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Exploring the role of the built and natural environment in encouraging active travel for different trip purposes in Montreal

Pegah Salsabilian
McGill University
pegah.salsabilian@mail.mcgill.ca

José Arturo Jasso Chávez
McGill University
jose.jassochavez@mail.mcgill.ca

Kevin Manaugh
McGill University
kevin.manaugh@mcgill.ca

Abstract: Transportation research has extensively examined the influence of both the built and natural environment on active travel. While most studies assume linear relationships, some evidence indicates that this might not always be the case. This paper addresses this by identifying the nature of the relationship between the built and natural environment (BNE) and active travel (AT) across several trip purposes: school, shopping, work, and leisure trips in Montreal, Canada. We also identify areas with low and high potential for active travel. Using Generalized Linear Models with the Tweedie family and including a spatial lag covariate, we found that the relationship between BNE and AT is not always linear. In some cases, higher access levels to sidewalks, bike lanes, walkable destinations, and transit stops, constantly increase AT but with cubic or logarithmic relationships. Other variables, such as dwelling density, intersection density, park access, tree coverage, industrial diversity, and proximity to water bodies, also encourage active travel but only up to a certain threshold, beyond which further increases do not increase AT, and in some cases, can lead to a decline, forming an inverted "U" relationship. These relationships vary across trip purposes. Central areas in Montreal show the best potential to support active travel, while the rest of the city displays low levels of support, depending on the trip's purpose. The findings highlight the importance of accounting for non-linear relationships, as improvements in the BNE do not always translate into higher levels of active travel.

Keywords: active travel, waking, cycling, built and natural environment, accessibility, non-linearity

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1 Introduction

In recent years, numerous studies have highlighted the importance of the built and natural environment (BNE) in shaping active travel (AT) behaviors and its potential to enhance public health, alleviate traffic congestion, and mitigate environmental impacts

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(Hallal et al., 2012; Handy et al., 2002). Some research has explored the effects of access to parks (Cohen et al., 2007) and access to green areas (Bartshe et al., 2021); others have focused on blue areas or water features on AT (Murrin et al., 2023). Other studies have found that diversity of land use (Badland & Schofield, 2005; Ewing & Cervero, 2010; Handy et al., 2002; Leslie et al., 2005; Saelens et al., 2003), dwelling density (Leslie et al., 2005; Saelens et al., 2003), walkable destinations (Baobeid et al., 2021), and proximity or density of transit stations (Wang & Cao, 2017) promote AT.

Most of these studies assume a linear relationship between these variables, but recent literature has found non-linear relationships between BNE variables and AT (Liu et al., 2021; Tao et al., 2023). Identifying these non-linear relationships is crucial, as increasing BNE attributes could not always lead to an increase in active travel. Instead, BNE could increase active travel, but beyond a certain point, additional improvements may yield diminishing returns or even lead to declines in active travel. This is known as a saturation threshold effect (Delbosc & Currie, 2018). Despite the importance of these studies, their findings are context-specific and cannot be extrapolated to other settings, making it necessary to identify how these relationships vary across different contexts. Additionally, most of these studies focus on understanding the effects for specific trip purposes, mainly for trips to school or work and, to a lesser extent, to other trip purposes (Cervero & Kockelman, 1997; Manoj & Verma, 2016). Studying variation across trip purposes is important because travel behavior often varies depending on the purpose of the trip.

This research examines the linear or non-linear relationship between built and natural environment variables and active travel (walking and biking) while assessing how this relationship varies across four trip purposes: work, school, leisure, and shopping. Furthermore, we seek to identify areas in Montreal with high potential for active travel based on their association with these variables. This article is structured as follows. First, we present a literature review examining studies that have addressed the impact of the built and natural environment on active travel across several trip purposes and the nature of this relationship. In the second section, we describe the data sources, the characteristics of the variables, and the methods used in the analysis. The third section presents the findings of our study, and lastly, we discuss implications for public policy and future work.

2 Literature review

In recent years, growing attention has been directed toward studying the built and natural environment, which encompasses the physical characteristics of the environment where individuals live, work, and participate in activities (Frank et al., 2005). This attention is driven by its impact on active travel, with potential benefits including improvements in public health, reduction of traffic congestion, and mitigation of environmental impact (Hallal et al., 2012; Rojas-Rueda et al., 2016). AT, which usually considers walking and cycling, has emerged as a sustainable and health-promoting transportation choice that is both available and feasible for most people (Handy et al., 2002).

Studies have shown that AT is strongly influenced by BNE characteristics (Schulz & Northridge, 2004). For example, literature has consistently found that proximity to parks and green spaces is associated with higher levels of walking and cycling (Cohen et al., 2007). Access to blue areas, which include water bodies and waterfronts, has shown its potential to encourage AT (Murrin et al., 2023). Research has also shown that areas with a high diversity of employment sectors, such as services, retail, and offices, tend to exhibit higher levels of walking and cycling (Rybarczyk, 2018; Wali et al., 2021). Population or dwelling density also influences walking and cycling behaviors. Higher densities foster shorter trip distances and lead to increased walking and cycling (Leslie et al., 2005; Saunders et al., 2013). Areas with high access to sidewalks and intersections have been found to have higher rates of walking compared to neighborhoods with low access to sidewalks (Berrigan et al., 2010; Handy et al., 2002; McCormack & Shiell, 2011; Wendel-Vos et al., 2007) and fewer intersections (Frank et al., 2005; Sun et al., 2014).

Most studies have focused on understanding walking or biking to work, partly because traveling to work is the most common travel for adults. For work trips, the literature has found that BNE variables such as accessibility to jobs, retail and service density, land use diversity, and pedestrian-bike-friendly design encourage higher levels of walking and cycling (Cervero & Duncan, 2003).

The second most frequent type of trip is commuting to school. However, due to the group's age heterogeneity of students, the effect of the BNE characteristics may change depending on the age group or level of studies. In general, BNE variables that explain walking or biking to school are proximity to school (De Meester et al., 2013), walkability (Mitra & Buliung, 2012; Wang et al., 2022), network connectivity (Berrigan et al., 2010; De Meester et al., 2013; Sun et al., 2014), road intersections (Sun et al., 2014), safety facilities (De Meester et al., 2013; Mitra & Buliung, 2012; Wang et al., 2022), and lower land use mix (De Meester et al., 2013).

For shopping trips, several studies have found that proximity to markets strongly influences the number of active trips (Handy et al., 2002; McCormack & Shiell, 2011). Other studies have found that BNE impacts AT in different ways depending on socioeconomic groups (Zhang et al., 2011). Finally, many scholars have found that BNE significantly affects walking and biking for leisure trips. Neighborhoods with higher street connectivity, well-designed pedestrian infrastructure (Cervero & Duncan, 2003), and a mix of local recreational and non-recreational destinations encourage AT (Loo & Wang, 2018).

