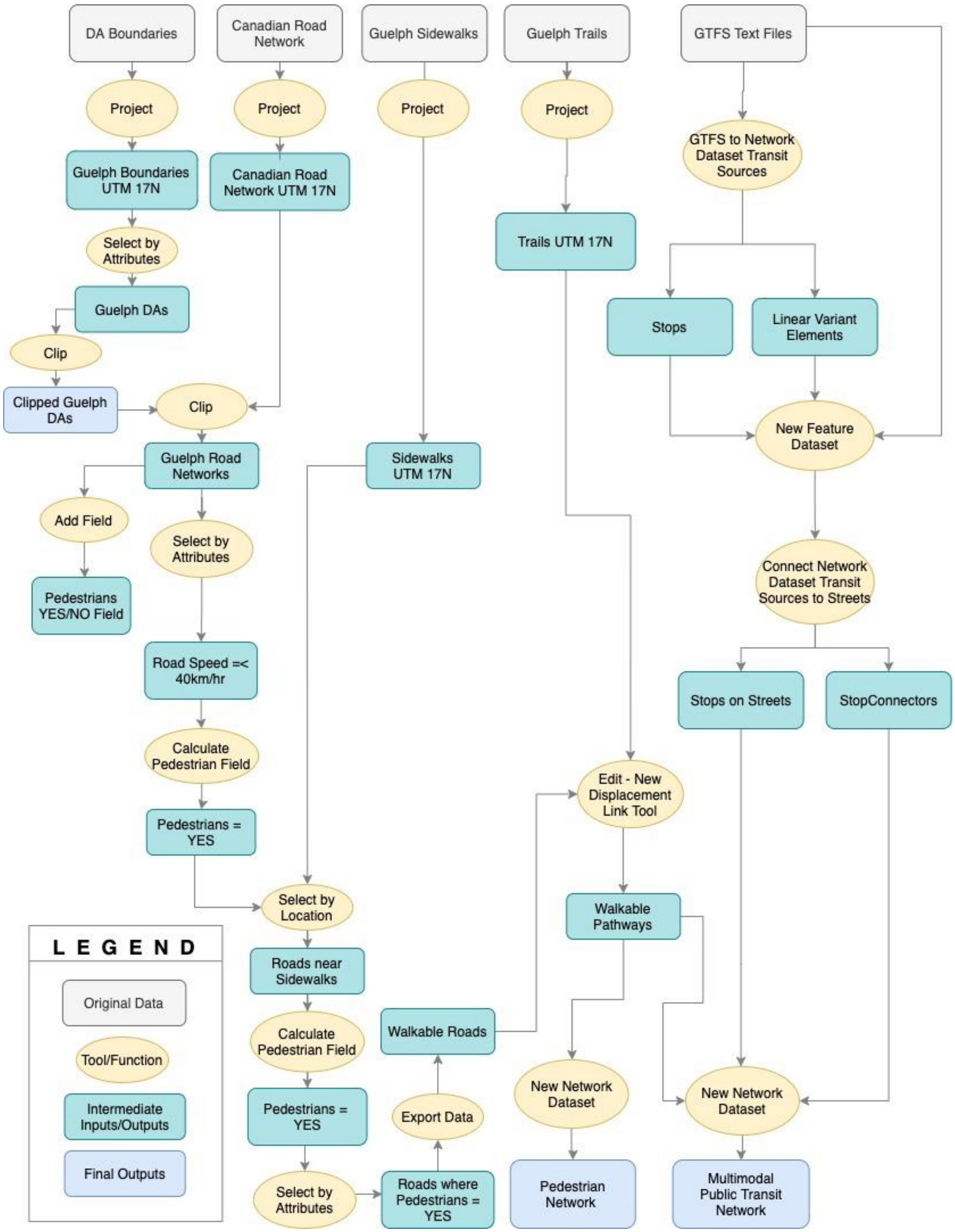

Figure 2. Flowchart that illustrates the input datasets and the chronological tools and functions that were carried out in ArcMap to create both the pedestrian and the multimodal public transit network model.

4. Creating Healthy, Moderately Healthy, and Unhealthy Service Areas

Sections 3.1 and 3.2 are repeated for each health and affordability class under each network model; the exact scenarios are summarized in Figure 3. For simplicity, we illustrated how one scenario (affordable) is run against one of our network models (Figure 4). SAs were produced around healthy, moderately healthy, and unhealthy FAPs to evaluate the accessibility of those FAPs. Households that fell within a FAP's SA were considered to have access to that specific food source (Larsen & Gililand, 2008).

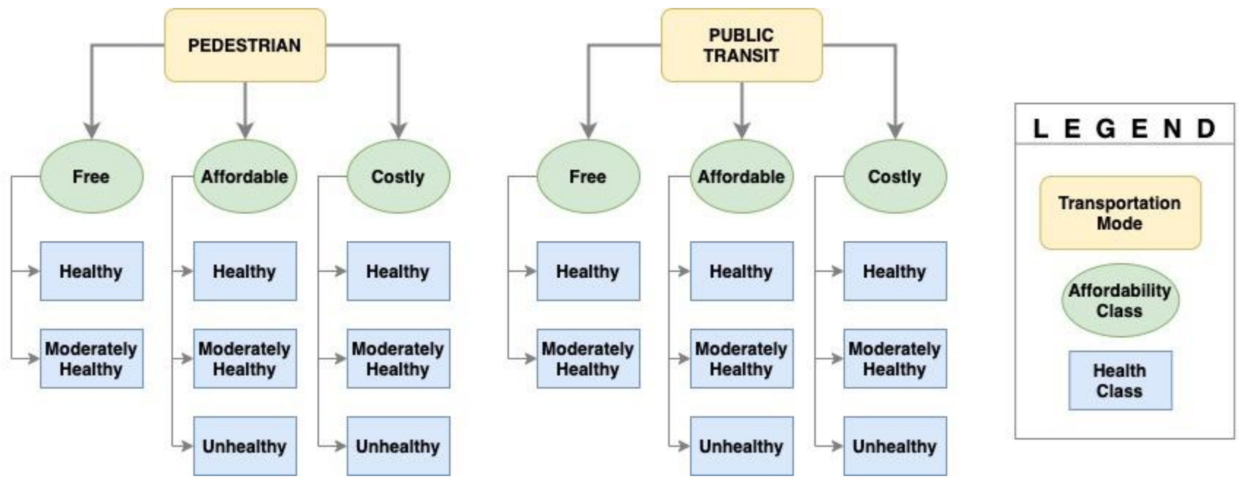

Figure 3. Scenarios used for analyses.

We created three rings around each point representing a different level of accessibility. SARs of equal times had their borders dissolved. We determined that 5, 10 and 20 minutes for walking and 10, 20 and 40 minutes for busing were appropriate time frames (McEntee & Agyeman, 2010; Benenson et al., 2011). We chose a 6pm weekday transportation network to consider that most people shop after their typical 9am-5pm workday and that individuals prefer to shop before the weekend (Widener et al., 2017; East et al.,1994).

Areas where healthy, moderately healthy, and unhealthy SAs overlapped one another according to equal ring times were erased according to Table 4 where justifications are outlined. After these overlaps were removed, SAs of the same health classes were combined again.

Table 4. Table explains overlaps and reasoning behind removal.

Overlap (Input + Erase Feature)	**Method**	**Result**	**Justification**
Unhealthy + Moderately Healthy	Erase portion of unhealthy SAR overlapping with moderately healthy SAR	Areas where people have access to unhealthy or maybe healthy foods.	If unhealthy and moderately healthy areas overlap, unhealthy is removed, since consumers can get moderately healthy or unhealthy foods and it is a matter of choice.
Unhealthy + Healthy ** This step uses the unhealthy SAR output from the previous erase*	Erase portion of unhealthy SAR overlapping with healthy SAR	Areas only containing access to Unhealthy foods.	If healthy and unhealthy areas overlap, unhealthy is removed, since consumers can get healthy or unhealthy foods and it is a matter of choice.
Moderately Healthy + Healthy	Erase portion of moderately healthy SAR overlapping with healthy SAR	Areas only containing access to moderately healthy foods	If moderately healthy and healthy areas overlap, then it is classified as healthy since there are healthy foods to choose from.

