NOVA
IMS
Information
Management
School

MDSAA

Master Degree Program in
Data Science and Advanced Analytics

WALKABILITY AND ITS RELATIONSHIP WITH TRAFFIC AND AIR QUALITY

A GEO WEIGHTED REGRESSION ANALYSIS FOR LISBON

Ezio Antonio Carvalho de Oliveira Filho

Master Thesis/Project Work

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

WALKABILITY AND ITS RELATIONSHIP WITH TRAFFIC AND AIR QUALITY:

A MULTI-DIMENSIONAL ANALYSIS FOR URBAN ENVIRONMENTS

By

Ezio Antonio Carvalho de Oliveira Filho

Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Data Science

Supervised by

Supervisor: Miguel de Castro Neto, PhD, NOVA Information Management School

Co-supervisor: Bruno Jardim, PhD, NOVA Information Management School

July 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Ezio Antonio Carvalho de Oliveira Filho

[Lisboa, 2024/07/15]

AKNOWLEGDEMENT

I would like to express my deepest gratitude to:

My parents, Ezio and Noemi, for their unwavering support throughout my life, especially during my master's studies. Your unconditional love and assistance have been invaluable.

My girlfriend, Ana, for her constant encouragement and help during this challenging period. Your support allowed me to focus on delivering my best work.

My grandmothers, Josefa and Neide, and my uncle Celso, for their endless enthusiasm and belief in my abilities. Your cheers have been a source of motivation and strength.

Your love and support have been instrumental in my journey, and I am profoundly grateful to have you all in my life.

ABSTRACT

This thesis explores the intricate relationship between walkability and urban environmental factors such as traffic and air quality. Walkability, a crucial element in urban planning, has increasingly been recognized for its significant impact on health, ecological balance, and social interaction within urban settings. The research employs a multi-dimensional analysis, utilizing variables from the walkability literature to analyze their impact on Car Traffic and Air Pollution, by the use of Geographically Weighted Regression of Gaussian and Poisson distributions. The findings suggest that some variables that are significant for Walkability might have an opposite impact on Car Traffic and Air Pollution or can greatly reduce both. This thesis contributes to urban planning discussions by providing more information on aspects of the city that can be thought out in a planning stage.

KEY-WORDS

Walkability; Urban Design; Indicators; Smart Cities; Air Pollution; Car Traffic

Objetivos do Desenvolvimento Sustentável (ODS):

3 GOOD HEALTH AND WELL-BEING

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

TABLE OF CONTENT

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

NEWS	Neighborhood Environment Walkability Scale
Can-ALE	Can-ALE - Canadian Active Living Environments Built Environment and Health Neighborhood Walkability Index
GWR	Geographically Weighted Regression
CRISP-DM	Cross Industry Standard Process for Data Mining
CO	Carbon Monoxide
NO	Nitrogen Oxide
NO2	Nitrogen Dioxide

1. INTRODUCTION

Recently, Walkability has been a topic with increasing interest in different fields in order to ensure a better urban environment (Blečić et al., 2020). This growing shift is driven by an understanding of the numerous benefits that walkable environments offer, including health, ecological, and social advantages (Frank et al., 2006). Walkable places or walkable environments are locations designed for easy and pleasant walking. Building upon this, Walkability is the measure of how accessible services and amenities are by walking.

Developing communities with walkability at their core is crucial for promoting physical activity and improving general health. Studies indicate correlations between neighborhood walkability, active transportation use, and favorable body mass index outcomes (Frank et al., 2006). Walkable places also show a positive relationship with mental health wellbeing through reduced environmental stressors and increased sense of community (X. Li et al., 2021).

From an environmental perspective, walkability plays a vital role in reducing reliance on motorized transportation, thereby decreasing greenhouse gas emissions and air pollution. This contributes to the fight against climate change and supports the creation of more sustainable cities (Gilderbloom et al., 2015). Additionally, walkability has been linked to economic benefits, including the impact on residential property values and housing markets (McCormack et al., 2023; Rafiemanzelat et al., 2017).

