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The influence of built environment on speeding behavior – a naturalistic approach☆

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A R T I C L E I N F O

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A B S T R A C T

The built environment elements in urban areas can have a significant impact on the performance of transport systems, including road safety. The primary objective of this research is to investigate the influence of the built environment on speeding behavior, as an indicator of road safety performance, using the city of Curitiba, Brazil, as the study's setting. The built environment comprises physical features within the city, such as development patterns and roadway designs, and can be categorized into six groups: density, diversity, design, destination accessibility, distance to transit, and demographics. The Geographically Weighted Regression (GWR) statistical model was employed to explore the correlation between built environment variables and the occurrence of speeding in a spatially nonstationary scenario. Additionally, Moran's *I* and Local Moran statistical methods were applied to investigate the spatial autocorrelation of speeding within the city. Data on speeding and location were collected through the application of a Naturalistic Driving Study. The measure of speeding was based on free-flow situations, considering the opportunity in which drivers could speed. In this study, the database included 1002 trips, 381.45 h of driving, and 9,443.83 km of travel within Curitiba and its metropolitan area from 2019 to 2021. The GWR model was applied using Curitiba's traffic analysis zones (TAZs) as the zonal level. GWR reduced residual spatial autocorrelation relative to the global linear model; however, the global model achieved a lower AICc. Only the variable "proportion of arterial roads" showed a statistically significant correlation with speeding at a 95 % confidence level, with an inverse correlation observed across 100 % of the TAZs. Furthermore, it was observed that speeding behavior in Curitiba exhibits spatial autocorrelation, justifying the use of the GWR model. Low-Low and High-High spatial clusters were identified, with statistically significant differences observed between them, including average income, density of commercial and service units, density of intersections, density of speed cameras, and traffic signal density. The characteristics of arterial roads in Curitiba, including infrastructure and traffic control, may be influencing the reduction of speeding behavior.

1. Introduction

1.1. Background

Following the principles of the safe systems approach, the design of both the road system and the surrounding built environment, including land use, roadway patterns, and other physical features should encourage safer behaviors among users, thus reducing overall speeds and minimizing conflicts (Wegman, 2017). Speeding behavior by vehicle drivers in urban environments constitutes one of the primary risk factors for the occurrence and severity of road crashes. The consequences of excessive speed extend to three critical aspects of traffic conflicts: reaction time, braking distance, and the force of impact (Mohan, 2016).

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It's important to recognize that the actual operating and mean speeds of road traffic are influenced by various factors, including the user's vehicle's power and stability, road and traffic conditions, the driver's perception of safety, levels of enforcement, personal characteristics, and the surrounding built environment (Ewing and Dumbaugh, 2009; Richard et al., 2013b; Shinar, 2017). In light of these considerations, it is evident that built environment designers should prioritize the integration of road safety considerations into their planning and design processes, particularly in urban areas where interactions between diverse road users are frequent and the consequences of speeding can be especially severe.

1.2. The impact of built environment on road safety

The built environment consists of physical elements and features, including the development pattern and roadway design of a city (Ewing and Cervero, 2010). Land use and transport plans influence the choice of destination, modal choice, travel distances, traffic volumes, traffic conflicts, and traffic speeds, thereby impacting road traffic safety performance (Ewing and Dumbaugh, 2009; Tiwari, 2016). Built environment variables are often characterized by five key dimensions known as the 'Five Ds': density, diversity, design, destination accessibility, and distance to transit (Ewing and Cervero, 2010). Additionally, investigations of the effects of the built environment on road safety performance sometimes include demographic variables representing characteristics of residents, such as income, age, and sex (Obelheiro et al., 2019). Other factors, such as driving task complexity (Onate-Vega et al., 2020; Ortiz-Peregrina et al., 2023), presence of law enforcement (Kaye et al., 2024), and road user distraction (Chen and Lym, 2021; Hinton et al., 2024), also play roles in road safety. Density measures a variable of interest per unit of area and can encompass the quantity of residents, housing units, and jobs, thereby indicating the 'hot-spots' of overall activity within a city. Diversity refers to the presence of various land use types within a specific area, ranging from single-use environments to more mixed land uses. The design category includes physical characteristics such as block size, types and quantities of intersections, street widths, traffic calming and control elements, as well as street network density. Destination accessibility evaluates how easily one can reach places of interest, including jobs, services, commerce, and districts of overall significance, based on the distance and time required to reach these destinations. Distance to transit is typically measured by the availability of transportation services, including the quantity of transit stops. Demographic factors, while not inherent features of the built environment itself, can influence the occurrence of speeding in urban environments, with income, age, and sex being notable examples (Ewing and Dumbaugh, 2009; Ewing and Cervero, 2010; Richard et al., 2013a; Obelheiro et al., 2020).

Previous studies investigated the impact of several built environment elements on the occurrence of road traffic crashes, including population density (Lee et al., 2015; Pirdavani et al., 2014), land use diversity (Ouyang and Bejleri, 2014; Rhee et al., 2016), density of intersections (Dumbaugh et al., 2013; Huang et al., 2018), density of speed cameras (Høye, 2015; Li et al., 2013), traffic signal density (Lovegrove and Sayed, 2006; Obelheiro et al., 2020), proportion of arterial roads (Ukkusuri et al., 2012; Yu and Xu, 2017), network density (Marshall and Garrick, 2010, 2011), density of commercial and services units (Ouyang and Bejleri, 2014), bus stop density (Wei and Lovegrove, 2013; Kim et al., 2010), and average income (Marshall et al., 2013). Generally, the results showed that population density showed mixed correlations with road crashes. An increase in population density can lead to more conflicts in the same unit of area, causing more traffic crashes (Dumbaugh et al., 2013; Lee et al., 2015; Pirdavani et al., 2014), but it can also be related to fewer vehicle-kilometers traveled (VKT), and therefore, less exposure to road crashes (Dumbaugh and Rae, 2009; Obelheiro et al., 2020). A positive correlation between land use diversity and road crashes was found in previous works (Ouyang and Bejleri, 2014; Rhee et al., 2016). More diverse environments can cause higher traffic volumes of different types of users, leading to more conflicts and crashes (Obelheiro et al., 2020, 2019).

Regarding design aspects of the built environment, Dumbaugh et al. (2013) and Huang et al. (2018) found a direct correlation between the density of intersections and road crashes; however, other investigations resulted in an inverted correlation between the same variables (Ouyang and Bejleri, 2014; Zhang et al., 2015). Mixed results in correlation were also found between the density of speed cameras and road crashes (Li et al., 2013; Park et al., 2019). Traffic signal density showed a positive correlation in previous research (Lovegrove and Sayed, 2006; Lee et al., 2015). According to Obelheiro et al. (2020), traffic signals are usually installed in areas with more traffic conflicts, thus serving as a proxy for higher traffic volumes and exposure to crashes. Street hierarchy also was found to influence road safety. Higher rates of road crashes were found in urban areas with a higher proportion of arterial roads (Ukkusuri et al., 2012; Yu and Xu, 2017). Regarding network density, Marshall and Garrick (2010) and Marshall and Garrick (2011) observed an inverted correlation between this design element and the occurrence of road crashes.