Most studies have assumed a linear relationship between BNE and AT, while non-linear relationships have received little attention. Some studies that have explored the nonlinear nature, such as Frank (1994), have found that mixed land use and density exhibit non-linear relationships with walking. Specifically, as employment density increases, walking increases up to a certain threshold, beyond which the relationship levels off. Similarly, the distance to parks and downtown, job density, and land-use entropy display non-linear associations with active travel in the Twin Cities, United States (Tao et al., 2023). The study found that as distance to parks increases, physical activity decreases and then levels off. Larger parks increase physical activity, but only up to a certain point. They also found that as job density increases, AT increases until a point at which it starts to decrease, followed by a slight but constant increase. Guo et al. (2023) examined the effects of variables such as population density, land use mix, intersection density, and commercial facility density on older adults' AT in Xiamen, China. Their findings reveal nonlinear associations between built environment variables and AT. For example, they identify a U-shaped relationship between intersection density and AT, while population density exhibits three inflection points. Importantly, these relationships differ between urban and suburban contexts. Similarly, Cheng et al. (2020) found nonlinear relationships and saturation threshold effects for several variables, such as population density, land use mix, and street connectivity, which exhibited an inverted "U" shape. In contrast, other variables, such as the distance to the nearest park or square, followed a U-shaped relationship. Yang et al. (2022) studied the effects of the built environment on active travel across gender for older adults. They observed a U-shaped relationship between population density and road density and active travel, with some differences between males and females. Liu et al. (2021) examined the associations between the built environment and active travel for work and shopping. They also identified non-linear relationships, particularly inverted “U” shapes, for most variables such as job density, intersection density, population density, and land-use mix. Mitra & Buliung (2012) found that job density, intersection density, population density, land use mix, and bus stop density demonstrate non-linear trends to AT to work, often presenting inverted U-shaped curves.

3 Methodology and data

3.1 Study area and data

We studied the case of the Island of Montreal in Quebec, Canada. The island has an approximate area of 473 km² and a population of around 2 million people across 16 municipalities, including the City of Montreal, the largest with approximately 1.7 million people. We used the Origin-Destination (O-D) Survey conducted by the regional public transport planning authority in the Montreal metropolitan region (ARTM, 2018). This survey has information regarding the residences of individuals and the location in which they start and end their daily trips (with a precision of 250 meters due to privacy concerns). We aggregated the origin of the trips at a dissemination area (DA) level, which is the smallest unit of analysis in which census data is available, to reduce the effects of the modifiable areal unit problem (Fotheringham & Wong, 1991). Our dependent variable, the percentage of individuals who walk or bike, was obtained from the O-D survey. However, not all the dissemination areas have enough sample representation. Accordingly, we predicted the percentage of individuals traveling by walking or biking for every DA (see Section 3.2).

Regarding the source of the independent variables, we obtained data of water bodies and the delimitation of parks from OpenStreetMap (2023), while tree coverage data was obtained from the City of Montreal (2019). The main difference between parks and tree coverage is that parks are designated green areas specifically designed for recreational activities. In contrast, tree coverage represents the sum of the projections on the ground of each crown or group of trees more than three meters high. While parks and tree coverage coincide in some areas, this is different in most instances. For example, parks are limited to specific designated areas, but tree coverage is more widespread. Data on the location and area of the sidewalks and bike infrastructure were obtained from the City of Montreal (2023). Dwelling density data were obtained from Statistics Canada (2022a), and information concerning transit stops and intersection density was sourced from Can-ALE (Hermann et al., 2022). Finally, we obtained the location of commerce and businesses from DMTI Spatial Inc. (2020) to build the industry diversity index and to identify walkable destinations. We identified walkable destinations mainly considering retail outlets where customers can easily purchase items and exit the stores. These include food or liquor stores, general merchandise stores, dollar stores, bookstores, pharmacies, and health-related stores. Finally, using the North American Industry Classification System (NAICS) (Statistics Canada, 2022b) and with some adjustments, we categorized industries into the following classifications: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary; wholesale trade; retail trade; finance, insurance, and real estate; services; and public administration. Using this classification, we measured industry diversity using the Herfindahl-Hirschman Index (HHI) (Song et al., 2013):

$$HHI = 1 - \Sigma(S_i)^2 \qquad (1)$$

Where: HHI is the industry diversity index, and S is the share of the i (the type of retail in the DA) expressed as a proportion. Areas with high industry diversity have values close to one, and areas with low industry diversity have values close to zero.

Out of the independent variables mentioned above, dwelling density, intersection density, and industry diversity were treated as such for every DA. For the rest of the variables, accessibility calculations were made, which in the first instance consisted of using the Rapid Realistic Routing with the "r5r" package in R (Pereira et al., 2021) to create a time matrix between the weighted population centroid of every DA with a time threshold of 30 minutes walking. In the case of the blue areas, only the distance between each centroid of DA to the nearest body of water was calculated. Tree coverage, parks, sidewalks, bike lanes, and walkable destinations were aggregated to a DA scale, and accessibility to each variable was calculated using the cumulative opportunities method, which counts the number of opportunities that can be reached within a specific time threshold (Equation 2). Table 1 shows a description of all the variables used in this research.

$$A_i = \Sigma_{j=1}^{n} O_j B_j \tag{2}$$

Where: A_i is the accessibility at zone i; B_j is a binary value equal to 1 if zone j is within the predetermined time threshold and 0 otherwise; and O_j are the opportunities in zone j.

Table 1. Description of the independent variables used in this research

Independent Variable	Description	Type	Source
Bike lanes	Accessibility to bike lanes within a 30-minute threshold (total area)	Continuous (km^2)	City of Montreal, 2023
Dwelling density	The number of dwellings per square km	Continuous (Number of Dwellings/km^2)	Statistics Canada, 2022a
Industry diversity (HHI)	Index of industry diversity in the DA	Ordinal (0 to 1)	DMTI, 2020
Intersection density	The density of intersections in the DA	Continuous (Number of intersections/km^2)	Hermann et al., 2022
Parks	Accessibility to parks within a 30-minute threshold (total area)	Continuous (km^2)	OpenStreetMap, 2023
Sidewalks	Accessibility to sidewalks within a 30-minute threshold (total area)	Continuous (km^2)	City of Montreal, 2023
Transit	The number of public transits stops or stations in 1 KM buffer around a DA centroid	Discrete (count)	Hermann et al., 2022
Tree coverage	Accessibility to tree coverage (higher than 3 meters) within a 30-minute threshold (total area)	Continuous (km^2)	City of Montreal, 2019
Walkable destinations (retail)	Accessibility to walkable destinations within a 30-minute threshold	Discrete (count)	DMTI Spatial Inc., 2020
Water bodies	Distance to the closest blue area (river, lake)	Continuous (km)	OpenStreetMap, 2023

In addition to the BNE variables, socio-economic variables such as income, age, gender, and household size were incorporated into the model as control variables to account for potential confounding factors. These variables were available in the O-D survey, used for modeling, and the Census Canada 2021 (Statistics Canada, 2022a) dataset, used for prediction (the prediction will be explained in Subsection 3.2). The income variable was categorized into five groups: lower income (Less than $30,000), lower middle income ($30,000 – $60,000), middle income ($60,000 – $90,000), upper middle income ($90,000 – $150,000), and upper income (More than $150,000). Age was divided into three categories to capture different age groups' travel patterns: youth population (16-24), middle-aged individuals (25-64), and seniors (above 65). Lastly, household size was defined into four groups: one person, two people, three to four people, and five people or more.