Furthermore, walkability is in line with several united nations sustainable development goals (SDGs). It directly supports sustainable cities and communities (Goal 11) by enhancing urban resilience and accessibility, and indirectly contributes to Goal 3 good Health and Well-being) and Goal 13 (Climate Action(Jano Reiss et al., 2022; Rubaszek et al., 2023).

However, while the benefits of walkability have been extensively studied, there is a notable lack of research examining the direct relationships between specific features that impact walkability and their effects on air quality and car traffic. This work aims to address this gap by utilizing an existing walkability indicator (Jardim et al., 2023) to analyze its impact on these crucial urban variables. By employing the features of the walkability indicator as independent variables in a regression model, this research will examine their effects on air pollution and traffic conditions. The goal is to reveal how various aspects of walkability contribute to changes in air quality and traffic patterns, thereby providing insights that can guide urban design and policy toward creating more sustainable and livable cities.

The structure of this thesis begins with a literature review that examines some well-known walkability indicators and their differences. It then explains why each independent variable was selected based on common walkability research and explores the relationship of car traffic and air pollution with walkability. The methodology chapter, following a CRISP-DM structure, details the steps taken to prepare the data and outlines which regressions and geographically weighted regressions will be used to model air pollution and car traffic based on the independent features of the walkability indicator. In the results chapter, the outcomes of the regressions and GWR models for each dependent variable are presented, analyzing the beta coefficients of the global regression model and the spatial betas. The thesis concludes with a summary of key insights and a discussion of their implications for future urban development and research.

2. LITERATURE REVIEW

This literature review explores various aspects of urban walkability, focusing on indicators, features, and their relationships with car traffic and air pollution. The chapter aims to provide a comprehensive overview of current research and methodologies in assessing and improving pedestrian-friendly environments in urban settings.

2.1. WALKABILITY INDICATORS

This section examines different tools and methods used to measure and evaluate walkability in urban areas. It covers popular indicators such as Walk Score®, Walkability Index, and newer approaches like the Street-Point Method, discussing their strengths, limitations, and applications in urban planning and development.

2.1.1. Walk Score®

The Walk Score is a convenient instrument that provides immediate feedback on the walkability of a specific location. Its primary advantage lies in its simplicity and user-friendliness. By quantifying the walkability of neighborhoods based on proximity to essential amenities, it offers a clear, easily understandable metric (Carr et al., 2011). This simplicity makes it an invaluable tool for real estate buyers and renters, helping them to quickly assess the pedestrian-friendliness of potential homes (Hirsch et al., 2013).

Another significant benefit of the Walk Score is its integration into various real estate and urban planning platforms. It has become a standard feature in many property listings, aiding individuals in making informed decisions about where to live based on walkability (Nykiforuk et al., 2016). Furthermore, Walk Score's popularity has raised public awareness about the importance of walkable urban design, encouraging cities to focus on improving pedestrian infrastructure (Koohsari et al., 2018).

While the Walk Score is highly regarded for its simplicity and widespread use, it does have notable limitations. Its reliance solely on the proximity to amenities can oversimplify the complex nature of walkability, not accounting for factors such as street design, pedestrian safety, and topography (Duncan et al., 2011). Additionally, the Walk Score tends to be less accurate in rural or suburban areas where distances to amenities are naturally greater, potentially misrepresenting the walkability of these areas (Carr et al., 2011).

2.1.2. Walkability Index

The Walkability Index stands out for its comprehensive approach to assessing pedestrian environments. Unlike tools that focus solely on proximity to amenities, this index considers a wider array of factors including street connectivity, land use diversity, and residential density (Stockton et al., 2016). Additionally, it considers aspects like aesthetics, social and environmental characteristics, and air pollution (Shafray & Kim, 2017). This multifaceted methodology offers a deeper understanding of an area's walkability, capturing the essence of what makes a neighborhood truly pedestrian-friendly.

In addition to its detailed analysis, the Walkability Index is particularly valuable for urban planners and policymakers. It provides a data-driven basis for decision-making, enabling the development of targeted interventions to enhance pedestrian infrastructure (Arifin et al., 2020). By identifying specific areas that need improvement, such as safer street crossings or better sidewalk connectivity, the index aids in the strategic allocation of resources for urban development. Furthermore, it considers the effectiveness of moving on foot and elements of the environment that encourage this type of mobility (Eynard et al., 2020).