Areas with easy access to destinations generate fewer vehicle-kilometers traveled, therefore reducing road traffic crashes (Ouyang and Bejleri, 2014; Welle et al., 2016). Bus stop density, representing the distance to transit, was found to have a direct correlation with road crashes. Bus stops lead to more traffic conflicts, serving as an increased activity generator, both as an origin and destination for pedestrians (Kim et al., 2010), but they can also reduce the free-flow speed of other motorized vehicles, reducing the opportunity for speeding (Bansal et al., 2014). The income level of an area or neighborhood is inversely correlated with road crashes. The income level of a region can directly represent the overall quality of its road system infrastructure. The age and maintenance level of vehicles can be related to the level of income, which is also a risk factor (Obelheiro et al., 2019).

1.3. Analytical approach to road safety in the built environment

Road safety performance in urban environments can be measured by the quantity, severity, and types of victims involved in traffic crashes. Other intermediate outcomes, such as speeding behavior, can also be used to analyze the operational conditions of traffic safety in cities. Naturalistic Driving Studies (NDS), as a type of observational, on-the-road study, can be implemented to gather data on speeding behavior in an uncontrolled scenario (Shinar, 2017). This method involves monitoring drivers' behavior in their vehicles, both in normal and safety–critical conditions. NDS provides a practically total immersion in the participants' everyday trips. Exposure to the experiment is usually higher in NDS, given that participants have data recorded over multiple trips. This results in a typically larger sample size but makes it harder to isolate the desired variables under investigation (Carsten et al., 2013).

In the last two decades (2003–2023), NDS research has been conducted in multiple countries. In the USA, the main studies included the 100-Car NDS (Neale et al., 2005) and The Strategic Highway Research Program 2 (SHRP 2) NDS (Njord and Steudle, 2015). Other NDS research has been conducted in Australia, known as the Australian Naturalistic Driving Study (Larue et al., 2019), in the European Union under the name UDRIVE (van Nes et al., 2019), Canada, which includes the Canadian Naturalistic Driving Study (CNDS, 2021) and Candrive I (Marshall et al., 2013), Japan (Uchida et al., 2010), China – The Shanghai Naturalistic Driving Study (Zhu et al., 2018), Iran (Sheykhfard et al., 2021), and Brazil – The Brazilian Naturalistic Driving Study (NDS-BR) (Bastos et al., 2020, 2021). Additionally, Amancio et al. (2023) investigated the correlation between vehicle speeds and speed bumps.

Most investigations of road safety and urban environmental elements have been performed at a micro level or macro level of analysis. Micro-level analysis focuses on elements of the road network, such as intersections (Arvin et al., 2019). Macro-level analysis involves aggregating variables into zones, including census sectors (Huang et al., 2018; Rhee et al., 2016) and traffic analysis zones (Hadayeghi et al., 2010; Pirdavani et al., 2014). Ziakopoulos and Yannis (2020) show that spatial approaches in road safety can be based on road segments, zonal areas, including census tracts and traffic analysis zones, and even regional areas as spatial units of analysis.

Previous research has shown that road safety performance indicators, such as the rate or quantity of traffic crashes, can exhibit spatial nonstationarity, a scenario where the behavior and correlation between variables vary by geographical location (Huang et al., 2018; Rhee et al., 2016). Therefore, it is important to consider a statistical model capable of analyzing the spatial dependency and heterogeneity expected in road safety factors related to the urban environment. One model that addresses this limitation is Geographically Weighted Regression (GWR), which allows the exploration of the relationship between variables in a context of spatial nonstationarity. The GWR model assumes that the model's nature must change over space to reflect the structure within the data, enabling the modeling and mapping of actual parameters for each location in space (Brunsdon et al., 1996).

1.4. The present study

The aim of this research is to investigate the influence of the built environment on speeding behavior using data from the NDS-BR dataset. Specifically, we aim to determine how various urban factors, such as road design and infrastructure, affect the prevalence of speeding in Curitiba. Additionally, we seek to identify spatial clustering of speeding behavior and analyze the characteristics of these clusters. Moreover, we assess the applicability of the Geographically Weighted Regression (GWR) model to understand the spatial variation in the relationship between the built environment and speeding tendencies. As a secondary objective, this research aims to provide insights for improving speed control strategies in urban areas, contributing to enhanced road safety and urban planning. The study is outlined in the following structure: Section 2 includes the methods of the research, with the data collection, processing and statistical modeling. Section 3 includes the results from the speeding data and statistical models, followed by the discussion in Section 4, limitations and future research in Section 5, and Conclusions in Section 6.

2. Methods

The current section includes the three main steps of the research methods: data preparation, and application of statistical methods: spatial autocorrelation and GWR.

2.1. Data preparation

2.1.1. The Brazilian Naturalistic Driving Study (NDS-BR)

The Brazilian Naturalistic Driving Study (NDS-BR) was executed in Curitiba, the capital city of the State of Paraná, in Brazil (location shown in Fig. 1). Curitiba has a population of almost 1.9 million people (IBGE, 2021) and has its own metropolitan region, including 28 other cities. Regarding other road safety indicators, in 2020 Curitiba presented 12.5 road crash deaths per 100,000 inhabitants, a value lower than the Brazilian rate of 15.4 in the same year (Ministry of Health, 2020).

The NDS-BR utilized non-intrusive instrumentation of vehicles, with two data acquisition systems (DAS). Each DAS contained three cameras, one GPS (Global Positioning System) sensor, one laptop, and one power supply. Two cameras were positioned on the windshield of the car, facing towards the front outside. One camera was positioned on the right window of the car, towards the inside of the vehicle, facing the driver. The inside camera was important for registering the drivers' behavior and to check if the subjects were really driving their cars – an important step in data preparation (Section 2.2).

Other crucial equipment was the GPS sensor, positioned near the car panel, which collected speed and location data, the two main input data in the analysis of this research. The GPS registered information including latitude and longitude coordinates, date, time, speed, heading, and altitude. The DAS allowed the acquisition of GPS and video data in synchronization, at a frequency of 1 Hz. The main controller of the data collection was the laptop. At the beginning of each trip, the driver needed to manually turn on the laptop after starting the car engine and before beginning the driving task. If the driver did not turn on the

Fig. 1. Curitiba's location (left) and street network (right).

equipment, intentionally or not, the data collection process was not executed.