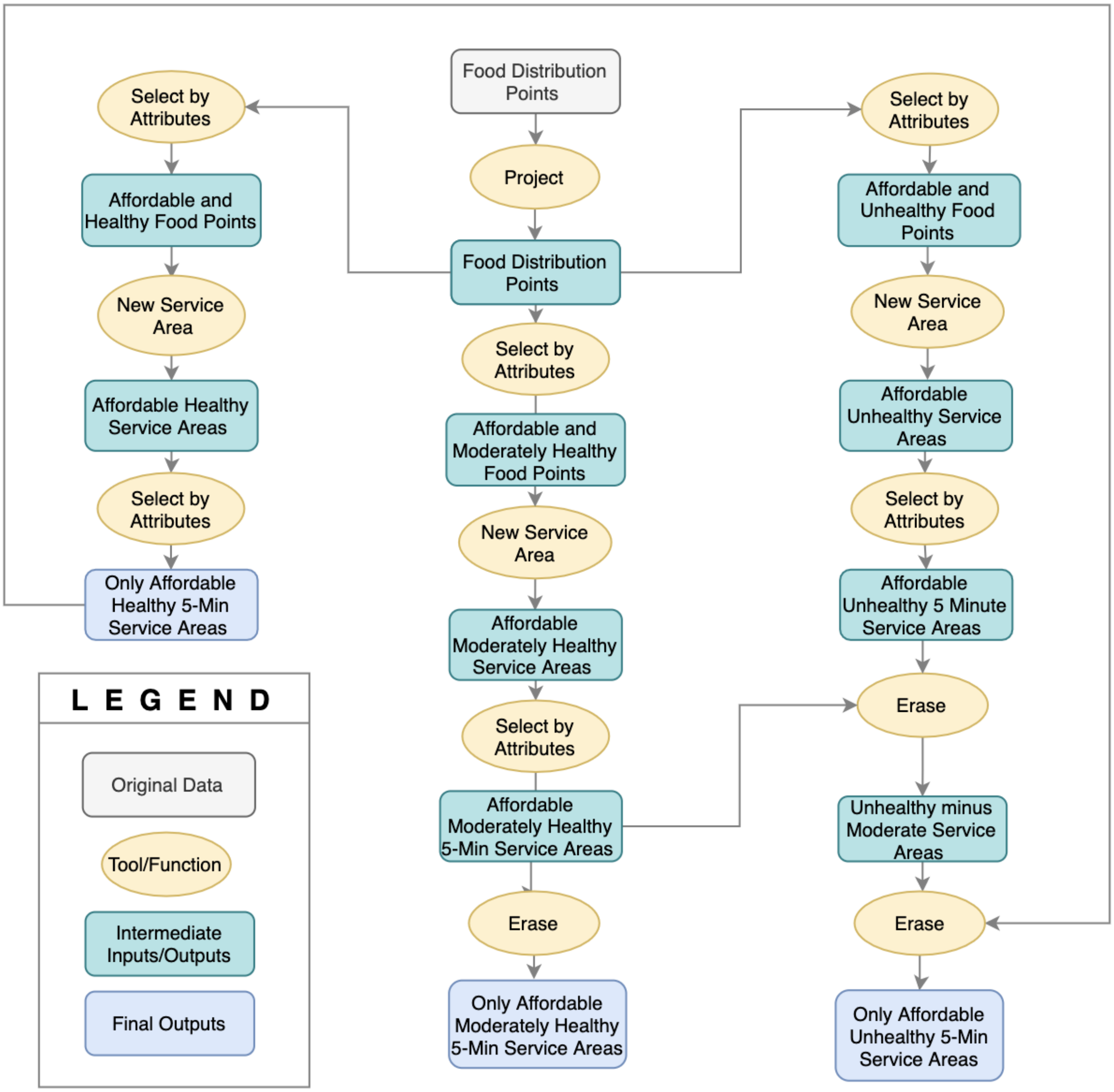

Figure 4. Flowchart illustrates the input datasets and the chronological tools and functions carried out in ArcMap to create SAs around healthy, moderately healthy, and unhealthy affordable food sources per DA in Guelph. This procedure was followed for each scenario under each time frame and applied to both network models.

We conducted our SA analysis on a DA level because they are the smallest census areas in which the marginal index values are available (Public Health Ontario, 2016). To determine the areas where healthy foods are inaccessible due to travel times being greater than our last service ring, we erased the DA areas where all healthy SARs overlap with the DAs (Figure 5). To compare our data to marginality, we intersected the SAs of the three health classes individually with the DAs. Afterwards, we derived the area (m^2) of each SAR under each health class on a DA per DA basis and compiled the data into a single summary table.

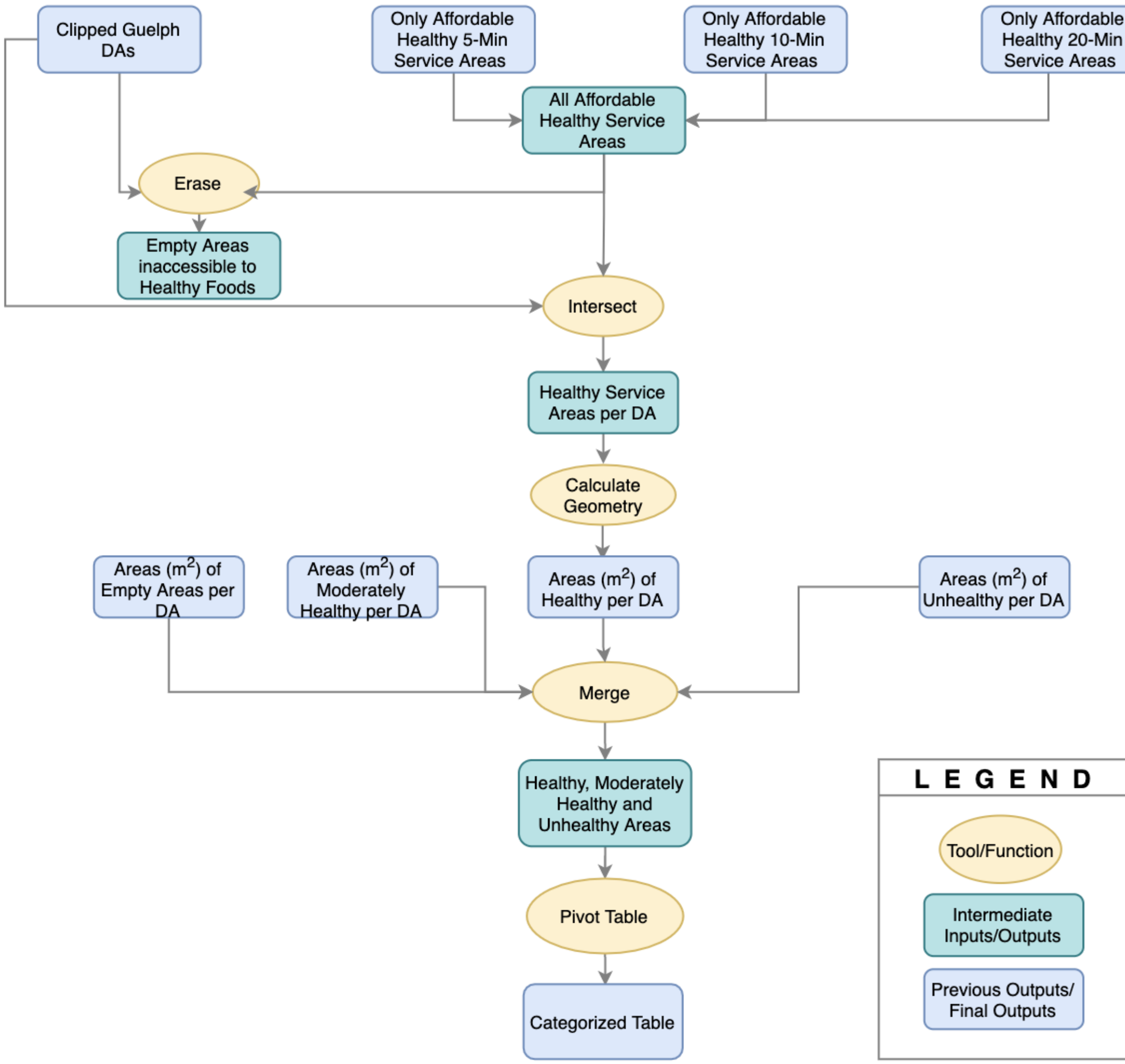

Figure 5. Flowchart illustrates the input datasets and the chronological tools and functions carried out in ArcMap to compute inaccessible areas and areas of SARs. This procedure was followed for each scenario.