The Walkability Index, despite its comprehensive approach, faces challenges. Its complexity and the need for extensive data can limit its applicability, especially in areas where detailed urban data is not readily available. Moreover, while it offers a detailed assessment, there's a risk of generalizing certain aspects and overlooking unique local factors that significantly influence walkability. This can result in a less accurate depiction of certain neighborhoods, especially those with unique geographic or cultural characteristics (Kaczynski et al., 2012).

2.1.3. Neighborhood Environment Walkability Scale (NEWS)

The Neighborhood Environment Walkability Scale offers a unique approach by capturing residents' perceptions of their neighborhoods (Cerin et al., 2006). This subjective assessment provides invaluable insights into how residents interact with their environment, highlighting the importance of pedestrian-friendly features such as safe sidewalks and traffic calming measures (Ding, 2003). The NEWS scale’s focus on resident feedback makes it a valuable tool for community-based urban planning, ensuring that improvements align with the actual needs and preferences of the people who live in these areas (Sallis et al., 2009). However, the subjective nature of this assessment can introduce biases and limit its reliability and comparability across different areas (McCormack et al., 2008).

2.1.4. (Can-ALE) - Canadian Active Living Environments Built Environment and Health Neighborhood Walkability Index

The Canadian Active Living Environments (Can-ALE) - Built Environment and Health Neighborhood Walkability Index is a significant tool, particularly in the context of public health. By linking the built environment to health outcomes, Can-ALE provides a critical understanding of how urban design can influence physical activity levels and overall well-being (Colley et al., 2019; Fry et al., 2018). This index is especially relevant in the Canadian context, where it informs urban planning policies aimed at promoting active living and reducing lifestyle-related health issues (Herrmann et al., 2019). However, its focus on Canada may limit its applicability elsewhere, and the extensive data requirements pose challenges for implementation (Moin et al., 2021).

2.1.5. National Walkability Index

The National Walkability Index offers a broad, standardized framework for assessing walkability across entire nations (Watson et al., 2020). Its ability to benchmark and compare different regions is invaluable for national policy development and infrastructure investment (Slater et al., 2013). By highlighting areas that lag in walkability, the National Walkability Index plays a crucial role in guiding national efforts towards creating more walkable, sustainable, and health-conscious urban environments (Giles-Corti et al., 2014). Yet, its broad scope might lead to oversimplifications, and the challenge of collecting consistent data across varied regions can impact its accuracy (Mavoa et al., 2018).

2.1.6. The Street-Point Method for Granular Walkability Assessment

This recent walkability indicator, developed by Jardim et al., 2023, addresses the shortcomings of current methods used in measuring walkability. As stated in the subsections above, traditional approaches often generalize walkability over large areas like neighborhoods, missing the finer details at the level of individual streets. This new method acknowledges that walkability can vary greatly within the same area.

By assigning a walkability score to every meter along a street, the indicator aims to capture the subtle complexities of urban environments. It considers factors such as the condition of the streets, the availability of amenities, and how accessible they are. This approach provides a deeper insight into how these elements influence walking decisions, recognizing that pedestrians are affected by their immediate surroundings.

This tool was created to serve urban planners and policymakers, offering a practical resource for local improvements. It empowers them with detailed information about the specific factors that most significantly affect walkability. This can guide improvements in infrastructure, amenities, and urban design, leading to more walk-friendly and sustainable urban areas. Overall, this walkability indicator is designed to provide a more precise and applicable measure for urban planning purposes.

This thesis aims to build upon the methodology previously implemented by Jardim et al., 2023, using the variables from the walkability model to analyze their impact in other variables, such as car traffic and air pollution. The analysis is based on the premise that factors like vehicular traffic and air quality have a significant impact on the walking experience.

2.2. FEATURES RELATIONSHIP WITH WALKABILITY

This section delves into the various urban features that influence walkability. It explores how elements such as crosswalks, educational institutions, entertainment venues, food establishments, and other urban amenities contribute to creating pedestrian-friendly environments and impact walking behavior.