The NDS-BR data collection started in August 2019. Until December 2021, the project collected data from 32 participants, which composed the sample of naturalistic data used in this work. The drivers participated in a survey that was divulged on social networks. The duration of data collection from each driver varied between 5 and 20 days. The age of the drivers varied between 21 and 63 years old, with 18 females and 14 males. Regarding the participants' vehicles, the model year varied between 2001 and 2020, with horsepower varying between 66 and 166 HP. Overall, a total of 1002 trips were performed, resulting in 381.45 h of driving and 9433.83 km of traveled distance. Four drivers occasionally made trips in carpooling situations and three drivers worked as mobility app drivers, which contributed to a significant portion of the total traveled distance. Among the participants, 27 lived in Curitiba and 5 lived in the neighboring cities inside the metropolitan region.

After data was extracted from the DAS, it was necessary to make a valid time check to exclude times from the original sample where the driver wasn't driving the vehicle, as shown in Fig. 2. For each trip, the period between the start of the car and when the participant started driving was considered invalid. During the trip, if the driver pulled over briefly and then started driving again, this period between the actions was considered as invalid as well. Finally, the gap between parking the car and turning off the DAS was discarded from the sample. Naturalistic data recorded outside of Curitiba were also discarded from the sample.

2.1.2. Speeding

To calculate speeding behavior, it was necessary to compare the performed speeds from drivers with the respective speed limit. Speed limit data was collected from the road axis data obtained from OpenStreetMap (OpenStreetMap, 2021), completing some missing information with speed limits from IPPUC (Institute of Research and Urban Planning of Curitiba) road axis data (IPPUC, 2021). Considering the collaborative and open-access nature of OpenStreetMap, a general check on speed limit data was performed on main corridors and on different road hierarchies, in order to guarantee that the data matched with observations from local road users. A spatial join between the NDS data and road axis data was performed to associate both information, considering a 10-meter buffer around each link of the road axes. Points outside the buffers (in the middle of street blocks, for example) were removed from the sample. Also, points without speed limit and performed speed data were removed from the sample. The spatial join process was conducted using the 'sf' package for the R programming language (Pebesma, 2018), based on both spatial buffer and naturalistic data.

The operational aspects of urban road traffic (mostly in interrupted flow conditions) arbitrarily reduce the amount of speeding being measured. To address this problem, it is necessary to keep only the free-flow situations of the trip from the total trip distance, removing situations in which drivers had no opportunity to speed. The selection of free-flow and speeding events followed a method defined by Richard et al. (2013a). As presented in Eq. (1), the occurrence of speeding (SP), which can vary between 0 and 1, is represented by the proportion of distance traveled at speeds above the speed limit (D_{sp}), divided by the distance performed in free-flow speeds (D_f).

$$SP = \frac{D_{sp}}{D_f} \tag{1}$$

In Brazil, a speeding infraction is considered when the driver exceeds the speed limit plus 10 % of the speed limit. Therefore, in a fast transit road with an 80 km/h speed limit, a driver would be fined if the speed reaches above 88 km/h. Considering other urban road hierarchies and limits defined by the Brazilian Traffic Code (Brazil, 2007), speeding in arterial roads (speed limit of 60 km/h) would be considered as speeds above 66 km/h; in collector roads (speed limit of 40 km/h) – speeds above 44 km/h; and local roads – speeds above 33 km/h (speed limit of 30 km/h). Therefore, based on the thresholds of 8 km/h, 6 km/h, 4 km/h, and 3 km/h, it was decided to establish a standard threshold for speeding of 5 km/h above the speed limit. Free-flow speeds included those higher than the speed limit minus 10 km/h (and lower than the speeding threshold). The free-flow threshold was based on the value established by Richard et al. (2017) of 5 mph. Direct conversion to km/h would result in 8.05 km/h. Therefore, the threshold was rounded up to 10 km/h.

The occurrence of speeding and built environment variables (as presented in Section 2.2.2) were calculated for each traffic analysis zone (TAZ) inside Curitiba. One hundred thirty-five TAZ, established in Curitiba's origin–destination survey made by IPPUC in 2018, was used for this work (IPPUC, 2018). The TAZ aggregates multiple census tracts with similar characteristics inside a defined territory. These tracts were defined in the last census with detailed data available in Brazil, performed in 2010 (IBGE, 2021).

2.1.3. Built environment

The built environment variables that were calculated are listed in

Table 1
Built environment variables.

Category	Variable	Description [unit]
Density	PD	Population Density [inhab/km^2]
Diversity	LDI	Land use diversity index
Design	DIS	Density of intersections [no./km]
	DSC	Density of speed cameras [no./km]
	TSD	Traffic signal density [no./km]
	PAR	Proportion of arterial roads
	SND	Street network density [km/km^2]
Destination accessibility	DCSU	Density of commercial and services units [no./km]
Distance to transit	BSD	Bus stop density [no./km]
Demographics	AVI	Average income [BRL]

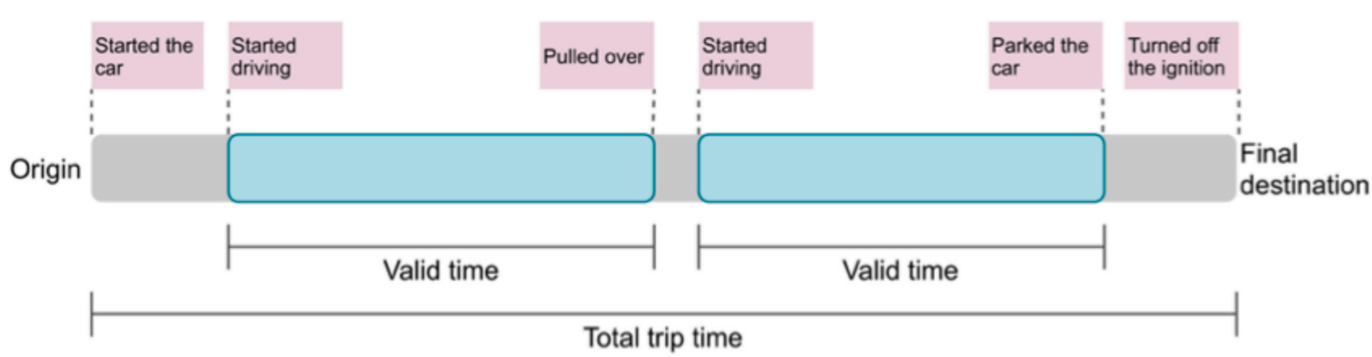

Fig. 2. Valid time selection.

Table 1. Inside the density category, population data were obtained from the last Brazilian Census in 2010 (IBGE, 2021). Using the available census tracts, it was possible to calculate the population density (PD) data in each TAZ.

The land use diversity index (LDI) was calculated based on a method described by Huang et al. (2018) and presented in Equation (2):

$$LDI = \frac{-\sum_i^n P_i \times ln(P_i)}{ln(n)}; \tag{2}$$

where i is the type of land use, n is the total number of land use types in a TAZ, and P_i is the proportional area of land use type i. Information from Curitiba's zoning plan was used as input (IPPUC, 2021; Curitiba, 2019). The density of intersections (DIS) was calculated based on the number of intersections divided by the length of roads. Also, the density of speed cameras (DSC) and traffic signal density (TSD) computation followed the same method of calculation, using data from the Municipal Office of Social Defense and Transit of Curitiba (SETRAN, 2020) and IPPUC (2021), respectively.