3.2 Methods

We first employed generalized linear models (GLM), which are well-suited for analyzing relationships between variables when the dependent variable follows a non-normal distribution. The dependent variable is the percentage of individuals walking or biking within a specific DA, whereas the independent variables are the BNE factors listed in Table 1. The dependent variable in our dataset, which represents the proportion of AT in DAs, exhibits a highly right-skewed distribution with a substantial number of zero values. Such a distribution can arise from limitations in sampling coverage that may underrepresent low levels of activity, as well as behavioral characteristics in certain DAs where AT is absent. We tested different approaches to improve the normality of the dependent variable using several transformations (e.g., logarithmic, square root). However, we found that these were not adequate as they did not successfully transform the distribution to normality. This indicated the need for a more appropriate statistical approach that better aligns with the distributional characteristics of the outcome variable. To address this, we employed the Tweedie distribution in a GLM framework. The Tweedie is a compound distribution that handles data with a large number of zero observations and a continuous distribution of positive values. It combines features of the Poisson distribution, which captures the probability of zero occurrences, with the Gamma distribution (with a variance power parameter between 1 and 2), which models the positively skewed non-zero values (Kurz, 2017). This makes the Tweedie distribution especially well-suited for our dependent variable, where both zero-inflation and right-skewness are present in the data.

We plotted the dependent variable against the independent variables for each trip purpose (work, school, leisure, and shopping) to identify which transformations of independent variables best capture the non-linear relationships between the variables. Using these transformations, we applied the Generalized Linear Model with compound Poisson-Gamma distribution, implemented via the "tweedie" package in RStudio (Dunn & Smyth, 2018).

Subsequently, we applied Moran's I test to identify spatial autocorrelation of the models' residuals. Work, shopping, and leisure purposes exhibited spatial autocorrelation. To address this issue and reduce spatial dependence in the model residuals, we implemented a two-step approximation of a spatial lag model, since no package currently allows fitting such models with a Tweedie distribution. First, we calculated the spatial lag of the dependent variable using a queen contiguity matrix. Second, we included this spatial lag as an additional covariate in the Tweedie GLM. A subsequent Moran's I test on the residuals confirmed that this adjustment substantially reduced spatial autocorrelation, demonstrating that incorporating the spatial lag covariate effectively accounted for spatial dependence in the model. However, this two-step approach is an approximation and may not fully capture the complex spatial interactions that a fully specified spatial lag model would, potentially leading to some residual spatial dependence or biased parameter estimates. Nevertheless, since Moran's I showed no significant spatial autocorrelation in the residuals, this method is appropriate for the purposes of this research, given the current limitations.

Then, we applied these fitted models to predict AT percentages for all DAs, while controlling for socioeconomic variables such as income, age, gender, and household size. The prediction was crucial for accurately representing many missing DAs or those with inflated values due to the small sample sizes. Lastly, we carried out Hot Spot analysis for mapping areas supporting AT and then plotted the relationships between AT (using the predicted values) and the BNE variables.

4 Analysis and findings

4.1 Descriptive analysis

According to the 2018 Montreal O-D Survey, there are 3,802,483 daily trips on the Island of Montreal. Regarding trip purposes, 19% are for work, 4% for school, 9% for leisure, and 10.6% for shopping. Of the total trips, 11% are made by walking or biking. By trip purpose, we found that AT is highest for shopping trips (16.6%), followed by leisure (14.3%), school (10%), and work (7%). Figure 1 illustrates the percentage of trips made by walking or biking, categorized by purpose. Shopping and leisure trips made by AT are widespread across the island, whereas work and school trips show a more centralized pattern, with smaller clusters appearing in other areas. In general, the higher levels of AT are located in central areas; however, outside central areas, there are a lot of DAs (849 DAs out of 3,228) that lack AT data, which could reflect unsampled information rather than an absence of trips.

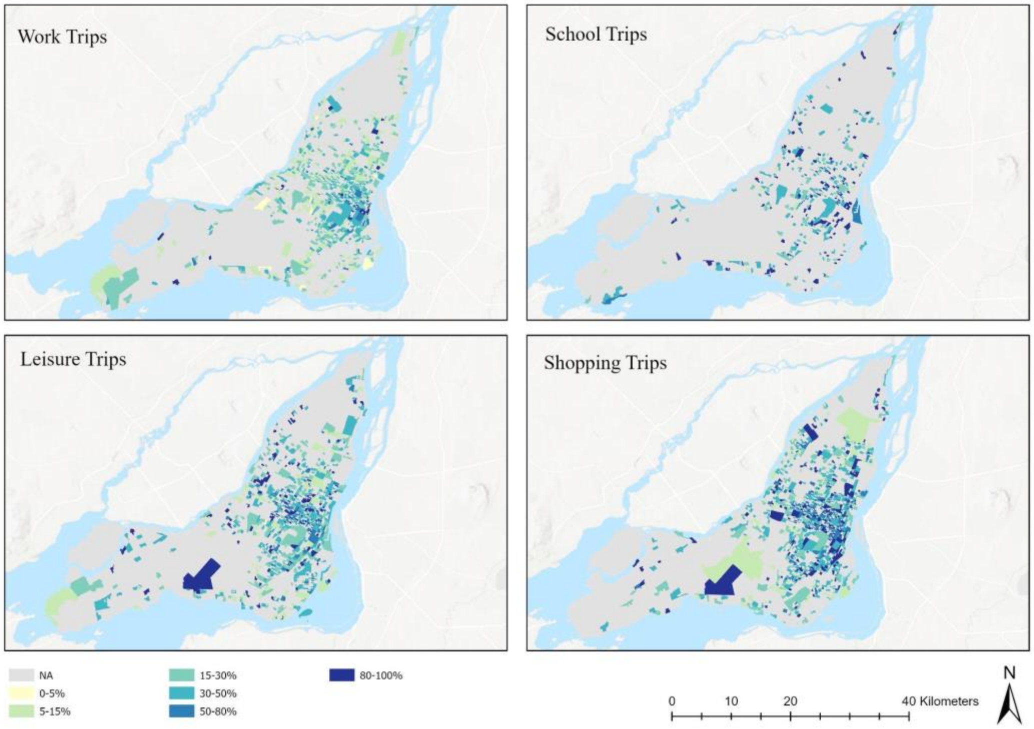

Figure 1. Reported AT by trip purposes at the DA scale

Figure 2 presents a visualization of the independent variables aggregated at the DA level for all variables. To represent the categories, we divided each of the values into quantiles. Darker shades of blue indicate higher values, while lighter colors indicate lower values. We observed that the higher values of dwelling density, access to sidewalks, bike lanes, walkable destinations, transit stops, and intersection density are in central areas, with very low levels in the other DAs, especially in the southwest part of the island. Other variables, such as access to parks and green coverage, are distributed across the entire island, with a higher concentration in the southwest and northwest areas. Additionally, higher levels of industrial diversity can be found in several areas across the Island of Montreal, with some clusters of low industrial diversity.