5. DA Classification of Healthy, Moderately Healthy, Food Deserts & Food Swamps

DA areas were joined with the Guelph DA spatial layer to project transformed values as attributes of the DAs (Figure 6). We assigned each SAR with a level of accessibility ranging from 0 to 1, where 0 is the least accessible and 1 is the most (Table 5). Using the SARs accessibility levels and areas, we computed a weighted accessibility score used for each health class, where

0 means no access to FAPs and 1 means access to FAPs within the shortest time frame (Equation 1).

Table 5. Level of accessibility assigned to each SARs.

Level of Accessibility	Pedestrian Service Area Ring	Public Transit Service Area Ring
1	5 Minutes	10 Minutes
0.6	10 Minutes	20 Minutes
0.3	20 Minutes	40 Minutes
0	Greater than 20 Minutes	Greater than 40 Minutes

Equation 1. Accessibility Score

$$S = \frac{f_1A_1 + f_2A_2 + f_3A_3 + f_4A_4}{A_T}$$

$where\ S\ is\ the\ accessibility\ score$

$f_i\ is\ the\ level\ accessibility\ for\ i\ service\ ring, where\ i = 1, 2, 3, or\ 4$

$A_i\ is\ the\ area\ in\ m^2\ for\ i\ service\ ring, where\ i = 1, 2, 3, or\ 4$

$A_T\ is\ the\ total\ area\ of\ the\ DA\ in\ m^2$

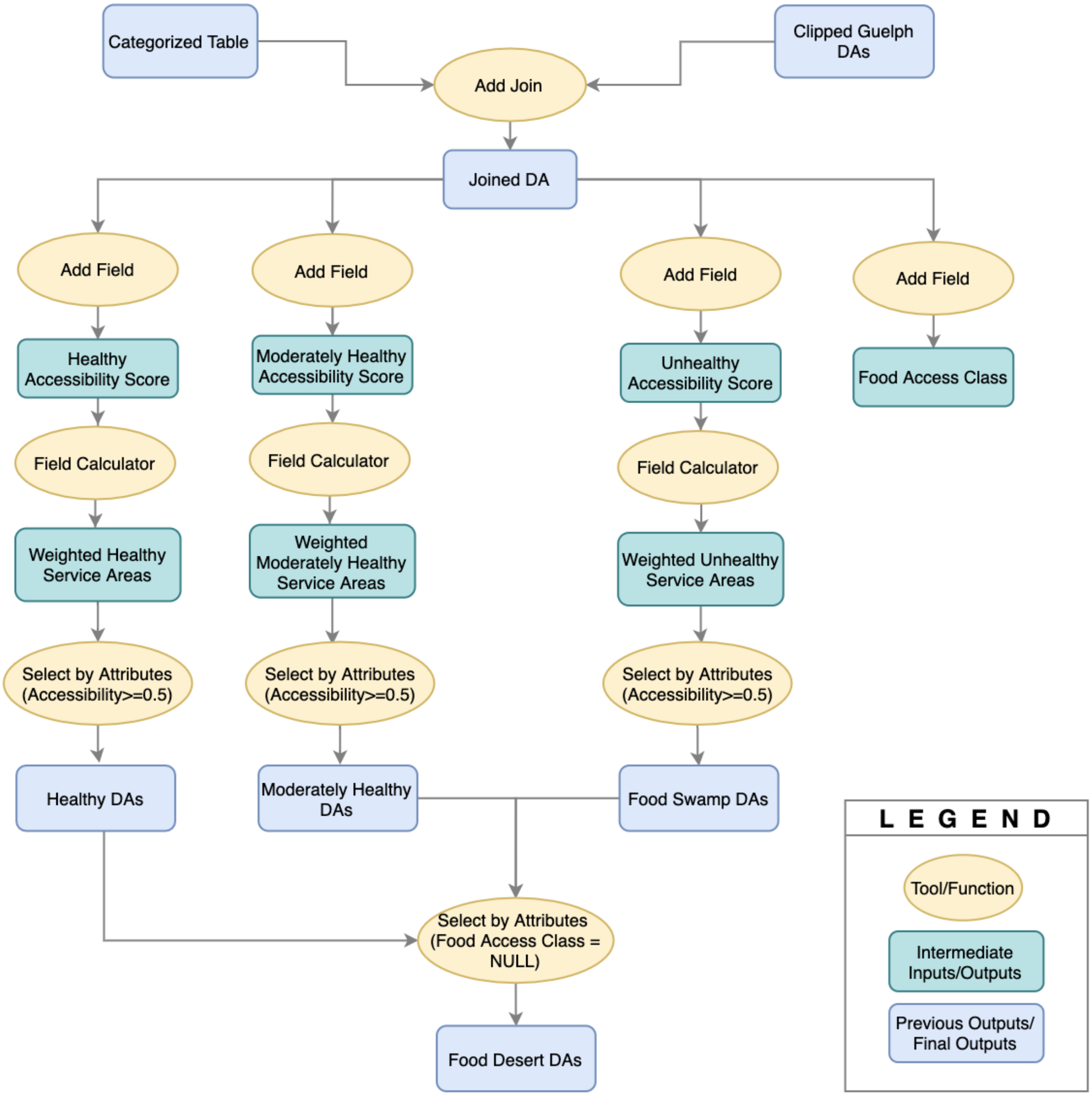

Figure 6. Flowchart illustrates the input datasets and the chronological tools and functions used in ArcMap to compute accessibility scores which were used to identify Healthy and Moderately Healthy DAs or DAs classified as food deserts or food swamps. This procedure was followed for each scenario.

Therefore, we computed a healthy, moderately healthy, and unhealthy accessibility score. Due to the absence of a definitive definition of what the area proportion is required to be classified as a food desert or swamp, we decided to use a threshold of 0.5 to classify the DAs. If a DA had a healthy or moderately healthy accessibility score greater than or equal to 0.5, the DA was classified as having access to healthy or moderately healthy foods. However, if a DA had an unhealthy accessibility score greater than or equal to 0.5, it was classified as a food swamp as the DA was dominated by easily accessible unhealthy foods. Lastly, any unclassified areas (i.e. DAs with scores below 0.5 for all three health classes) were determined to be a food desert because access to any type of FAPs were considered scarce.

6. Statistical Analyses

To explore the relationship between the access of varying FAPs and existing marginalized groups in Guelph, we used the Public Health Ontario's (2016) marginality data based on four marginal indexes – residential stability, deprivation of resources, dependency, and ethnicity. We averaged the quintiles of all four categories for an overall measure for each DA, where 5 means high marginality and 0 means low marginality.