The calculation the proportion of arterial roads (PAR) was also based on the IPPUC road axis data. In this variable, fast transit and arterial roads were combined into one category representing arterial roads. Therefore, the proportion of arterial roads was based on the fraction between arterial and total road length. Street network density (SND) is the total road length divided by the area in square kilometers of the respective TAZ. The density of commercial and services units was calculated based on data provided by IPPUC (2021), considering data from 2019. Bus stop density (BSD) considered data provided by URBS, the company that manages the public transport of Curitiba. Finally, the average income (AVI) was obtained from the Brazilian Census of 2010 (IBGE, 2021).

2.2. Spatial autocorrelation of speeding

The first step to analyze the spatial autocorrelation of speeding behavior in Curitiba-PR was the application of Moran's I method. This test is designed to reject the null hypothesis of spatial randomness in favor of an alternative of spatial clustering or dispersion (Getis and Ord, 2010). The results of Moran's I test vary between -1 and 1, where -1 represents a perfect dispersion pattern and 1 represents a perfect clustering pattern of the data. Results close to 0 and/or without the desired statistical significance (p-value) represent a lack of spatial autocorrelation. Moran's I consist of the following equation:

$$I = \frac{n}{W} \times \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}; \tag{3}$$

where n is the sample size, w_{ij} is the matrix of spatial weights, W is the sum of all w_{ij}, x is the variable of interest, indexed by i and j, and $\bar{x}$ is the mean of x (Getis and Ord, 2010).

Other than observing if speeding behavior is spatially autocorrelated or not, it was necessary to map this spatial behavior, identifying hot and cold spots in the data, in addition to possible spatial outliers. For this objective, the Local Moran statistic was applied. Local Moran is a local counterpart of Moran's I, and classified as a local indicator of spatial association (LISA), characterized for providing a spatial autocorrelation statistic for each location (Anselin, 2010, 2020).

Following Moran's I method shown in Eq. (3), the Local Moran statistic for each observation i is:

$$I_i = \frac{\sum_j w_{ij} z_i z_j}{\sum_i z_i^2}; \tag{4}$$

where z is the deviation from the mean of the variable of interest ($x - \bar{x}$). The denominator is fixed in the local configuration, therefore, it can be ignored. Replacing the denominator with a constant c and rearranging the equation, the obtained expression is:

$$I_i = c \times z_i \sum_j w_{ij} z_j; \tag{5}$$

representing the product of the value at a location i with the weighted sum of the values at neighboring locations j. Both Moran's I and Local Moran methods were applied using the queen contiguity-based spatial weight of first order. The queen criterion defines neighbors as spatial units sharing a common edge and/or vertices. In this configuration, all neighbors contain the same spatial weight (Bivand et al., 2013).

After identifying the location of spatial clusters, the final step of the spatial analysis of speeding is to investigate if there are any differences between Low-Low and High-High clusters regarding built environment variables, using the Wilcoxon Rank Sum Test. This test is commonly used to check if the median difference between pairs of observations is not zero (alternate hypothesis) (Hollander and Wolfe, 2015).

2.3. Geographically weighted regression

Prior to implementing the GWR model, certain criteria needed to be applied to organize the data. These criteria were associated with the distribution of naturalistic data concerning traveled distances within the Traffic Analysis Zones (TAZ). Firstly, zones where the distances traveled accounted for less than 10 % of the total road length within that particular zone were excluded from the sample. Secondly, TAZ lacking free-flow episodes were also excluded from the analysis.

These steps were essential to ensure a meaningful and representative dataset for subsequent analysis using the GWR model. The GWR allows the exploration of the relationship between variables in a spatial non-stationarity context, considering that the nature of the model must alter over space to reflect the structure within the data and allow the actual parameters for each location in space to be modeled and mapped (Brunsdon et al., 1996). The following equation includes the basic form of GWR:

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} x_{ik} + \epsilon_i; \tag{6}$$

where y_i is the dependent variable at location i, x_{ik} is the value of the kth independent variable at location i, m is the number of independent variables, β_{i0} is the intercept parameter at location i, β_{ik} is the local regression coefficient for the kth parameter at location i, and ϵ_i is the random error at location i. The GWR model depends on a spatial weighting function called w_{ij} that controls the contribution of point j on the calibration of a model for point i. This function represents the idea that observations closer to i have more influence in the estimation of i's parameters (Gollini et al., 2013). These influences are calculated by a weighted least squares approach, described in the following equation:

$$\hat{\beta}_i = \left(X^T W(u_i, v_i) X\right)^{-1} X^T W(u_i, v_i) y; \tag{7}$$

where X is the matrix of the independent variables with a column of 1 s (ones) for the intercept, y is the dependent variable vector, $\hat{\beta} = (\beta_{i0}, ..., \beta_{im})^T$ is the vector of $m+1$ local regression coefficients and W_i is the diagonal matrix denoting the spatial weighting (w_{ij}) of each observed data for regression point i at location (u_i, v_i) (defined by the selected spatial weighting function). The spatial weighting function is also known as the kernel function. This function can have multiple configurations. Six configurations tested in this research: Gaussian, Exponential, Boxcar, Bisquare, Tricube, and Global configurations.

The distance between observations i and j is defined by d_{ij}, inside a chosen b bandwidth. The bandwidth can have two configurations: fixed or adaptive. Fixed bandwidth consists of an absolute value of distance, and adaptive bandwidth consists in choosing a fixed quantity of neighbors for each regression point i. The second configuration works better for zonal levels with irregular sizes, including traffic analysis zones

(TAZ) and census tracts (Yu and Xu, 2017), therefore, it was selected for this research. The optimal size of bandwidth was chosen with the testing of multiple values to reach a lower value of corrected Akaike Information Criterion (AIC_c).

The final step was to analyze the performance between the GWR models based on different kernel configurations. This analysis was based on four performance indicators: AIC_c, R^2, adjusted R^2, and the value of Moran's I (Eq. (3)) on the models' residuals. A regression model with a good spatial analysis performance shows a lack of spatial autocorrelation on its residuals. Higher values of R^2 and adjusted R^2 indicate a better performance.

3. Results

The process of removing invalid times from the total sample and choosing the traveled data that happened in Curitiba resulted in 5687.70 km of traveled distance and a total of 821 trips, representing a traveled time of 220.35 h. Incomplete trips – when only a portion of the trip happened inside Curitiba – were kept in the sample, without the sections that were traveled outside the city borders. Overall, all trips in the sample had a mean distance of 6.92 and a median of 4.54 km traveled. The average quantity of trips per driver was 26, with a median value of 24 trips. The range of trips performed by drivers varies from a minimum of 3 trips to a maximum of 56 trips. Regarding time of the day, most of the traveled distance happened between 7 am–8 am and 6 pm–7 pm. Considering distance traveled per TAZ (Fig. 3), the TAZ with the highest traveled distance had 205.29 km, and the lowest had 0.01 km. Five zones had no traveled distance. The data arrangement process reduced the total sample of 135 TAZ into 117 TAZ. The remaining sample included 3419.19 km performed in free-flow speeds and 1508.05 km performed in speeding.