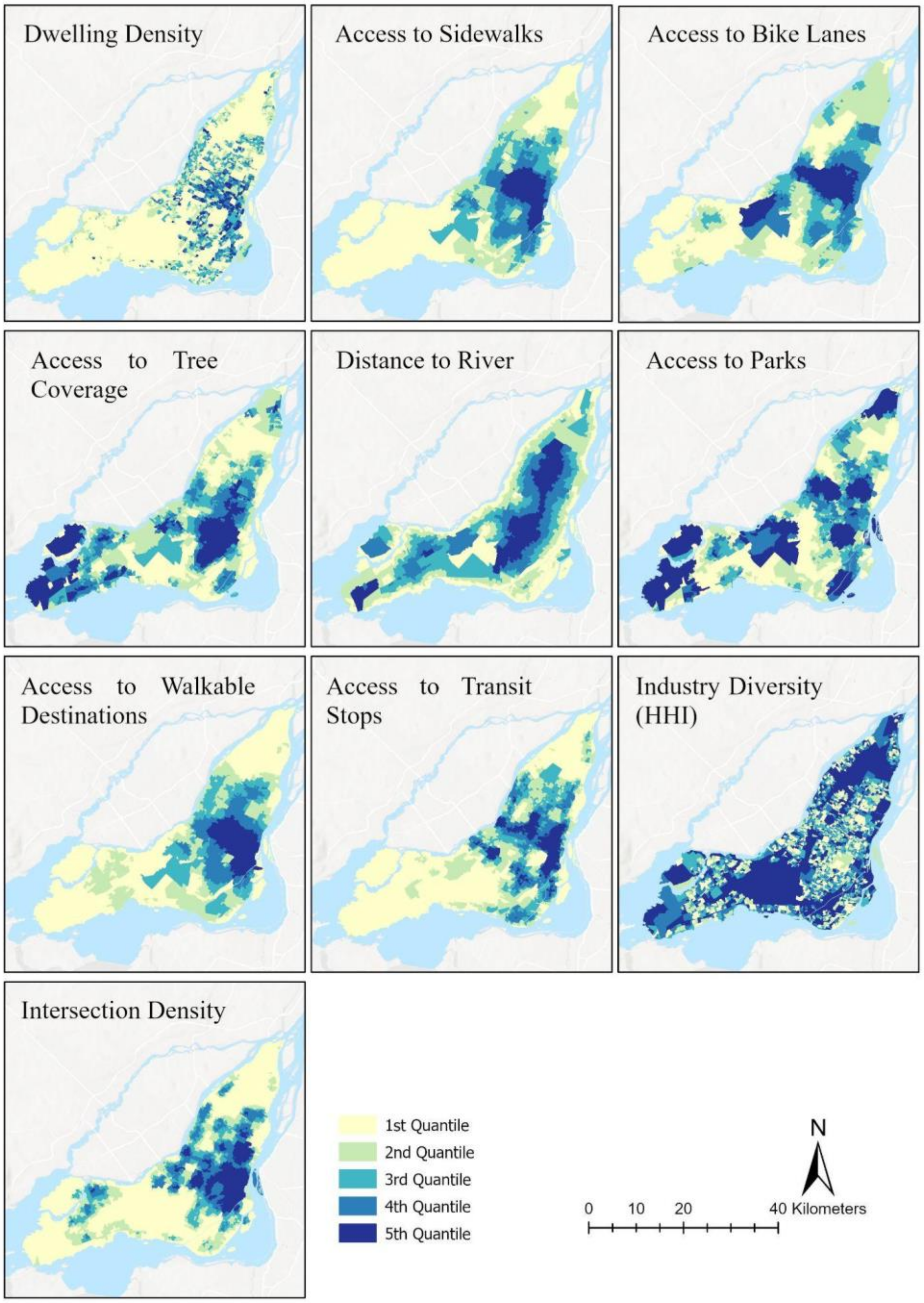

Figure 2. Spatial distribution of BNE variables at the DA level

4.2 Generalized linear and spatial models

We ran GLM to identify the relationship between AT and the BNE[1]. After running the GLMs for the four trip categories, we applied Moran's I test to examine spatial autocorrelation among the model residuals. The results of Moran's I test, based on queen contiguity spatial weights matrix (DAs sharing a common border or vertex), indicate the presence of spatial autocorrelation in the residuals of the work (p-value = 0.010), shopping (p-value = 0.000), and leisure (p-value = 0.001) models, suggesting spatial dependency in the residuals. However, there is no significant spatial autocorrelation at a 90% significance level for the school model (p-value = 0.868). The absence of spatial autocorrelation in the residuals of the school model suggests that geographic proximity does not influence the relationships within this trip purpose. This could be because decisions to walk or bike to school, especially for younger children, often depend on parental choices (Tavakoli et al., 2024).

To account for spatial dependence, we computed a spatial lag of the dependent variable using a queen contiguity weights matrix and included this spatial lag as an additional covariate in the work, shopping, and leisure models. This approach helps capture spatial spillover effects and reduces potential bias due to unmodeled spatial structure (Lambert et al., 2010). We transformed the variables to account for the assumed non-linear relationship between AT and the BNE, as shown in Figure 3. To identify the best transformation, we created scatterplots of the dependent variable against each independent variable and tested several transformation types, including linear, quadratic, logarithmic, and cubic. We then selected the transformation that best matched patterns in the data, based on both visual inspection and model performance metrics. In some cases, the transformation that provided the best statistical fit did not closely resemble the pattern we initially interpreted from the raw scatterplots. This discrepancy occurs because relying on a visual inspection of the scatterplots might overlook complex patterns in the data.

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[1] We initially used three additional prediction algorithms: Random Forest (RF), Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost). But we found that GLM performed better. Three evaluation metrics of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) were calculated to evaluate the explanatory power of models. We observed that SVM exhibited a better MAE value than other models. However, when considering RMSE and R-squared, the GLM outperformed all other models across all four trip purposes.