2.2.1. Crosswalks

Crosswalks play a pivotal role in enhancing walkability in urban environments. Research indicates that introducing speed humps at main crosswalks can significantly increase campus walkability by reducing stops and traffic conflicts (Fernandes et al., 2019).Furthermore, crosswalks have been shown to reduce pedestrian crashes, thereby improving walkability in cities (De Paiva Neto et al., 2021). They are a critical element of walkability, alongside other factors such as pedestrian facilities and pedestrian-vehicle conflicts (Dannenberg et al., 2005) .

The presence of crosswalks, especially high-visibility ones, has become more common around US transit stations, enhancing safety and walkability (M. Li et al., 2023). Crosswalks are also important predictors of active transportation, contributing significantly to the overall walkability of a street (Jensen et al., 2017). In neighborhoods, crosswalks are significantly associated with walking for transportation among older adults (Corseuil Giehl et al., 2017). The severity of pedestrian injuries is likely to be lower at non-signalized crosswalks and intersections than at signalized ones (Park & Ko, 2020). Thus, crosswalks are integral to creating pedestrian-friendly urban landscapes.

2.2.2. Education

Educational institutions play a crucial role in enhancing walkability, as studies show that proximity to schools and colleges encourages walking and cycling (Gallagher & Morris, 2016). The design of school neighborhoods, particularly in terms of street connectivity and traffic volume, significantly influences the likelihood of children walking to school (Giles-Corti et al., 2011). Furthermore, the distribution and accessibility of facilities on university campuses have been found to impact walkability, affecting physical health and productivity (Mu & Lao, 2022). The presence of walkable communities around schools, coupled with fewer perceived barriers to walking, increases the frequency of students walking to school (Napier et al., 2011). Additionally, the overall walkability of a neighborhood, including factors like distance from school, plays a key role in active school commutes (Macdonald et al., 2019).

2.2.3. Entertainment

The presence of entertainment venues like art centers, casinos, cinemas, community centers, nightclubs, and theatres significantly impacts walkability. These venues affect the relationship between walking behavior and the physical environment, contributing to city sustainability (Rafiemanzelat et al., 2017). Walkable communities with entertainment options improve residents' health, reduce crime, and support local economies by encouraging neighborhood shopping (Cubukcu, 2013). Additionally, the availability of walkable destinations, including entertainment venues, is associated with increased walking, bicycling, and public transit use (Glazier et al., 2014). These venues also facilitate the generation and maintenance of social capital, an important component of quality of life in urban areas (Rogers et al., 2011)

2.2.4. Food

Having a variety of food establishments such as bars, cafes, fast-food restaurants, ice cream shops, pubs, and restaurants within walking distance is highly beneficial for urban walkability. These food outlets not only serve as key destinations for residents and visitors, but they also encourage pedestrian activity, contributing to a vibrant street life (Cerin et al., 2011).The presence of diverse food options within a walkable range can significantly enhance the appeal of walking as a mode of transportation, offering both convenience and enjoyment. Furthermore, the accessibility of these food outlets on foot can lead to better weight regulation and healthier lifestyles, as people are more likely to engage in walking when attractive destinations like food outlets are readily accessible (Sun et al., 2021). Additionally, the social aspect of food-related establishments, particularly in the context of parklets and public spaces, can foster community interactions and encourage more active, less sedentary lifestyles (Lindsey, 2021). Therefore, the integration of various food outlets within walkable distances is not only a matter of convenience but also a significant contributor to the overall health, social cohesion, and vibrancy of urban communities.

2.2.5. Finance

The proximity of financial services like banks and ATMs enhances urban walkability by contributing to transport-related walking, especially among women (Cerin et al., 2007). Street network configuration, including access to financial services, is a significant predictor of walking accessibility (Bielik et al., 2018). Walk Score, validates the importance of having financial services within walking distance (Carr et al., 2011). Furthermore, higher walkability levels, which include access to financial services, are associated with increased physical activity and healthier weight (Frank et al., 2006).