3.1. Speeding behavior

The map in Fig. 4 shows the results of SP per TAZ and Local Moran results based on SP values. SP varied between 0.04 and 0.77, with a mean value of 0.46 and a median of 0.47. Regarding Local Moran results, the Low-Low clusters indicate lower values of SP in 14 zones of the city. Two Low-High outliers were detected between the High-High clusters. High-High clusters can be observed at eight different zones. One High-Low cluster was detected. Moran's I statistics on the SP values resulted in 0.246 with a p-value of 0.001. This is an indication that SP is spatially autocorrelated.

Considering the Wilcoxon Rank Sum Test between TAZ in Low-Low ($n = 14$) and High-High ($n = 8$) clusters, five independent variables showed p-values (< 0.05) where the null hypothesis could be rejected: AVI, DIS, TSD, DCSU and DSC, indicating a significant difference. Fig. 5 shows a pair of boxplots for each variable and cluster group. AVI, DCSU, DSC and TSD values are higher in Low-Low clusters. On the other hand, DIS values are higher in High-High clusters.

3.2. Model results

Table 2 includes the descriptive statistics of the 11 variables, considering the 117 TAZ. DSC, LDI, PAR and TSD values resulted in zero for some TAZ, indicating a lack of speed cameras, land use diversity, arterial roads, and traffic signals in these zones.

In Table 3, the model diagnostics of five GWR and one global linear model is shown, based on four performance indicators: AIC_C, R^2, Adjusted R^2, and Moran's I on residuals. The p-value indicates the statistical significance of Moran's I results. The global linear regression presented the best AIC_C, with a value of -142.372. Regarding R^2 and adjusted R^2, the GWR model with bisquare kernel showed the best diagnostic, presenting values of 0.342 and 0.195, respectively. The bisquare kernel presented the lowest value of Moran's I on residuals (0.106). All GWR models presented a better performance compared to the global linear model when considering the spatial autocorrelation of the residuals, but the global model performed better when considering AIC_C values. Given that speeding behavior is spatially autocorrelated (Fig. 4), it was decided to discard the global linear model in favor of a GWR model. Among GWR kernels, bisquare produced the highest R^2 / adjusted R^2 and the lowest residual Moran's *I, while Gaussian and Boxcar yielded lower (better)* AICc; we therefore selected bisquare to balance explanatory power and spatial diagnostics.

The coefficient estimates of the linear regression model are presented in Table 4, including the standard error, t-values, and p-values. The only

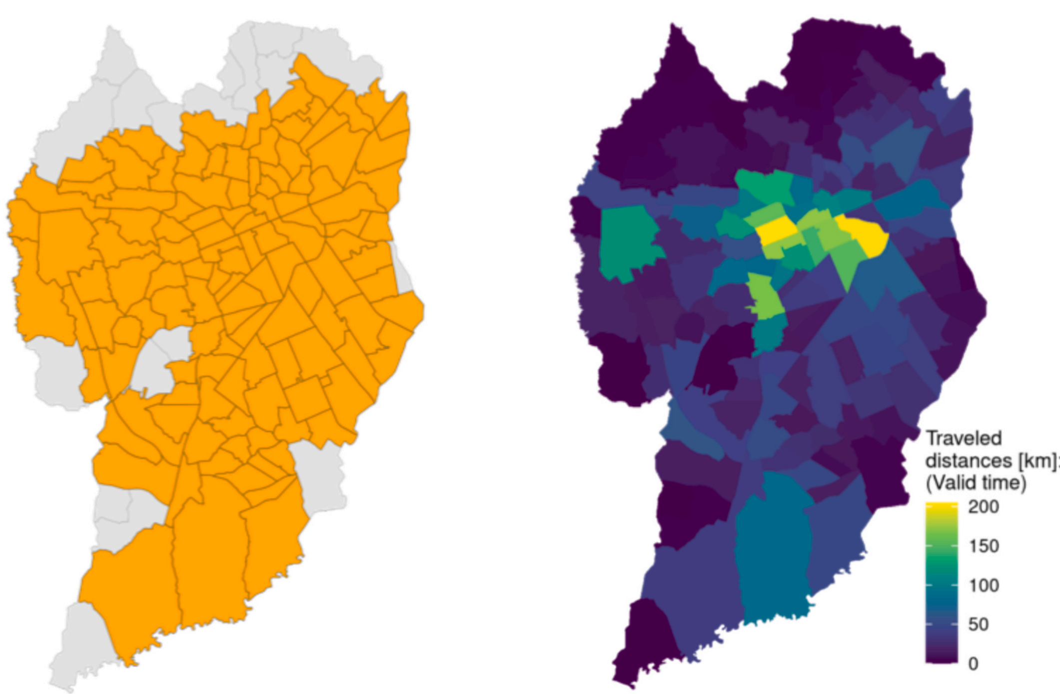

Fig. 3. Remaining TAZ in the sample (left) and traveled distances per TAZ (right).

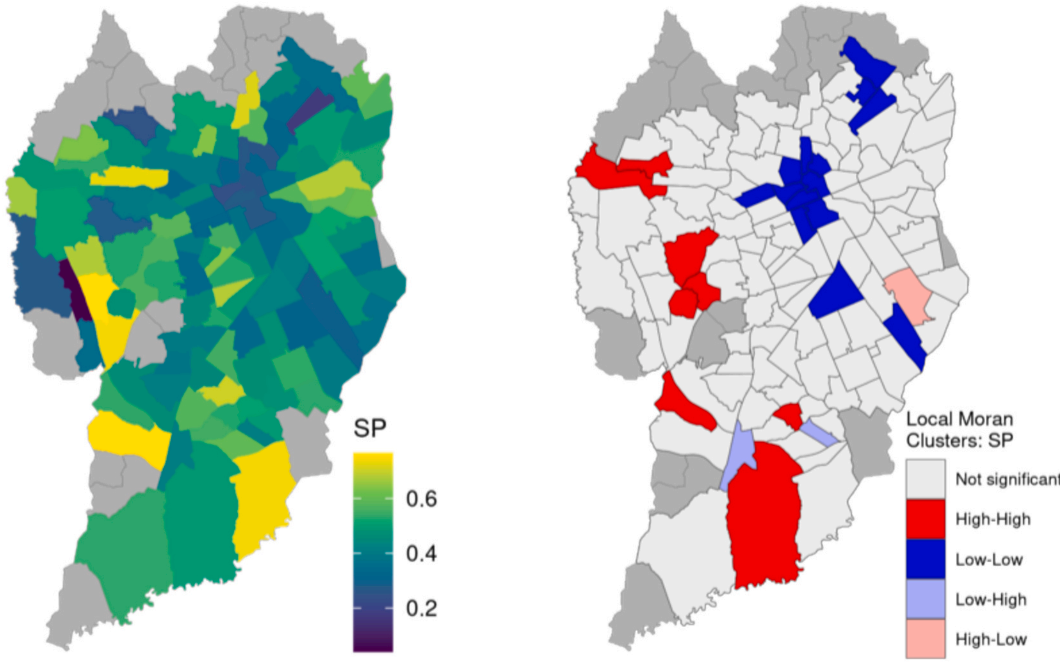

Fig. 4. SP per TAZ (left) and Local Moran results (right).