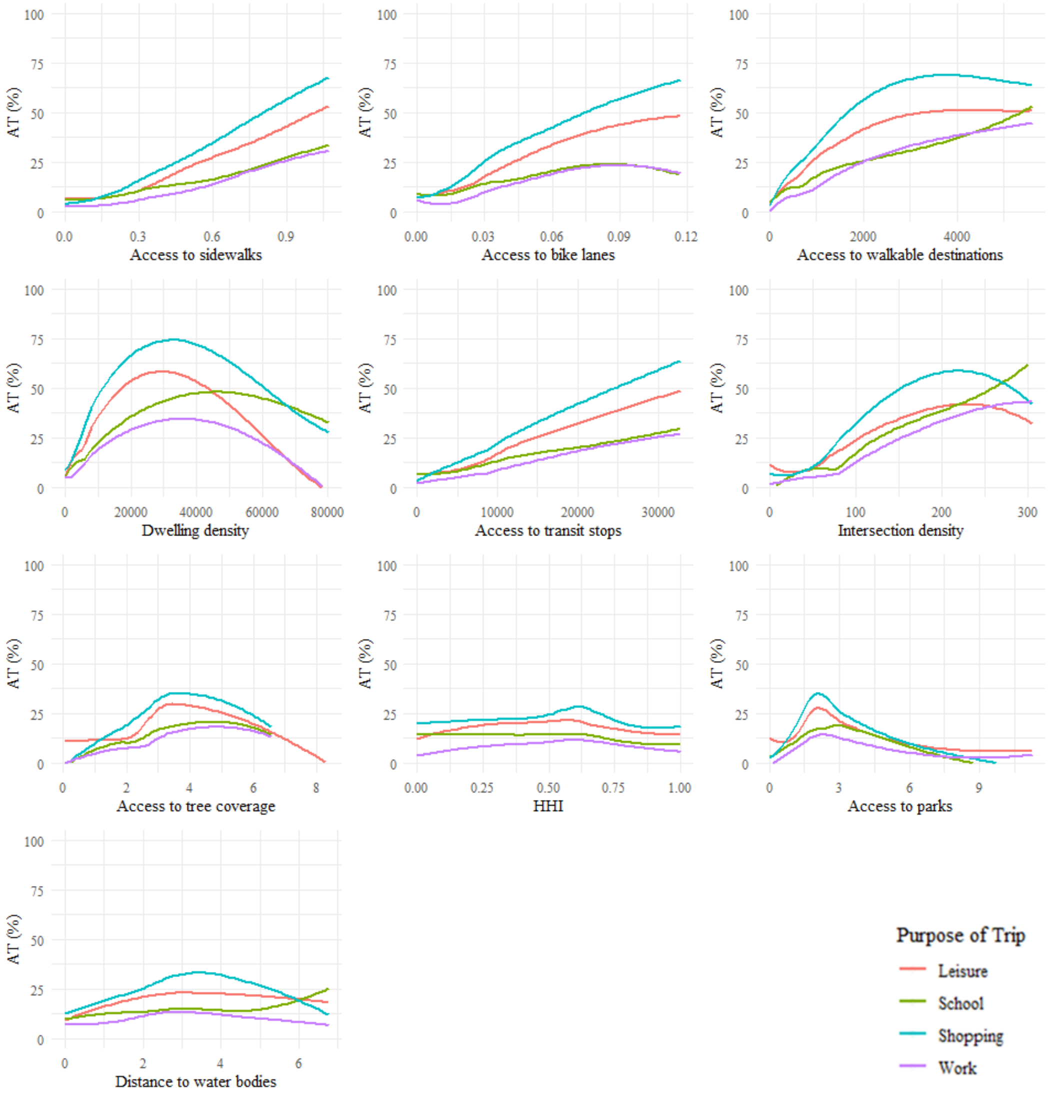

Figure 3. Non-linear relationship between AT and BNE variables

Table 2 presents the coefficients, significance levels, and variable transformations of the GLM for each trip purpose. The models for work and shopping trips explain more variation in AT than those for school and leisure trips. The BNE variables were transformed into logarithmic, quadratic, and cubic forms. A quadratic transformation includes both the original value (x) and its square (x^2) to capture U-shaped (convex) or inverted U-shaped (concave) relationships (as shown in Table 2, with 1 for the original value and 2 for the squared value). A cubic transformation extends this by incorporating the original value, its square, and its cube form (x, x^2, x^3) to account for cases where the effect of a variable changes direction twice (as shown in Table 2, with 1 for the linear value, 2 for the square, and 3 for the cube). A positive quadratic coefficient indicates a U-shape, while a negative one suggests an inverted U. For a cubic term, a positive coefficient typically shows a decrease, then an increase, then another decrease, whereas a negative coefficient suggests the opposite pattern. However, the shape of a cubic relationship depends on the combined effects of both the cubic and quadratic terms.

For school trips, the significant variables were intersection density, access to tree coverage, access to parks, and distance to water bodies. Specifically, higher street intersection density slightly increases active school trips, while better access to tree coverage also encourages AT. Access to parks follows a concave pattern, indicating that its positive effect diminishes after reaching a peak. Distance to water bodies exhibits a nonlinear relationship with AT. Initially, AT decreases as distance increases, but the decline slows, and eventually AT begins to rise again.

For work trips, access to sidewalks, walkable destinations, dwelling density, access to transit stops, industry diversity, access to tree coverage, access to parks, and distance to water were significant. Access to sidewalks is positively associated with AT. AT initially increases with access to walkable destinations, peaks at moderate levels, and then declines, with a possible slight rebound at very high access levels. Dwelling density exhibits a concave shape, while access to transit stops is significant but has a near-zero coefficient, indicating a minimal effect on AT. Industry diversity also follows a concave relationship. Access to tree coverage generally has a positive effect on AT, while access to parks and distance to water bodies are primarily negatively associated with AT.

For shopping trips, AT is significantly influenced by access to transit stops, dwelling density, intersection density, industry diversity, and access to parks. Dwelling density follows a concave pattern, while access to transit stops and intersection density both show a positive association with AT. Industry diversity exhibits a convex relationship, indicating that its effect initially declines and then increases. Access to parks follows a concave pattern, with a slight initial increase followed by a sharp decrease. For leisure trips, AT is positively associated with access to walkable destinations. The relationship with tree coverage follows a convex pattern, showing a general increase. In contrast, the relationship with distance to water bodies is also convex but characterized by a sharp decrease.

Although some variables may not be statistically significant, it is important to include them in the model to ensure comprehensive predictions of AT across all DAs and to capture the full range of factors that may influence the outcome. In Section 4.3, we show the shape of these relationships based on the predicted values.

Table 2. Coefficient of BNE characteristics based on the purpose of travel

	School			Work			Shopping			Leisure		
	R squared: 0.100			R squared: 0.248			R squared: 0.272			R squared: 0.192		
Independent variable	Trans	Coeff	Pr	Trans	Coeff	Pr	Trans	Coeff	Pr	Trans	Coeff	Pr
Access to sidewalks	Log	1.944	0.251	Log	2.561	0.036 **	Log	0.582	0.481	Log	1.277	0.145 .
Access to bike lanes	Cubic	1) -2.447 2) 2.375 3) -2.404	0.631 0.387 0.287	Cubic	1) 3.770 2) -1.523 3) -2.399	0.392 0.512 0.201	Log	3.595	0.206	Original	2.042	0.502
Access to walkable destinations	Cubic	1) -5.019 2) 4.222 3) -0.071	0.356 0.253 0.977	Cubic	1) 12.230 2) -7.826 3) 3.572	0.014 ** 0.014 ** 0.074 *	Quadratic	1) -2.078 2) 0.339	0.532 0.853	Log	0.171	0.088 *
Dwelling density	Quadratic	1) 3.473 2) -2.104	0.126 . 0.294	Quadratic	1) 2.980 2) -5.497	0.155 . 0.065 *	Quadratic	1) 3.660 2) -2.885	0.012 ** 0.059 *	Quadratic	1) -0.052 2) -5.435	0.980 0.130 .
Access to transit stops	Original	0.000	0.560	Original	0.000	0.100 *	Log	0.320	0.002 ***	Log	0.079	0.507
Intersection density	Log	0.459	0.063 *	Cubic	1) 1.043 2) 1.457 3) -1.548	0.744 0.521 0.379	Cubic	1) 5.462 2) -2.123 3) 0.711	0.017 ** 0.255 0.626	Cubic	1) -2.270 2) 0.783 3) 0.465	0.357 0.678 0.758
Industry diversity - HHI	Quadratic	1) -2.550 2) 1.663	0.255 0.479	Quadratic	1) 7.458 2) -4.304	0.002 *** 0.065 *	Quadratic	1) 0.207 2) 2.866	0.888 0.054 *	Quadratic	1) 0.815 2) -0.503	0.638 0.776
Access to tree coverage	Cubic	1) 7.015 2) 1.184 3) -1.877	0.051 * 0.649 0.511	Cubic	1) 9.402 2) 2.814 3) -1.814	0.003 ** 0.198 . 0.387	Quadratic	1) 2.642 2) 0.843	0.225 0.617	Quadratic	1) 5.826 2) 0.264	0.016 ** 0.892
Access to parks	Quadratic	1) -9.814 2) -10.550	0.013 ** 0.065 *	Quadratic	1) -7.185 2) 1.280	0.009 *** 0.637	Quadratic	1) -6.407 2) -0.982	0.002 *** 0.737	Quadratic	1) -3.430 2) 2.129	0.101 . 0.331
Distance to water bodies	Cubic	1) -7.748 2) 4.870 3) 2.714	0.011 ** 0.038 ** 0.212	Quadratic	1) -8.477 2) -0.514	0.002 *** 0.812	Quadratic	1) -2.709 2) -2.073	0.144 . 0.180 .	Quadratic	1) -4.819 2) 1.231	0.020 ** 0.474

Significant at the 1% (***), 5% (**), 10% (*) and 20% (.) levels.