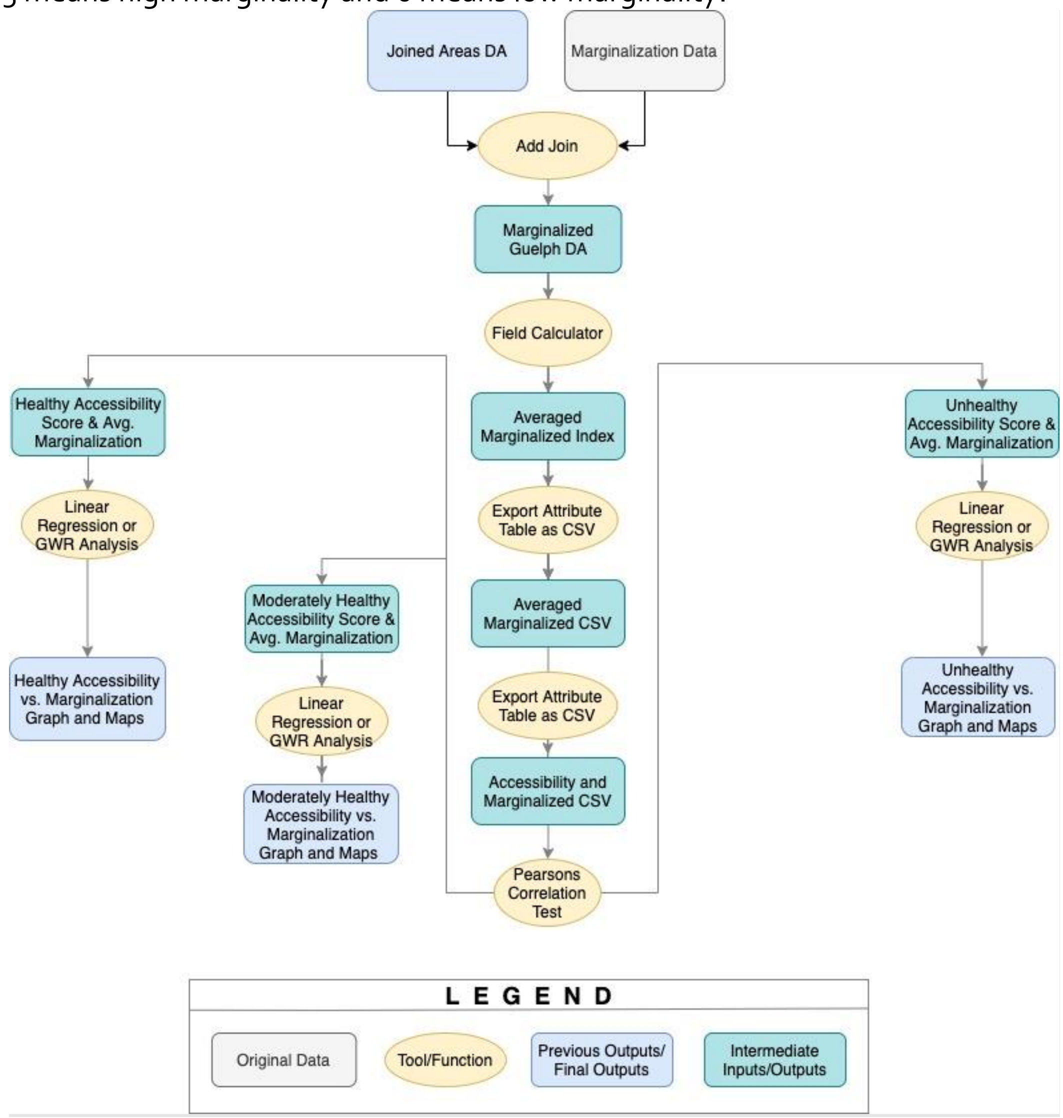

Figure 7. Flowchart illustrates the input datasets and the chronological tools and functions carried out in ArcMap and R to identify the relationships between marginalization and food accessibility. This procedure was followed for each scenario.

We used the statistical computing software, R, to run a Pearson's Correlation test and linear regression against marginality and all three health class accessibility scores. We used the coefficient, p-value, and regression to determine the degree of correlation and significance of the relationship.

These tests were run for each all classes under both networks. We plotted pedestrian and public transit results of similar affordability and health classes on the same graph to examine how the relationship changed depending on transportation mode.

Finally, to analyze how the strength of these relationships varied spatially across Guelph, we computed a geographically weighted regression (GWR). We mapped the regression slopes and the R^2 values for every DA and analyzed how and where slopes and R^2 values changed throughout Guelph. By doing so, we located areas of stronger and weaker relationships and areas of high and low R^2 values illustrating locations where the model is explaining a lot or not as much of the variance.

V. RESULTS AND DISCUSSION

1. Service Areas

SAs generated by the pedestrian model show that south-end pedestrians will not have access to free FAPs (Figure 9A) and will have more access to unhealthy affordable FAPs than north-end pedestrians (Figure 10A). However, all pedestrians will have relatively equal access to healthy costly FAPs (Figure 11A). In contrast, when people have access to public transit, majority of Guelph has access to healthy FAPs under all affordability classes (Figures 9B, 10B, & 11B). Although moderately healthy and unhealthy SAs are not as prominent, the healthy SARs covering these SAs are the 40-minute rings, which is not necessarily as accessible as a 10-minute bus ride to an unhealthier FAP masked below.