2.2.6. Government

The deregulation of services, including government services, has led to increased accessibility by foot, enhancing urban walkability (Vilhelmson & Elldér, 2021). Workplace proximity, particularly to government workplaces, is a significant contributor to transport-related walking (Cerin et al., 2007). The proximity of government institutions is crucial for better perceptions of the walking environment (Ariffin & Zahari, 2013). Additionally, street network configuration, which includes access to government institutions, strongly predicts walking accessibility (Bielik et al., 2018)

2.2.7. Health

The availability of health institutions like clinics, dentists, hospitals, and pharmacies within walking distance is associated with better self-rated health (Rohrer et al., 2004). High street connectivity and low traffic volume, which facilitate access to health institutions, increase the likelihood of walking in neighborhoods (Giles-Corti et al., 2011). Neighborhood walkability characteristics, including proximity to health institutions, are linked to better physical health among older adults (Blackwood et al., 2021). Additionally, a 2 standard deviation increase in functional proximity to a vaccination clinic is associated with a 6.4 percentage point increase in the probability of (Beshears et al., 2016).

2.2.8. Leisure

The presence of leisure facilities like gardens, marinas, parks, and playgrounds is closely linked to improved walkability. Living in neighborhoods with high walkability and access to recreational facilities like parks increases walking habits among older adults (Y. Li et al., 2020). Individuals living within 10 minutes walking distance from leisure amenities like exercise facilities are more likely to engage in leisure time physical activity (An & Zheng, 2014). Proximity to recreation facilities, including parks and playgrounds, is moderately correlated with walking for transportation among older adults (Shigematsu et al., 2009). Men residing in neighborhoods with proximity to leisure facilities are more likely to meet recommended levels of walking for transport (Pelclová et al., 2013).

2.2.9. Office

The proximity of offices significantly influences walkability. Workplace proximity is a major contributor to transport-related walking, especially among women (Cerin et al., 2007). Proximity to shared service and amenity areas in the workplace is positively associated with step counts and job satisfaction for office workers (Hua & Yang, 2014). Greater walkability, including access to offices, is associated with higher values in commercial real estate investments (Pivo & Fisher, 2011). Higher levels of stress are generally associated with walking in proximity to areas with mixed land uses, such as offices (Lajeunesse et al., 2021)

2.2.10. Parking

The presence of parking facilities like parking lots, parking entrances, taxi stops, and bicycle parking spaces can narrow the space for pedestrians and vehicles, impacting walkability (Darmawan & Rahmi, 2021). Perceived difficulties in parking near local shopping areas are negatively related to transport-related walking, especially among women (Van Dyck et al., 2012). Placing parks and retail shops within walking distance of homes, rather than prioritizing parking, increases pedestrian travel and interaction among neighbors (Lund, 2003). Neighborhood walkability attributes, including the management of parking spaces, are strongly associated with higher frequency of walking for transport (Owen et al., 2007).

2.2.11. Public Transportation

Walkable route segments near public transportation like subways and bus stops are characterized by more traffic, environmental, and social safety, as well as positive social and attractive environmental features (Brown et al., 2007). Neighborhood walkability, including access to public transit stops, is a key determinant of walking for transportation (Knuiman et al., 2014). Safety and connectivity near public transportation stops positively correlate with walkability, while an increase in private vehicles shows a negative correlation (Sukor & Fisal, 2020). Accessibility and safety against crime near public transportation facilities are crucial for enhancing walkability and increasing public transport patronage (Tiwari, 2015).

2.2.12. Sport

Proximity to sports facilities like fitness centers and sports centers is related to higher frequency rates of walkers and cyclists, especially in areas like college campuses (Gallagher & Morris, 2016). The spatial distribution and clustering of gyms, which are key sports facilities, impact walkability and influence healthy city planning strategies (Jing et al., 2021). Living within 10 minutes walking distance from an exercise facility significantly increases the likelihood of engaging in leisure time physical activity (An & Zheng, 2014). An increase in distance to sports facilities and a decrease in their number are associated with reduced physical activity levels (Halonen et al., 2015).

2.2.13. Sidewalk Width

Sidewalk width significantly influences walkability, with designs that consider pedestrian preferences and movement characteristics leading to improved walkability (Kim et al., 2011). The width of sidewalks plays a crucial role in the mobility of wheelchair users, impacting overall accessibility (Campisi et al., 2021). Sidewalk width is identified as a key factor influencing pedestrian route choices, affecting aspects such as passability and security (Ertz et al., 2021). Furthermore, the perceived walkability of an area is greatly affected by the useful width of sidewalks, alongside other environmental and architectural factors (Blečić et al., 2016).