Quadratic equation: $y = a_1x + b_2x^2 + c$. In the table, "a" corresponds to 1 (the original value), and "b" corresponds to 2 (the squared value).

Cubic equation: $y = a_1x + b_2x^2 + c_3x^3 + d$. In the table, "a" refers to 1 (the original value), "b" to 2 (the squared value), and "c" to 3 (the cubic value).

Log equation: $y = \log_e (x+1)$

4.3 Predicted relations between the built and natural environment and active travel

We use the fitted models obtained from this analysis to predict the values of AT for all purposes for each DA based on the population characteristics. Figure 4 illustrates the relationship between walking and cycling levels in Montreal on the Y-axis and the independent variables on the X-axis. We found that access to sidewalks, bike lanes, and transit stops shows a similar pattern. As access to these amenities increases, AT constantly increases for leisure and shopping trips. There is a small but steady increase for school, while for work, there is a sharp rise followed by a plateau and a slight decline. For access to walkable destinations, AT consistently increases for leisure, shopping, and work, but eventually levels off and slightly decreases for leisure and shopping. For school, there is a slight increase before it flattens out. A similar pattern is observed for intersection density, although the decline at the end is more pronounced for leisure and shopping trips. For school, there is an inverted "U" relationship, while work shows a consistent increase.

Regarding dwelling density, access to tree coverage, and industry diversity, an inverted "U" relationship is observed across all four purposes. This indicates that beyond a certain threshold, in which higher values in these variables do not lead to more AT, and in some cases lead to a decline. Notably, the inverted "U" pattern is more gradual for industry diversity. Access to parks follows a similar trend, though the peak of the inverse "U" is reached more quickly. For distance to water bodies, an inverted "U" relationship is seen for all purposes except school.

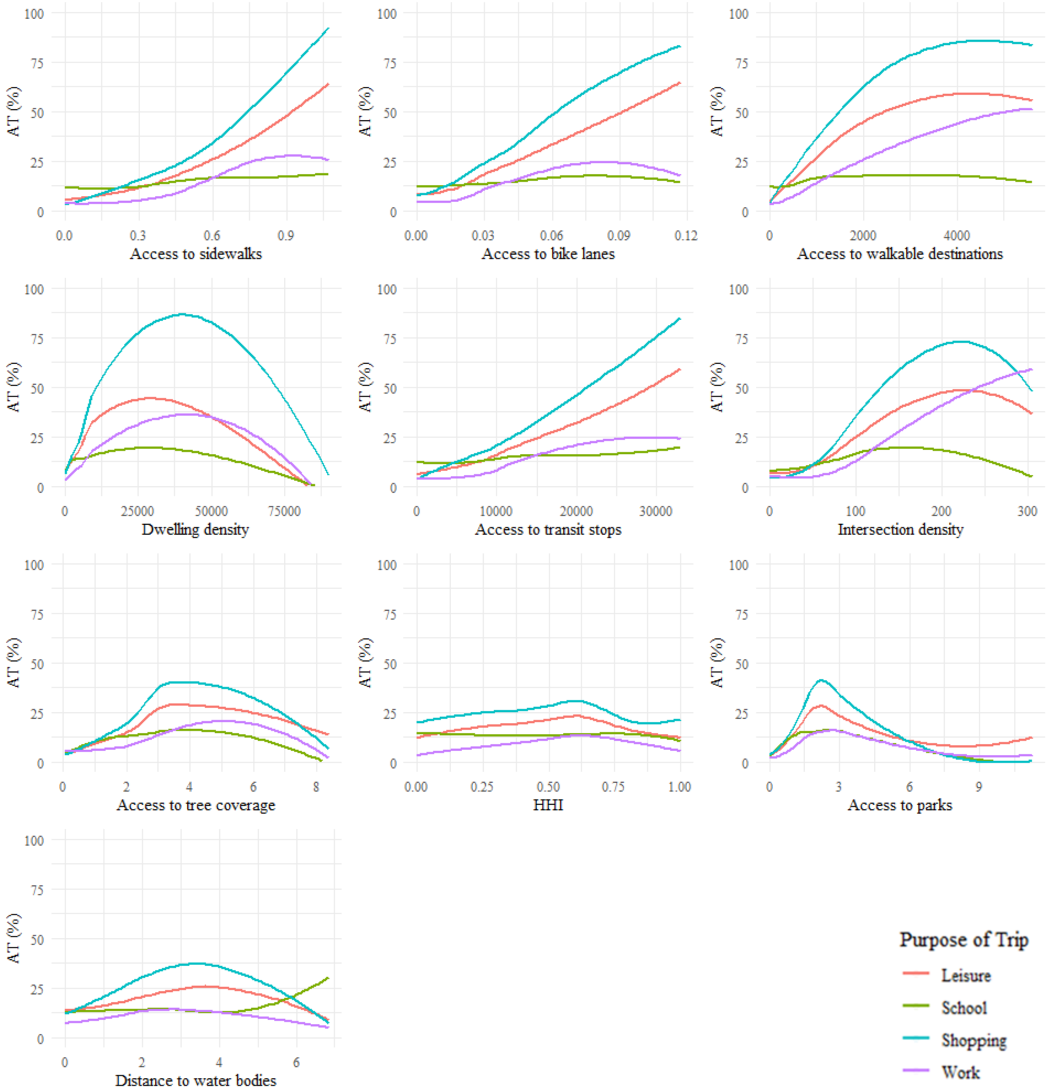

Figure 4. Predicted relationship between AT and BNE variables

4.4 Predicted values and Hot Spot analysis

Figure 5 illustrates again the distribution of the AT across purposes, but now using the predicted values. We observe a consistent pattern for work, leisure, and shopping trips, where most trips are concentrated in central areas characterized by a higher value of built environment features. Conversely, peripheral areas exhibit lower values. However, for school trips, we found a higher dispersion of higher values across the island.