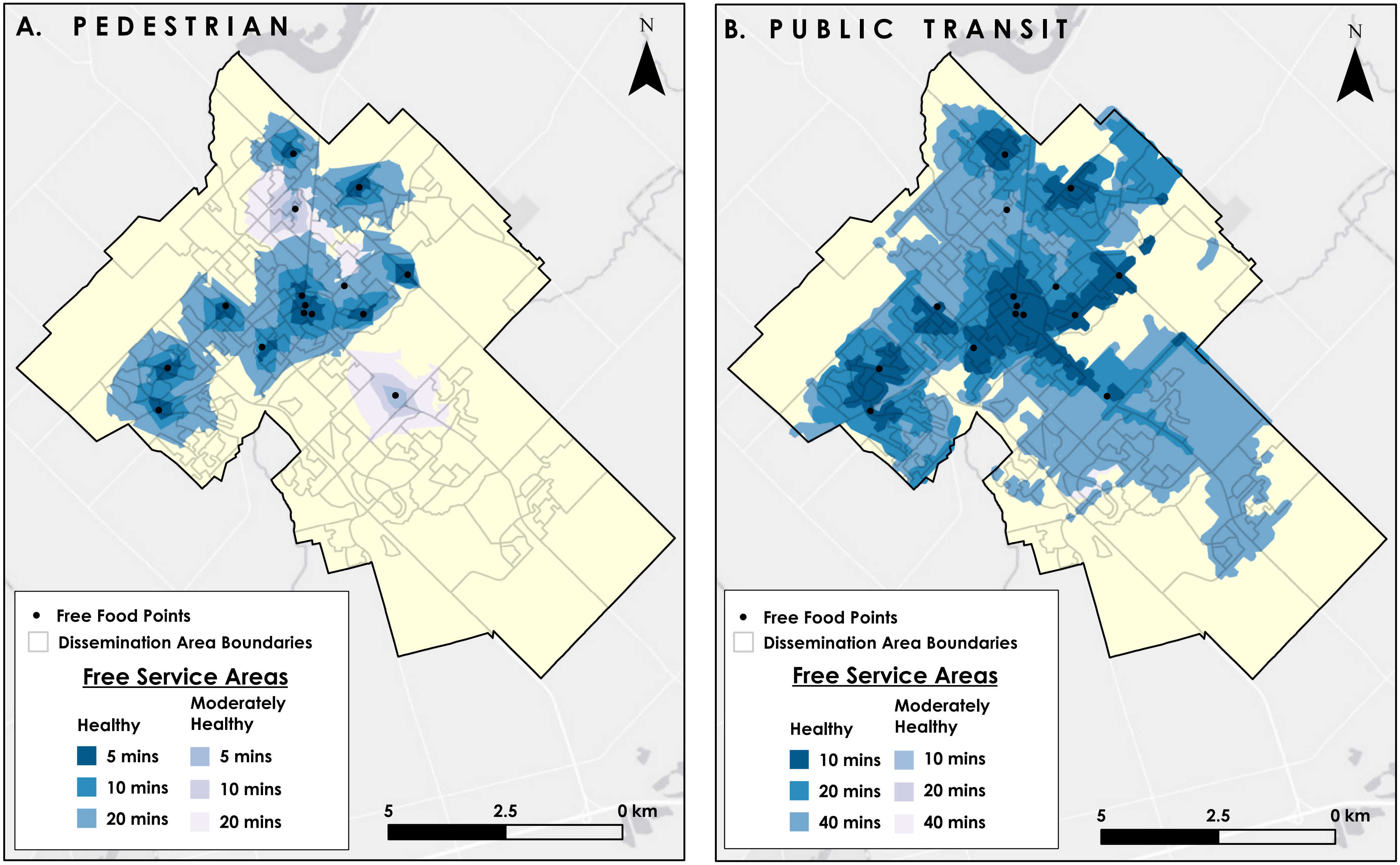

Figure 8. Healthy and moderately healthy SAs around free food sources in Guelph

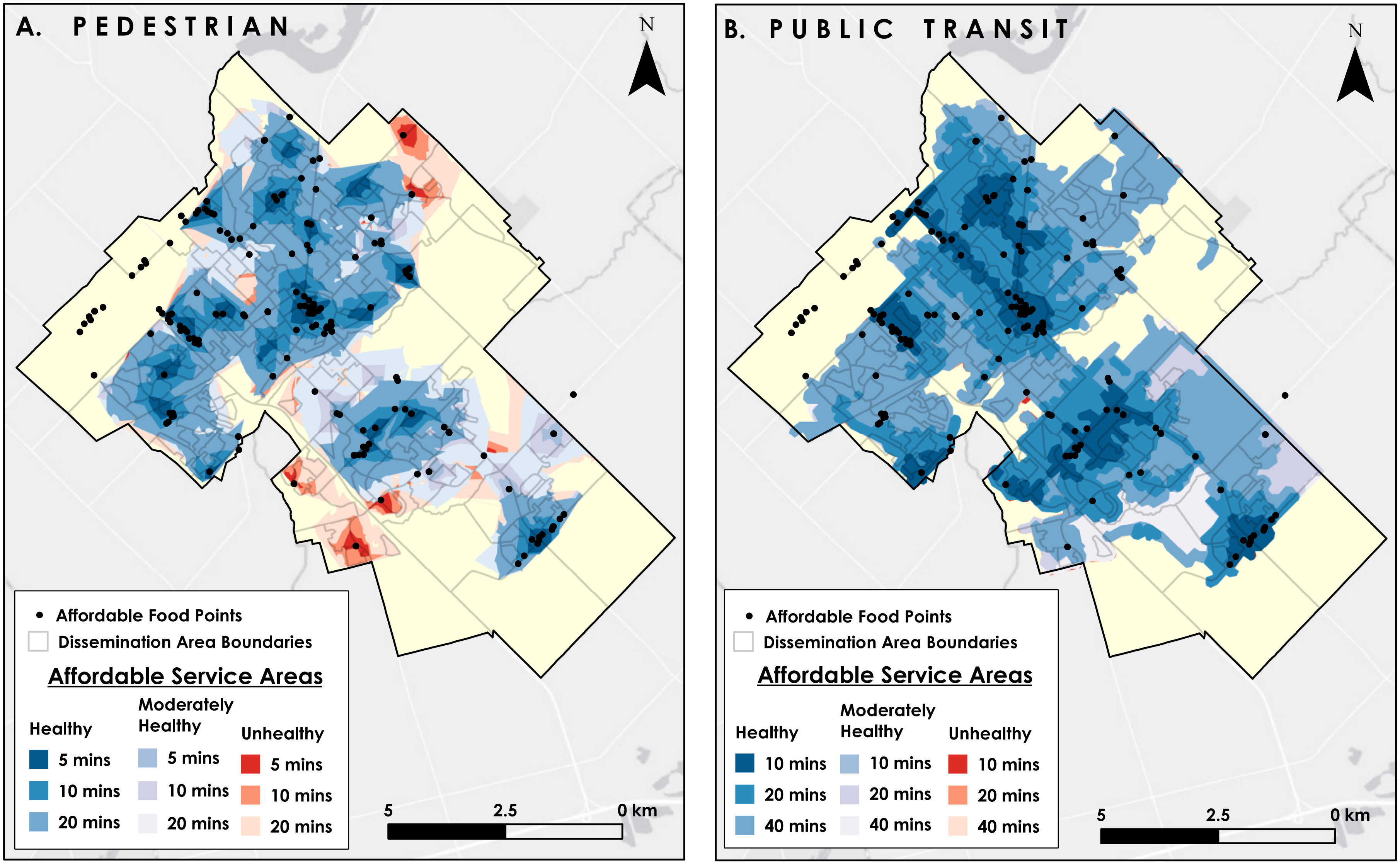

Figure 9. Healthy, moderately healthy, and unhealthy SAs around affordable food sources in Guelph

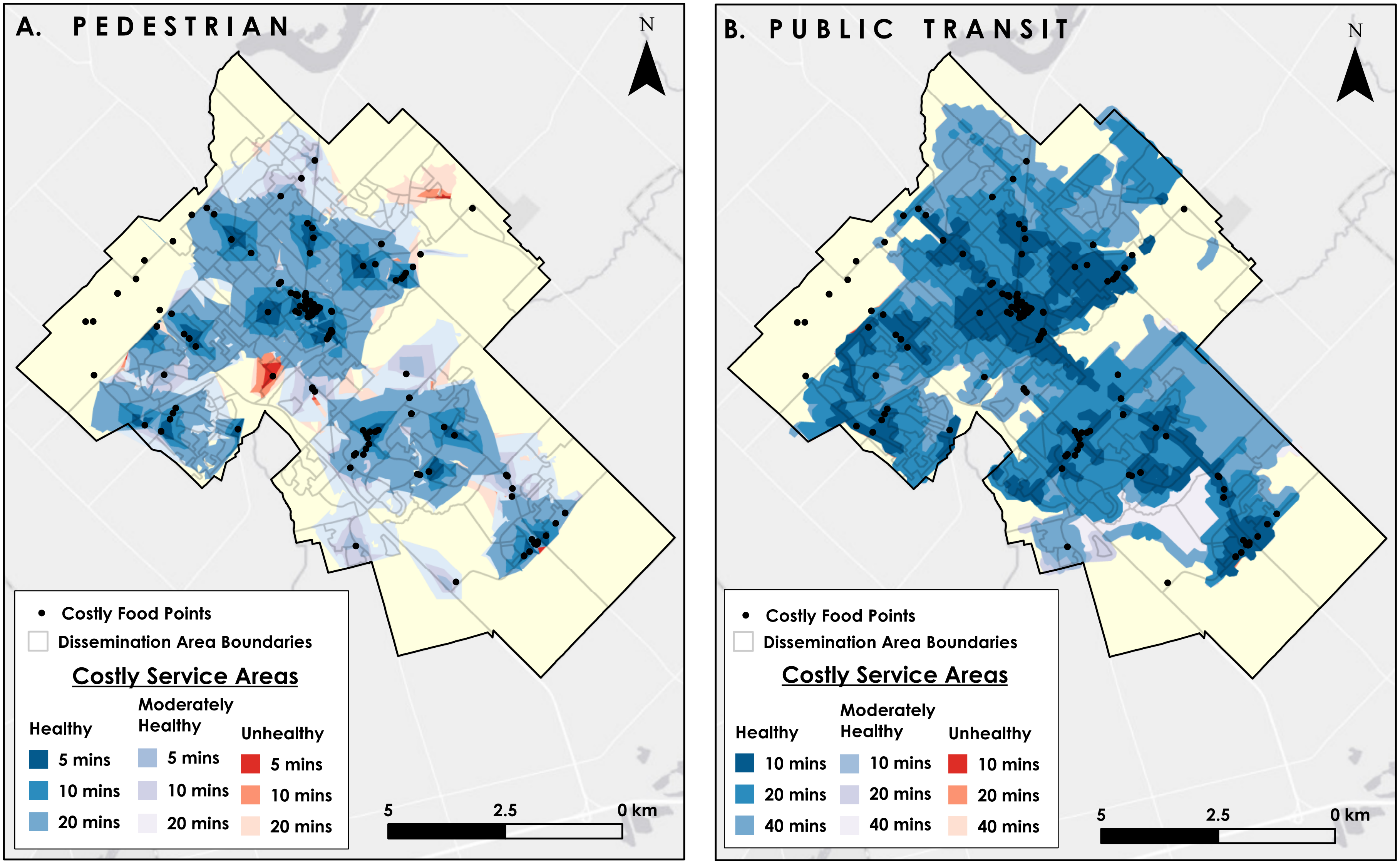

Figure 10. Healthy, moderately healthy, and unhealthy service areas around costly food sources in Guelph