2.2.14. Slope

Slope, along with sidewalk length, affects walkability, particularly in relation to factors like security and attractiveness (Nigro et al., 2018). The slope of sidewalks significantly influences the difficulty of movement and perceived interferences for visually impaired people, impacting their walkability (Campisi et al., 2021). In cognitive maintainers, sidewalk quality and slope are related to walking habits, indicating the importance of slope in walkable environments (Rosso et al., 2021). Additionally, the presence of street trees on narrow, sloped sidewalks can negatively affect perceived walkability (Fujiwara et al., 2018).

2.2.15. Trees

Trees and green areas in neighborhoods significantly promote walkability, contributing to sustainable urban living (Zumelzu et al., 2019). However, street trees in narrow sidewalks can sometimes negatively impact perceived walkability (Fujiwara et al., 2018). The presence of trees along streets increases walking behavior, especially among non-sedentary individuals (Domeneghini et al., 2022). Additionally, street trees are effective in reducing peak mean radiant temperature by 4.23 °C, thereby improving thermal comfort and walkability (Jia & Wang, 2021).

2.2.16. Water

Water features like rivers, bays, and fountains enhance walkability by improving aesthetics, social interaction, and reducing congestion in urban areas (Shafray & Kim, 2017). These features also influence individual reactions and perceptions of safety and comfort, impacting walkability (Abdelfattah & Nasreldin, 2019). Accessibility and safety against crime provided by water features contribute to walkability (Tiwari, 2015). Additionally, the presence of water features can lead to varied definitions of walkability, influencing urban design (Forsyth, 2015).

2.3. CAR TRAFFIC AND AIR POLLUTION RELATIONSHIP WITH WALKABILITY

This final section investigates the relationships between walkability, car traffic, and air pollution in urban settings. It examines how vehicular movement and air quality affect pedestrian experiences and the overall walkability of cities, highlighting the challenges and potential solutions in creating sustainable, walkable urban environments.

2.3.1. Car Traffic

Car traffic significantly impacts walkability in various ways. In urban-rural fringe areas, car traffic leads to less developed pedestrian mobility and increased dependence on cars for everyday chores (Blecic et al., 2017). Cars occupying urban spaces alter city structures to accommodate motor vehicles rather than pedestrians, negatively impacting walkability (Sirjani & Szabó, 2021). Heavy vehicular movement reduces walkability on narrow roads, affecting various population groups of pedestrians (Biswas & Roychowdhury, 2022). Car traffic used for access to urban railway stations affects walkability and safety for pedestrians (Ozawa et al., 2021).

2.3.2. Air Pollution

Air pollution and oxygenation through greenery are key factors impacting walkability, essential for urban regeneration projects (Shafray & Kim, 2017). Walking within a few hundred meters of a major road leads to higher pollution exposure than walking further away from the road, affecting walkability (Liu et al., 2017). Increased physical activity in high-walkability neighborhoods may be offset by adverse effects of air pollution exposure, potentially affecting population health (Hankey et al., 2012). Air pollution and urban heat island (UHI) impact human health through opportunities for physical activity and air quality and creating compact and walkable urban areas with green infrastructure can help reduce these impacts (Piracha & Chaudhary, 2022).

While existing research has explored the relationships between walkability, car traffic, and air pollution, there remains a significant gap in understanding how specific walkability features influence these urban environmental factors. To date, no study has thoroughly examined the individual components of walkability and their potential impacts on car traffic patterns and air pollution levels. This study aims to address this gap by using advanced statistical methods, specifically Gaussian and Poisson regression models, as well as their geographically weighted regression (GWR) counterparts. By using the features that constitute walkability as independent variables and modeling air pollution and car traffic as dependent variables, this research seeks to provide a clearer understanding of these complex urban dynamics. This approach will not only add to the existing body of knowledge but also offer valuable insights for urban planners and policymakers in creating more sustainable, healthier, and pedestrian-friendly urban environments.