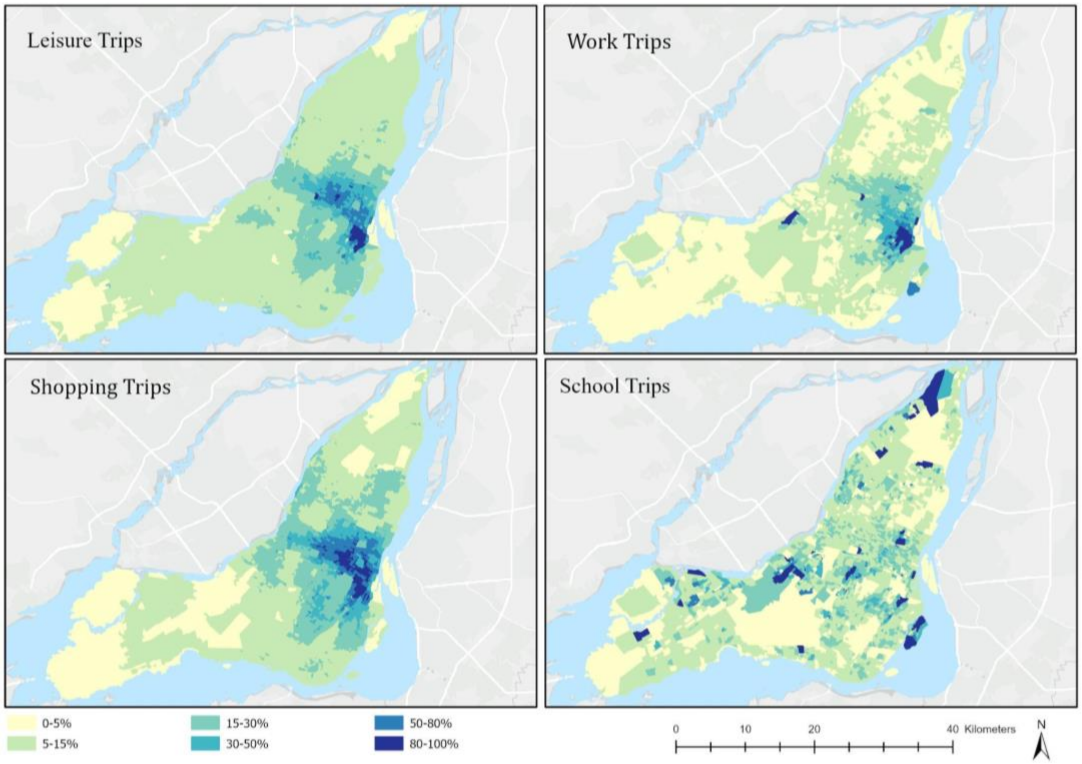

Figure 5. Predicted AT by trip purposes at the DA scale

Using the predicted values, we utilized Hot Spot Analysis (Getis-Ord Gi* statistic) to gain insights into spatial patterns and identify statistically significant clusters of high and low values. Results show that central areas have clusters of high levels of active travel for work, leisure, and shopping trips. The patterns differ for school trips, where we observed small, scattered hotspots rather than prominent clusters. Areas identified as cold spots, characterized by low participation in AT, represent opportunities for targeted interventions to encourage walking and cycling (Figure 6).

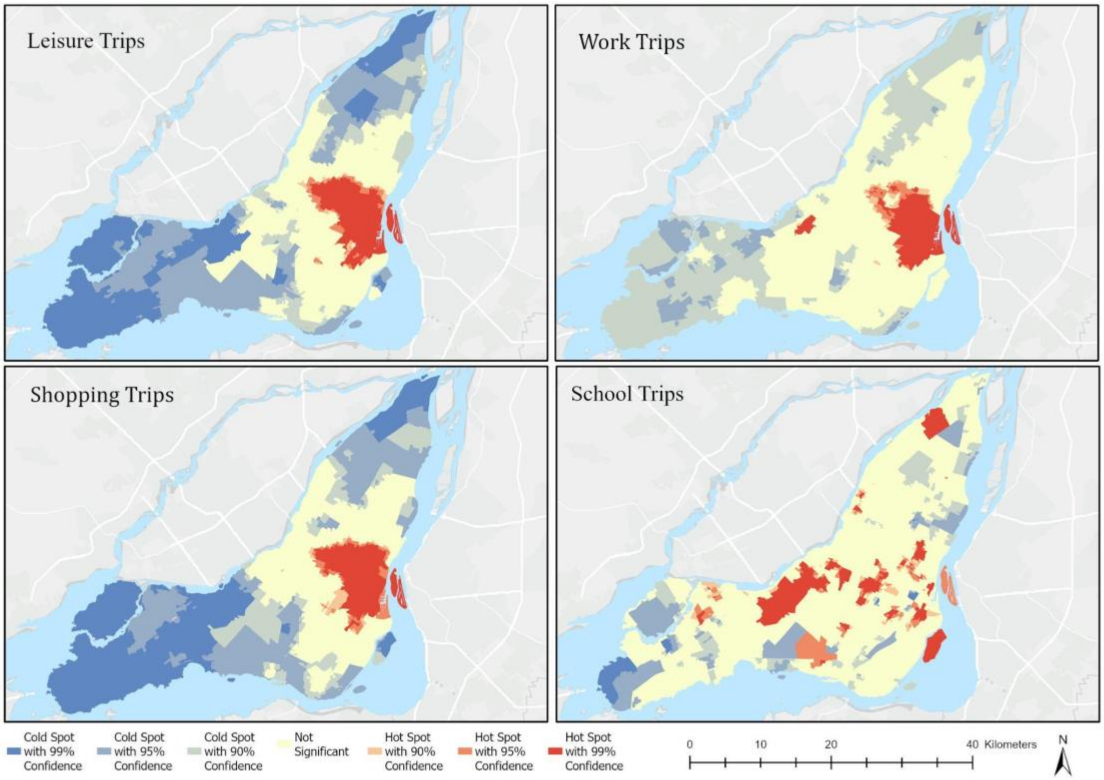

Figure 6. Hot Spot analysis of predicted AT by trip purposes

Figure 7 shows areas of the city that, due to the current BNE values, have low and high potential to support AT. In Map "A," a significant portion of the areas has low potential to support AT. Specifically, 31 DAs do not support any form of active trips, while 114 DAs lack support for all trips except school. Additionally, 494 DAs highlighted in dark green on the maps do not support AT for leisure and shopping, indicating potential areas for improvement to benefit residents in these neighborhoods. Furthermore, DAs on the island's southern edge fail to support AT for school purposes, underscoring the need for targeted interventions in these areas. In Map "B," we can see that the central part of Montreal primarily supports AT for all trip purposes, with some areas not facilitating AT for school. Notably, only approximately one-fourth of DAs are supportive of AT.