2. DA Classification

Figure 11 depicts how free FAPs are not common within Guelph. Just by walking, emergency food suppliers are only accessible to people in 17 of 200 DAs across Guelph. Although the number of DAs accessible to these FAPs greatly increases with access to buses, most of these DAs are in the mid-northwestern part of the city. People residing in the southeastern side would have to travel much longer than 40 minutes to obtain these FAPs. Furthermore, it is important to consider that people depending on emergency food providers may not have the funds to purchase bus tickets and monthly passes. As of 2021, Guelph Transit charges $80.00 for adult monthly passes and approximately $40.00 for an affordable bus pass, if the user qualifies (City of Guelph, 2021). Regardless, these funds for low-income families could be used for other necessities, rather than spending it on the bus passes they require to obtain food. Thus, it illustrates how more emergency food providers may be needed around the southeastern end of Guelph.

When looking at affordable FAPs, the locations are more evenly distributed throughout Guelph (Figure 12). However, more DAs are dictated as food swamps for pedestrians, indicating that these people only have access to unhealthy foods if walking. Expectedly, these swamps decrease in number when people have access to buses, since the accessibility of healthy and moderately healthy FAPs increases under the bus network.

In contrast, when looking at costly FAPs, all health classes are relatively evenly distributed across Guelph (Figure 13). However, not as many DAs have access to them just by walking. When people have access to public transportation, DAs that have access to healthy, costly foods greatly increases. The number of DAs that have access to healthy foods is greatest when looking at the costly class in comparison to free and affordable sources.

Regardless of transportation mode, health class, and affordability class, the eastern, the upper northwestern, and lower southeastern section of Guelph remain as food deserts throughout all analyses. Although some of these DAs do have FAPs located within them, it is evident that they remain inaccessible by walking and public transit. By looking at the locations of the FAPs, we suggest that the city look into adding more FAPs in these areas.

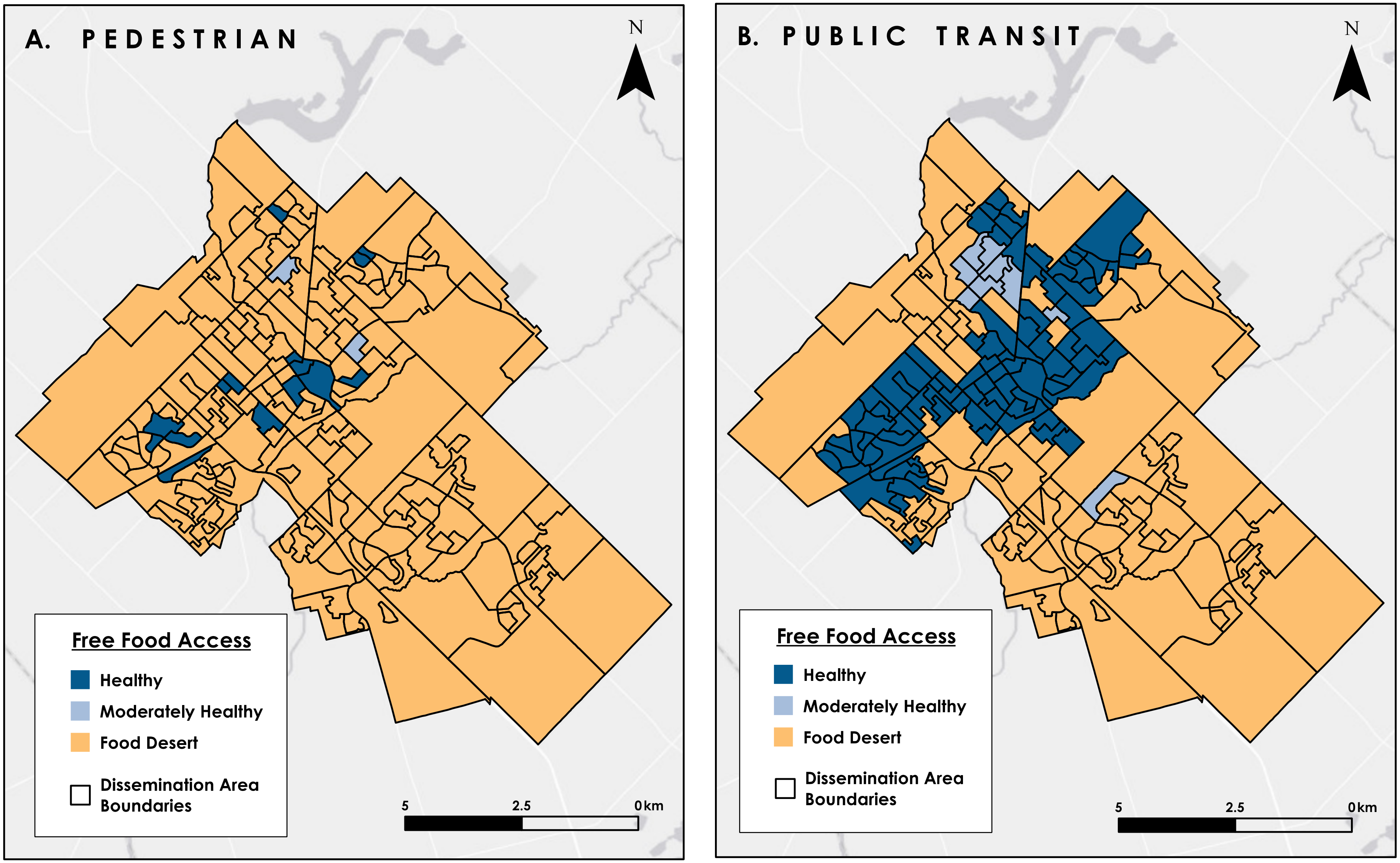

Figure 11. Map classifying DAs within the City of Guelph as having access to free healthy or free moderately healthy foods or as food deserts.