3. METHODOLOGY

Our analysis follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, a well-established framework for data science projects. This approach ensures a systematic and comprehensive exploration of the relationship between walkability indicators, air pollution, and car traffic in Lisbon, particularly focusing on the Parque das Nações area. The CRISP-DM process includes six main phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. In this study, we primarily focus on the first five phases, as they are most relevant to our exploratory analysis.

3.1. BUSINESS UNDERSTANDING

This project seeks to enhance urban planning in Lisbon by investigating the relationships between the features to construct a walkability indicator, air pollution, and car traffic. To conduct this analysis, we utilized three primary data sources: walkability variables for Parque das Nações from Jardim et al. (2023), air pollution data provided by the Lisbon City Council, and car traffic data collected from the Waze app. By examining these interconnected factors, we aim to provide valuable insights for improving the city's urban design and residents' quality of life.

3.2. DATA UNDERSTANDING

This section outlines the three datasets used in our analysis: Amenities Accessibility Scores, Car Traffic Data, and Air Pollution measurements. We describe the sources of these datasets, their content, and the methods used to collect or calculate the data within them.

3.2.1. Amenities Accessibility Scores:

The dataset provided by Jardim et al., 2023, details Amenities Accessibility Scores for 470.552 unique geo-location points throughout the 187 unique streets of Parque das Nações, Lisbon. Each point in this dataset already includes calculated accessibility scores based on the proximity to various amenities, those being categorized in the 16 variables described in the chapter 2, sub chapter 2. These scores represent an assessment of how accessible each amenity is to the residents and visitors of the area, calculated to help understand urban accessibility dynamics.

To compute these scores, The Cumulative-Gaussian impedance function, proposed by Vale & Pereira in 2016 (referenced in Equation 1), was employed to assess the distance from each network point, denoted as point i, to the location of various features, indicated as point j. This function is particularly designed to provide a non-linear interpretation of walking distances, thereby more accurately reflecting human perception of distance. It operates based on two pivotal parameters: firstly, the a threshold, which determines what is considered an acceptable walking distance; and secondly, the v parameter, which is instrumental in modulating the rate at which the calculated score diminishes with increasing distance.

$$Distance\ Score_{ij} = \begin{cases} 1, & for\ d_{ij} \leq a \\ e^{-\frac{(d_{ij}-a)^2}{v}}, & for\ d_{ij} > a \end{cases}$$

Equation 1 Distance Score

Incorporating the methodology established by Vale and Pereira in 2016, the threshold term was configured to represent a 5-minute walking duration, approximately equating to a distance of 400 meters, where the score attains its maximum of 1. Concurrently, the parameter 'v' was precisely calculated to ensure that the score is adjusted to 0.50 at the 10-minute mark, corresponding to a value of 37. Figure 1 graphically presents the variation in scores over time, demonstrating the impact of different alfa and v values through a series of combinations.

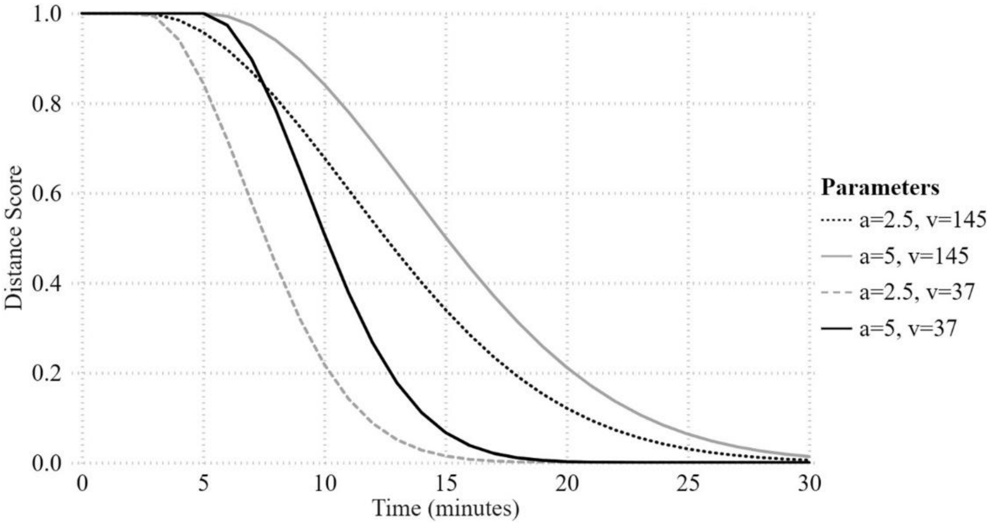


Figure 1 Core decay for different values of parameters a and b (Jardim et al., 2023)