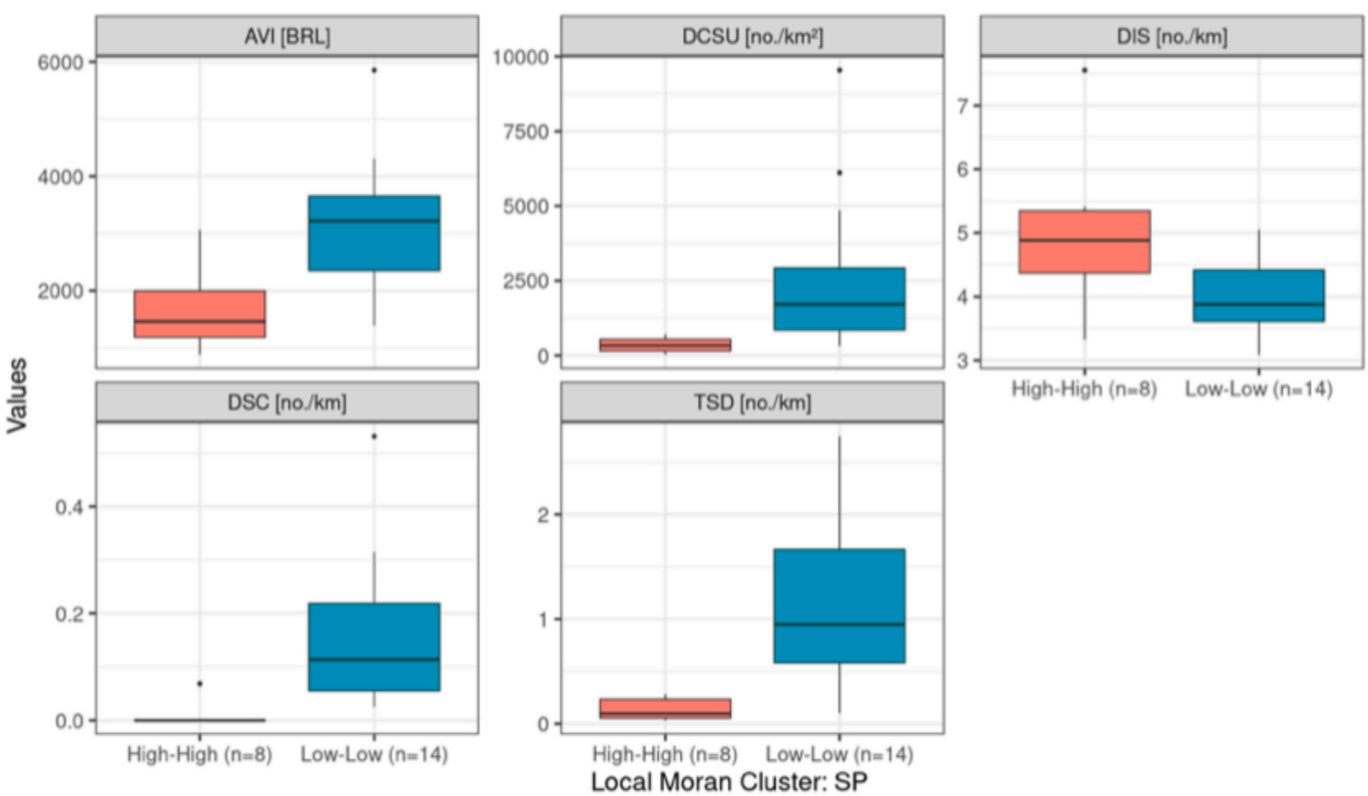

Fig. 5. Built environment variables in High-High and Low-Low SP clusters.

statistically significant coefficient at the 95 % level was the proportion of arterial roads (PAR), which expressed an inverted correlation to speeding. Observing the *p*-values of the linear model it is possible to identify statistical significance of the GWR parameters estimates, considering that GWR does not have a diagnostic value to analyze coefficient significance (e.g., *p*-value).

Table 5 includes the descriptive statistics of the chosen GWR model coefficient estimates and Fig. 6 includes all maps, apart from the Intercept, of these coefficient estimates. Regarding the only statistically significant coefficient estimate – the proportion of arterial roads (PAR) – all values resulted in negative coefficients, representing an inverted correlation to speeding.

In Table 6 is presented the percentage of TAZ with positive and negative coefficient estimate for each independent variable. TSD, PAR,

Table 2
Descriptive statistics of model's variables.

Variable	Mean	SD	Min.	1Q	Median	3Q	Max.
AVI	2,635.66	1,562.12	807.21	1,407.53	2,102.42	3,603.45	9,293.81
BSD	3.05	2.15	0.29	1.79	2.50	3.55	13.90
DCSU	852.48	1,188.07	12.30	340.66	536.74	881.25	9,539.73
DIS	4.64	1.11	0.88	3.89	4.53	5.19	7.70
DSC	0.06	0.09	0.00	0.00	0.03	0.08	0.53
LDI	0.61	0.22	0.00	0.52	0.65	0.74	0.99
PAR	0.05	0.05	0.00	0.00	0.05	0.08	0.21
PD	5,692.36	3,118.80	114.68	3,285.42	5,591.78	7,248.87	16,142.06
SND	15.10	4.43	3.68	12.60	15.72	18.15	25.78
SP	0.46	0.14	0.04	0.35	0.47	0.54	0.77
TSD	0.38	0.48	0.00	0.09	0.20	0.41	2.75

Table 3
Model diagnostics.

Model	Kernel	AIC_C	R^2	Adj.R^2	Moran's I	p-value	Bandwidth
GWR	Gaussian	−141.905	0.282	0.186	0.130	0.013	115
	Bisquare	−138.502	0.342	0.195	0.106	0.031	115
	Tricube	−136.661	0.324	0.192	0.112	0.028	115
	Boxcar	−141.828	0.273	0.190	0.122	0.016	105
	Exponential	−141.122	0.324	0.190	0.121	0.018	115
Global Linear	–	−142.372	0.262	0.192	0.137	0.008	–

Table 4
Summary of linear model estimates.