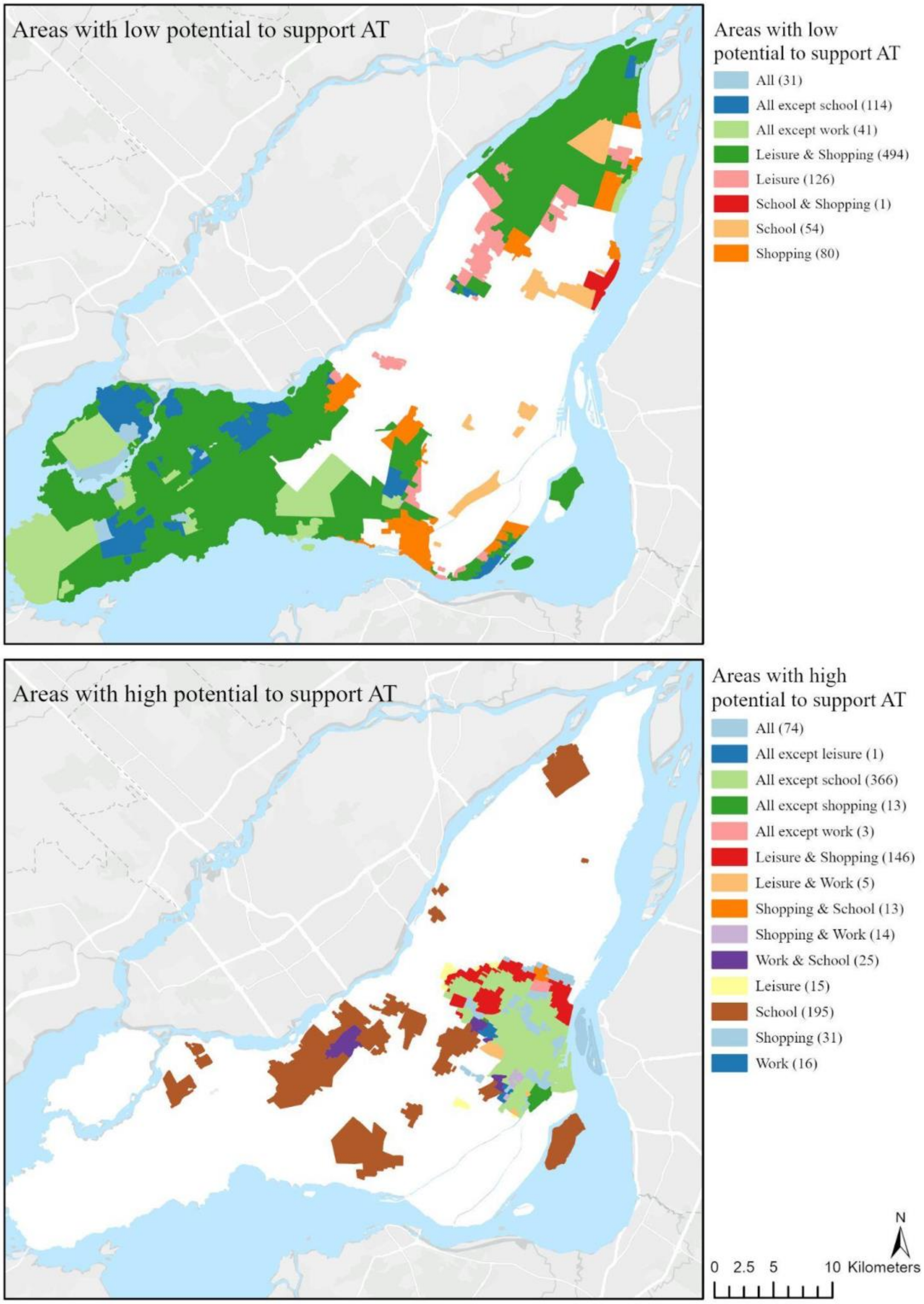

Figure 7. Areas with low (A) and high (B) potential to support AT

5 Discussion

One of the objectives of this research was to examine relationships between built and natural environment variables and active travel across trip purposes. We found that non-linear patterns are common in these relationships, and these can vary depending on the trip purpose. To achieve these results, this study predicted AT for all DAs on the Island of Montreal, as we found that some DAs were undersampled. In this model, although not all variables are statistically significant across all trip purposes, including them is important to capture the full complexity of how different BNE factors influence AT. Similar approaches, which prioritize understanding relationship patterns over significance testing, are common in the literature (Dong et al., 2025).

The results support findings from other studies that have found non-linear relationships between BNE and AT but with some differences (Frank, 1994; Liu et al., 2021; Mitra & Buliung, 2012; Tao et al., 2023; Yang et al., 2022). In this study, we found that some variables, such as access to sidewalks, transit stops, and bike lanes, tend to increase AT, albeit at different rates. In some cases, there is a threshold beyond which further increases in the independent variable yield no additional benefits and may even lead to a decline. We identified an inverted U-shaped relationship for several variables: intersection density, dwelling density, industry diversity (HHI), access to parks, tree coverage, and proximity to water bodies. However, some exceptions were observed depending on the purpose of the trip.

Consistent with Liu et al. (2021), we found an inverted U-shaped relationship between intersection density and AT, which was common for most of the purposes. Low active travel levels in areas with low intersection density may be attributed to a limited availability of sidewalks. However, at very high intersection densities, AT decreases, possibly due to longer waiting times at traffic lights, increased travel times, and a higher risk of pedestrian and cyclist collisions with vehicles. The observed inverted "U" relationship of industry diversity aligns with previous literature (Liu et al., 2021). Areas with low industry diversity may discourage AT due to a lack of diverse destinations. Conversely, extremely high diversity, such as in industrial zones or areas near airports, may also discourage AT, as these areas are often inaccessible by walking or biking and typically require motorized transportation. For dwelling density, we found an inverted U-shaped relationship across all trip purposes, which contrasts with findings from Yang et al. (2022), who reported a U-shaped relationship. For walkable destinations, we found that an increase tends to lead to higher AT values, but it reaches a saturation point at which increasing access to walkable destinations does not lead to higher AT.

Increasing access to sidewalks, bike lanes, and transit stops consistently increases AT, making it a key priority for urban planners. However, a balanced approach is needed for factors such as park access, industry diversity, intersection density, and tree coverage, with some variations depending on the purpose of the trip. While these elements generally encourage active travel, there is a threshold beyond which their impact diminishes or even becomes negative. Recognizing these saturation thresholds is important for designing effective policies. For example, ensuring good intersection density can improve connectivity, but excessive density may lead to longer wait times at crossings, discouraging walking and cycling. Policymakers should account for these trade-offs to design environments that maximize AT while implementing cost-effective policies.

The second objective was to identify areas in Montreal with high potential for active travel based on the BNE across trip purposes. Our results show clear spatial variation in BNE features, which in turn shapes the potential of different areas to support AT. Areas where the BNE already supports AT for all travel purposes are primarily found in the central parts of the city. Conversely, AT levels are significantly lower in peripheral areas for most travel purposes, needing substantial improvements in terms of transportation and land use planning. These areas should be prioritized, but considering several strategies depending on the trip purpose, to support and increase AT.

6 Conclusion

We conclude that BNE variables could have non-linear relationships with AT, and that these relationships vary depending on the purpose of the trip. These results suggest that, in many cases, continuously maximizing or increasing certain built or natural environment variables may not lead to higher active travel, as there may be a threshold beyond which further increases no longer lead to gains in active travel. These changes depend on the purpose of the trip. Therefore, it is important to consider these patterns in transportation and land-use planning, as they can provide more efficient and targeted strategies to promote active travel.

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Author contribution

The authors confirm their contribution to the paper as follows: Conceptualization: P. Salsabilian, J. A. Jasso Chávez, and K. Manaugh; Visualization: P. Salsabilian; Validation: P. Salsabilian and J. A. Jasso Chávez; Software: P. Salsabilian and J. A. Jasso Chávez; Resources: P. Salsabilian, J. A. Jasso Chávez, and K. Manaugh; Methodology: P. Salsabilian, J. A. Jasso Chávez, and K. Manaugh; Investigation: P. Salsabilian and J. A. Jasso Chávez; Formal analysis: P. Salsabilian and J. A. Jasso Chávez; Data curation: P. Salsabilian and J. A. Jasso Chávez; Writing – original draft: P. Salsabilian and J. A. Jasso Chávez; Writing – review & editing: K. Manaugh; Supervision: K. Manaugh.

Data Availability

The original data on the locations of commercial establishments and businesses was obtained from DMTI Spatial Inc. as geospatial data. The file contains detailed information on business locations, including geographic coordinates, industry classification, and business type. Due to commercial restrictions, the data cannot be shared publicly.

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