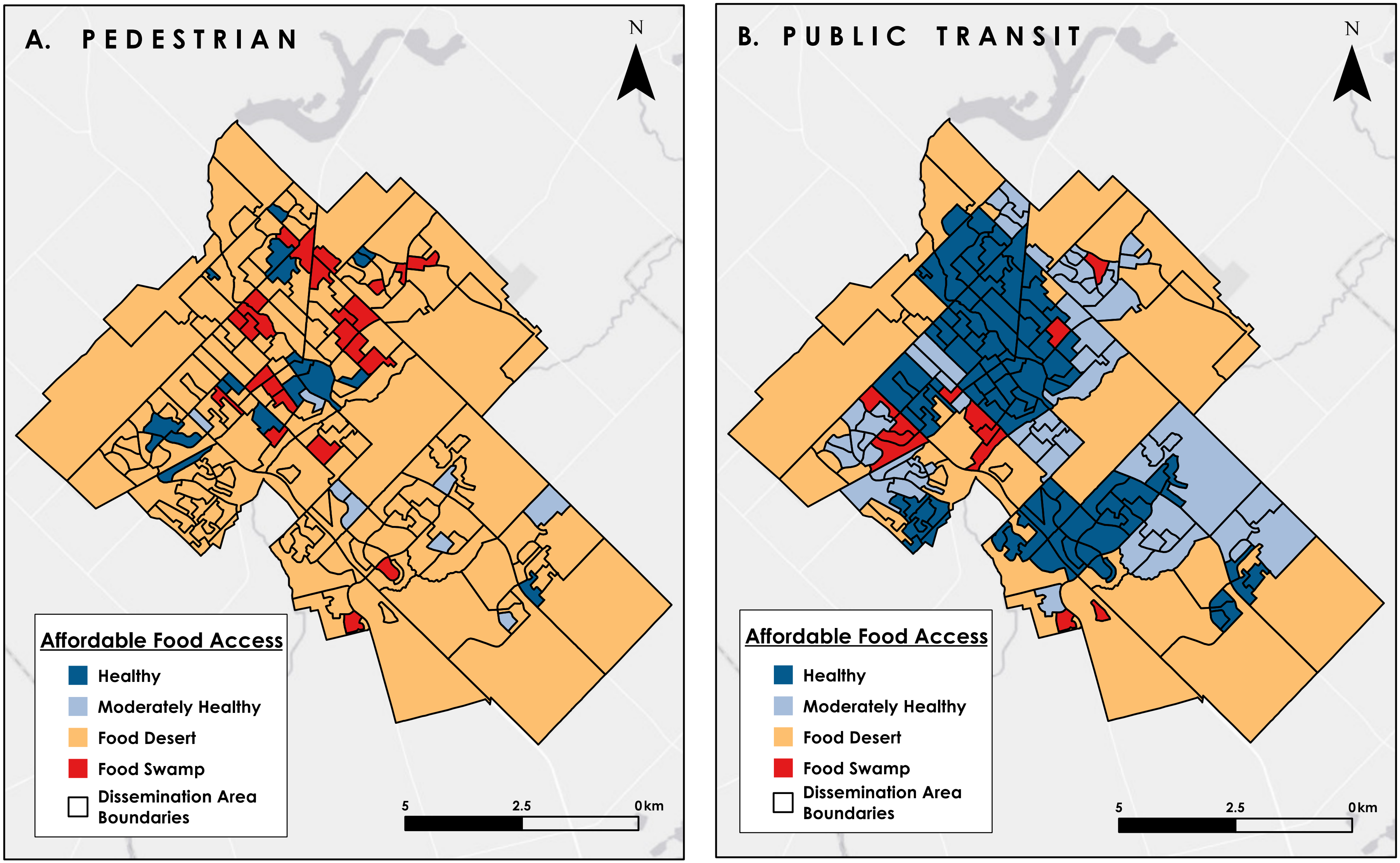

Figure 12. Map classifying DAs within the City of Guelph as having access to affordable healthy or affordable moderately healthy foods or as food deserts or food swamps.

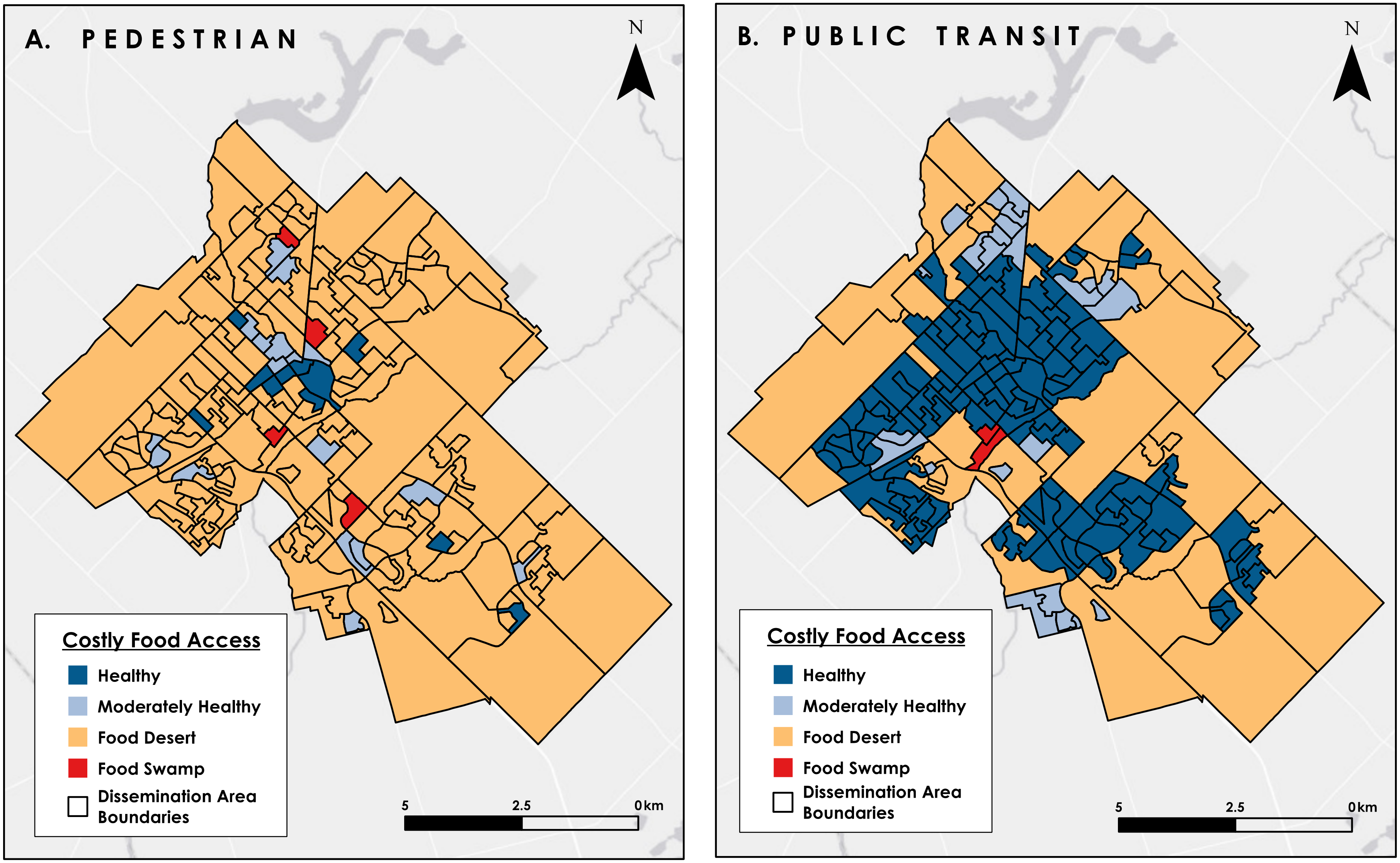

Figure 13. Map classifying DAs within the City of Guelph as having access to costly healthy or costly moderately healthy foods or as food deserts or food swamps.

3. Linear Regression

Accessibility to free food providers showed a positive correlation to healthy foods, regardless of transportation mode (Table 7). In contrast, free, moderately healthy foods had an insignificant relationship while walking, whereas a significant positive relationship with public transit. However, the R^2 values for all these scenarios are relatively small, indicating that the model explains only little of the variance contained within the data.

Similarly, for both transportation modes, the affordable, healthy scenario exhibited the strongest positive relationship with marginalization, depicting that more marginalized DAs have increased access to food. Even as the strongest and most significant relationship, there was a weak correlation between marginality and accessibility to food as a value between 0.1-0.39 represents a weak correlation (Schober et al., 2008).

In contrast, the weakest significant relationship was between costly, healthy food when the mode of transportation was walking). Likewise for costly, unhealthy foods, there is a weakly significant positive correlation in walking, but a non-significant positive weak correlation in bus. Overall, these trends depict that these costly FAPs are accessible by highly marginalized groups but does not entail these marginalized groups will be able to afford these food places.

Ultimately, there is no strong relationship seen between marginalization and food accessibility. The highest R^2 value of 0.06707 reveals that only 6.7% of the data is represented by the marginalization. This is consistent with the fact that the points representing accessibility and marginality through A-H have high variation around the regression lines. Therefore, there are likely better explanatory variables such as food preferences or the convenience of take-out that explains food accessibility (Widener & Shannon, 2014; Jekanowski et al., 2001).