Coefficient	Estimate	Std. Error	t-value	p-value
Intercept	5.362e−01	8.322e−02	6.444	3.52e−09
TSD	−5.747e−02	5.425e−02	−1.059	0.2919
PAR	−5.743e−01	2.864e−01	−2.005	0.0475*
DCSU	−9.240e−06	1.842e−05	−0.502	0.6169
AVI	−2.949e−06	8.748e−06	−0.337	0.7367
BSD	−1.781e−03	7.530e−03	−0.236	0.8135
LDI	6.655e−02	5.754e−02	1.156	0.2501
DSC	−2.636e−01	1.919e−01	−1.374	0.1724
SND	−3.196e−03	4.646e−03	−0.688	0.4930
PD	1.106e−06	6.756e−06	0.164	0.8703
DIS	3.565e−03	1.470e−02	0.243	0.8088

DCSU and DSC presented negative coefficient estimates on 100 % of the TAZ, representing an inverted correlation to speeding. On the other hand, only LDI presented positive coefficient estimates on 100 % of the TAZ. AVI, BSD, SND, PD and DIS presented mixed results, depending on the geographical position in the city.

4. Discussion

This study examined the relationship between the built environment and speeding behavior in Curitiba, using the NDS-BR dataset. Spatial analysis through Moran's I and Local Moran's I revealed clear patterns of spatial autocorrelation in speeding rates across defined Traffic Analysis Zones (TAZs). "High-High" clusters refer to areas where a TAZ with a high speeding rate is surrounded by neighboring TAZs with similarly high rates. Conversely, "Low-Low" clusters represent areas where a TAZ with a low speeding rate is bordered by TAZs with similarly low rates. In total, 8 zones were classified as High-High and 14 as Low-Low, with the latter predominantly located in the city's central region. The concentration of Low-Low clusters in central areas—indicative of reduced speeding—may be linked to the statistically significant differences observed between the two cluster types, as identified by the Wilcoxon Rank Sum Test.

Upon closer examination, the Low-Low clusters displayed distinct socioeconomic and infrastructural characteristics. These areas had higher Average Income values (AVI) and a greater density of commercial and service units (DCSU), suggesting zones of socioeconomic affluence and commercial activity. From an infrastructural perspective, these clusters also showed a higher concentration of speed control mechanisms, particularly speed cameras (DSC) and traffic signals (TSD). This pattern may reflect a deliberate strategy to manage vehicle speeds in these areas. In contrast, the High-High clusters were marked by a notably higher density of intersections (DIS), a design feature that may contribute to the elevated speeding rates observed in these zones.

Traffic control and speed enforcement measures—represented by traffic signal density (TSD) and speed camera density (DSC)—were more

Table 5
Descriptive statistics of GWR coefficient estimates.

Coefficient	Min.	1Q	Median	3Q	Max.
Intercept	4.5052e−01	4.8525e−01	5.1751e−01	5.4015e−01	0.5908
TSD	−1.0215e−01	−6.8228e−02	−5.8685e−02	−4.7568e−02	−0.0180
PAR	−1.1447e + 00	−9.6812e−01	−7.9620e−01	−6.4543e−01	−0.5257
DCSU	−2.1754e−05	−1.5861e−05	-1.3686e−05	−1.2182e−05	-7.3097e-06
AVI	−1.1639e−05	−5.3192e−06	−1.4183e−06	2.9770e−06	7.8683e-06
BSD	−1.3013e−02	−2.8248e−03	1.4463e−03	4.6713e−03	0.0093
LDI	2.9687e−02	6.3914e−02	9.5462e−02	1.3020e−01	0.1748
DSC	−3.3630e−01	−2.5344e−01	−2.0223e−01	−1.6457e−01	−0.1194
SND	−5.7131e−03	−4.2905e−03	−3.4024e−03	−2.2709e−03	0.0005
PD	-1.2511e−06	1.8165e−06	3.0573e−06	4.5435e−06	6.3239e-06
DIS	−6.3914e−03	−4.3202e−04	1.0566e−03	2.8706e−03	0.0088

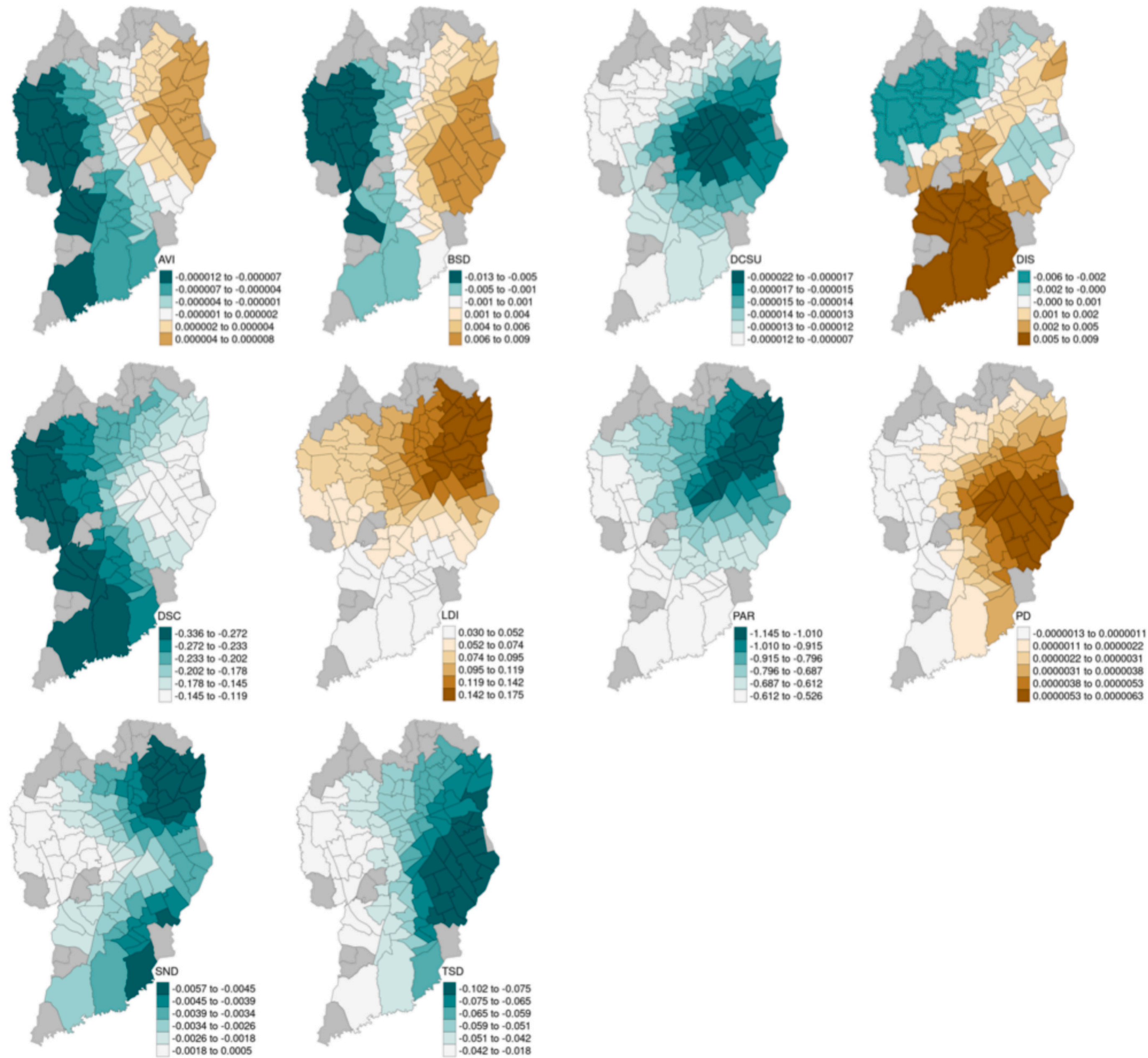

Fig. 6. GWR coefficient estimates.