Table 7. Statistics summary of correlation values, p-values and R^2 values under each scenario and transportation model. P-values were conducted at 95% confidence level (alpha=0.05). Asterisks are placed next to the p-values that are statistically significant.

	Pedestrian			**Public Transit**		
	Pearson Correlation Value	**P-value**	**R^2 value**	**Pearson Correlation Value**	**P-value**	**R^2 value**
A (Free, Healthy)	0.1540596	0.0294*	0.02373	0.1473086	0.03738*	0.0217
B (Free, Moderately healthy)	0.1184045	0.09494	0.01402	0.1575541	0.02587*	0.02482
C (Affordable, Healthy)	0.2589716	0.0002132*	0.06707	0.2048108	0.003623*	0.04195
D (Affordable, Moderately Healthy)	0.09532716	0.1794	0.009087	-0.0964723	0.1792	0.009307
E (Affordable, Unhealthy)	0.1164268	0.1006	0.01356	-0.02321051	0.7442	0.0005387
F (Costly, Healthy)	0.1447891	0.0408*	0.02096	0.1245665	0.07884	0.01552
G (Costly, Moderately Healthy)	-0.01996706	0.779	0.0003987	-0.06429499	0.3657	0.004134
H (Costly, Unhealthy)	0.1599854	0.02364*	0.0256	0.05095541	0.4736	0.002596

4. Geographically Weighted Regression (GWR)

Furthermore, Figure 14 shows that food access is affected by marginalization more strongly at the edges of Guelph regardless of transportation, where most relationships were positive possibly because they often contain smaller neighbourhoods that only occupy a portion of the DA. This lower sample size suggests that the marginalized index may be of lower accuracy in these areas. The same trends are seen across all scenarios.

The majority of Guelph overall does not have strong relationships between access to foods and marginality. Through most of the scenarios, one DA in the south of Guelph consistently showed a negative relationship between marginality and food access suggesting that increases in marginalization cause decreased access to these areas even by busing. This is in support with the southern part of Guelph being a food desert.

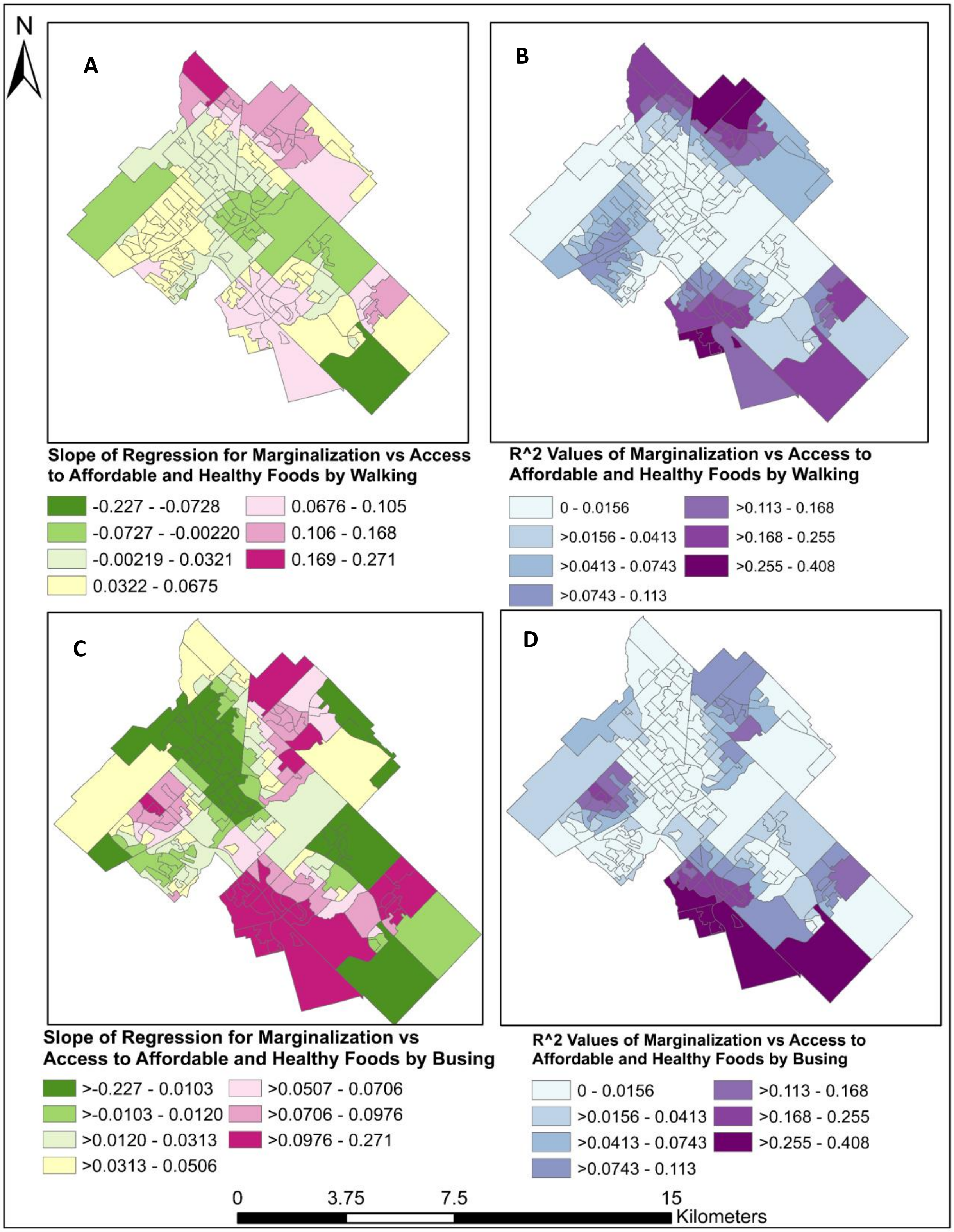

Figure 14. GWR maps for affordable, healthy sources under the pedestrian and public transit model. A and B illustrate slopes of regression and corresponding R^2 values for walking, while C and D illustrate slopes of regression and corresponding R^2 values for busing.

5. Limitations and Accuracy

The marginalization index dataset is based on four indices evaluated independently from one another (Public Health Ontario, 2016). However, to compare the indices to one another, they transformed each index value into a single integer, assuming all four factors are equal. Thus, all marginalization factors are weighted equally and so, a high marginalization value could be coming from one severely marginalized category (ex. high ethnic concentration) which is not always directly related to access to food. By using the quintiles, we may have introduced indices that may or may not have strong relationships with accessibility, which could explain the variation across our results.

Additionally, since we extracted our food locations from Google maps, it may be possible that some food establishments were missed or were not available on google maps. We also recognize that our affordability and health classes could be biased and that other researchers may not classify food establishments in similar ways.

Overall, our largest limitation revolves around the years our datasets are produced. We combined multiple datasets collected in different years, which changed the connectivity within our network models. Since the latest census was collected in 2016, we aimed to produce network models based on 2016 data, however, the GTFS data was only available in 2020. Bus routes 17, 18 and 20 runs through the northwestern end of Guelph, but since no walkable roads were detected nearby, these bus routes were not used. Thus, the SAs and the computed accessibility scores we produced, may not be illustrative of current day accessibility to food.

VI. CONCLUSION & FUTURE RESEARCH

Our classification of the DAs access highlights northwestern and southeastern Guelph as food deserts regardless of affordability and health classes. These food deserts may be due to lack of FAPs being nearby or lack of transportation networks. Additionally, individuals who only have access to walking are more limited in their access to healthy foods while individuals with public transit access have increased healthy food access. Through our statistical analyses, there were not any strong, prevalent trends associated with food accessibility and marginality.

It may be possible that the averaged marginalized quintile we used may be masking the relationships between food access and individual indices. Thus, we suggest that future research be focused on evaluating these marginalized groups as separate entities.

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