Table 6
Percentage of TAZ with positive/negative coefficients.

Coefficient	Negative	Positive
Intercept	0 %	100 %
TSD	100 %	0 %
PAR	100 %	0 %
DCSU	100 %	0 %
AVI	55 %	45 %
BSD	38 %	62 %
LDI	0 %	100 %
DSC	100 %	0 %
SND	96 %	4 %
PD	7 %	93 %
DIS	36 %	64 %

prevalent in Low-Low clusters. This aligns with previous findings suggesting that such infrastructure can influence driving behavior, although prior studies have reported mixed effects of traffic signals on speeding. These effects often depend on factors such as signal cycle length, progression speed, and the spacing of signalized intersections (Elvik et al., 2009; Furth et al., 2018). The effectiveness of speed cameras in reducing speeding has also been discussed in the literature (Li et al., 2013; de Oliveira et al., 2015; Truelove et al., 2023). In this study, TAZs within Low-Low clusters consistently showed lower levels of speeding, suggesting a potential link between these control measures and reduced speeding behavior. Regarding intersection density (DIS), prior research generally associates higher DIS with lower speeding rates. However, in this case, TAZs in High-High clusters—those with elevated speeding—exhibited higher DIS values, indicating that other local factors may be influencing this unexpected outcome.

After testing five configurations of the Geographically Weighted Regression (GWR) model, the version using the bisquare kernel demonstrated the best performance. However, none of the models adequately addressed the spatial autocorrelation in the residuals, indicating the presence of spatial nonstationarity in speeding behavior across Curitiba. This suggests that a more tailored regression approach may be needed to account for spatial variation. Among the tested variables, the proportion of arterial roads (PAR) remained statististically significant in the global model ($p = 0.00475$), supporting its inclusion alongside spatially varying effects observed in the GWR analysis. This inverse correlation contrasts with findings from previous studies, which reported a positive relationship, implying that local contextual factors in Curitiba may be influencing this difference. While earlier research has primarily used GWR to examine the relationship between built environment features and road crashes, the present study highlights the model's potential for investigating speeding behavior as well.

This investigation offers a comprehensive analysis of how the built environment influences vehicular speeding behavior in Curitiba. The identified patterns of spatial autocorrelation—driven by variables such as traffic signal density, speed camera density, and intersection density—highlight the close relationship between urban infrastructure and driver behavior. These findings have important implications for urban planners, traffic engineers, and policymakers. First, understanding the links between specific urban features and speeding behavior allows for more precise and effective interventions. Practitioners can use this insight to strategically deploy traffic control measures—particularly in High-High and Low-Low cluster areas—to reduce speeding and improve road safety. Second, the observed patterns of average income (AVI)-with higuer AVI linked to less speeding in some clusters but not uniformly accross the city-point to the need for a more equity-focused approach to urban development. Policymakers should address disparities in traffic safety and prioritize, or at least equally support, infrastructure improvements in lower-income neighborhoods. In addition, the negative correlation between arterial roads and speeding found in this study calls for a re-evaluation of how these corridors are designed. Potential strategies may include implementing speed-calming infrastructure, increasing public awareness through safety campaigns, or fundamentally redesigning arterial roads to discourage speeding (Welle et al., 2016). Finally, this research underscores the importance of adopting a data-driven, region-specific approach to addressing speeding and road safety. By applying these insights, cities can move toward building safer, more efficient, and more equitable environments for all residents.

5. Limitations and future research

This study, while offering insights into the relationship between the built environment and speeding in Curitiba, is not without limitations. Notably, the sample size, in comparison to other NDS studies, was constrained and predominantly centered around the city's core, thus not providing a comprehensive representation of all Traffic Analysis Zones in Curitiba. The performance of the GWR models was suboptimal, with spatially autocorrelated residuals suggesting that these models did not always surpass the efficacy of linear regression. Furthermore, it's imperative to consider extraneous variables beyond the built environment—such as driver characteristics, vehicular conditions, additional speeding countermeasures and temporal factors—that might significantly influence speeding. The behavioral dimension, especially road users' risk perception, plays a pivotal role in speeding and deserves mention. Other speeding thresholds can be tested in order to investigate different levels of speeding. Future research avenues should include the deployment of more robust spatial regression models like GWR to delve deeper into spatial intricacies. There's potential value in leveraging satellite imagery to derive a precise portrayal of land use, and examining various zonal systems, such as census tracts, could mitigate concerns like the modified areal unit problem. To cultivate a more holistic understanding, expanding the dataset and juxtaposing results from diverse urban settings will be beneficial.

6. Conclusions

In conclusion, this study closely examined how the built environment influences speeding behavior in Curitiba, Brazil, using two main methods: the Naturalistic Driving Study (NDS-BR) and Geographically Weighted Regression (GWR). After testing multiple kernel configurations, the bisquare kernel was found to be the most effective for the GWR analysis. The results revealed a statistically significant inverse correlation between the proportion of arterial roads (PAR) and speeding across all sampled Traffic Analysis Zones (TAZs). Additionally, spatial autocorrelation in speeding behavior (SP) was assessed using Moran's I and Local Moran's I, confirming that speeding patterns were not randomly distributed but spatially dependent. The Local Moran's analysis identified High-High and Low-Low speeding clusters within the city, which enabled comparisons of built environment characteristics across these zones. Most Low-Low clusters were concentrated in the city center, and this spatial distribution corresponded with notable differences in key variables such as average income, density of commercial and service units, intersection density, speed camera density, and traffic signal density.

These findings highlight the crucial role of urban design in shaping driver behavior. For urban planners and designers, this underscores the importance of carefully considering how built environment elements impact road safety. The study's results show that features such as road type, infrastructure density, and socioeconomic context can significantly influence speeding behavior. Therefore, integrating road safety considerations into the early stages of planning and development can help build safer and more resilient urban communities.

CRediT authorship contribution statement

Pedro Augusto Borges dos Santos: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Oscar Oviedo-Trespalacios:** Supervision, Investigation, Conceptualization. **Silvana Camboim:** Writing – original draft, Investigation. **Jorge Tiago Bastos:** Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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