3.2.2. Car Traffic Data:

Vehicle traffic data was collected from the Waze Maps application, which holds the information regarding traffic irregularities, alerts and traffic jams. This dataset has this information organized by the start and end time of each event (irregularities, alerts and traffic jams), together with the geographic length of those incidents, marking the start and end point of each incident. The Fig 2. Represents how the data of one traffic jam event is represented in a map.

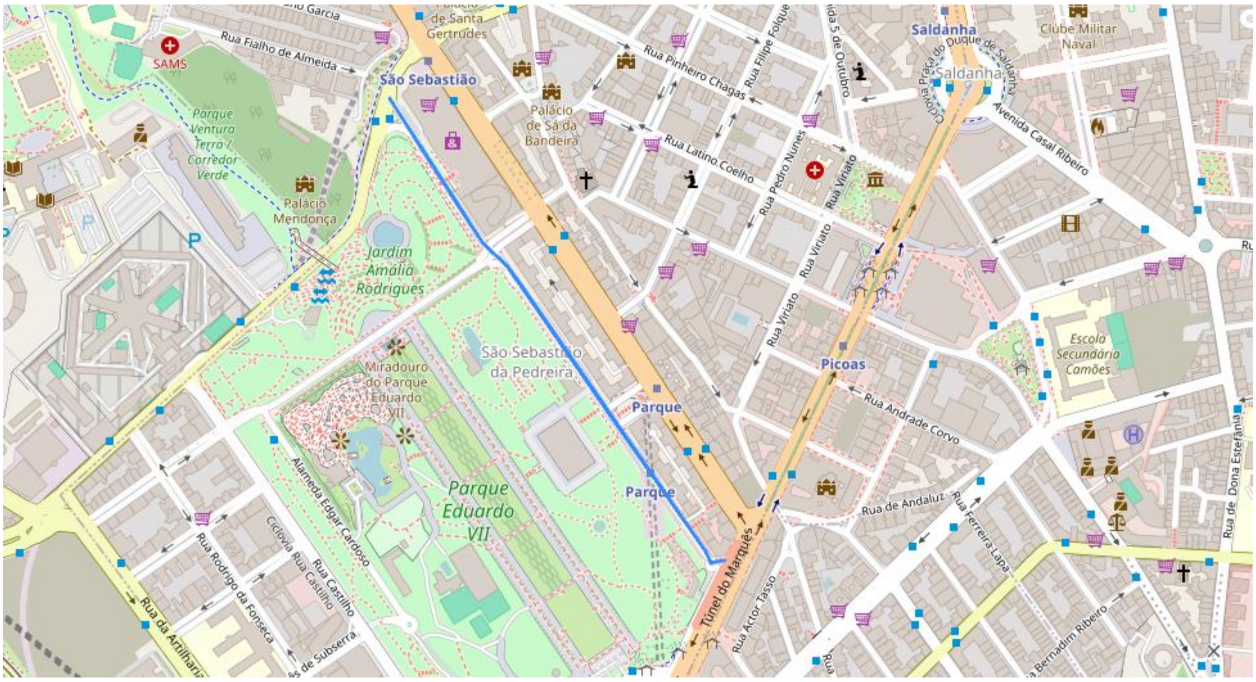


Figure 2 LineString representation for Traffic Jams regarding "Av. Sidónio Pais"

3.2.3. Air Pollution:

Air quality data was provided by the Lisbon City Council, where the sensors operate capturing concentrations of several pollutants including carbon monoxide (CO), nitric oxide (NO), and nitrogen dioxide (NO2). These sensors provided pollution level readings every 15 minutes. We have in total 46 sensors spread across Lisbon as shown in Fig 3., but only a few will be relevant for us to access data for Parque das Nações, as they are closer to this area.

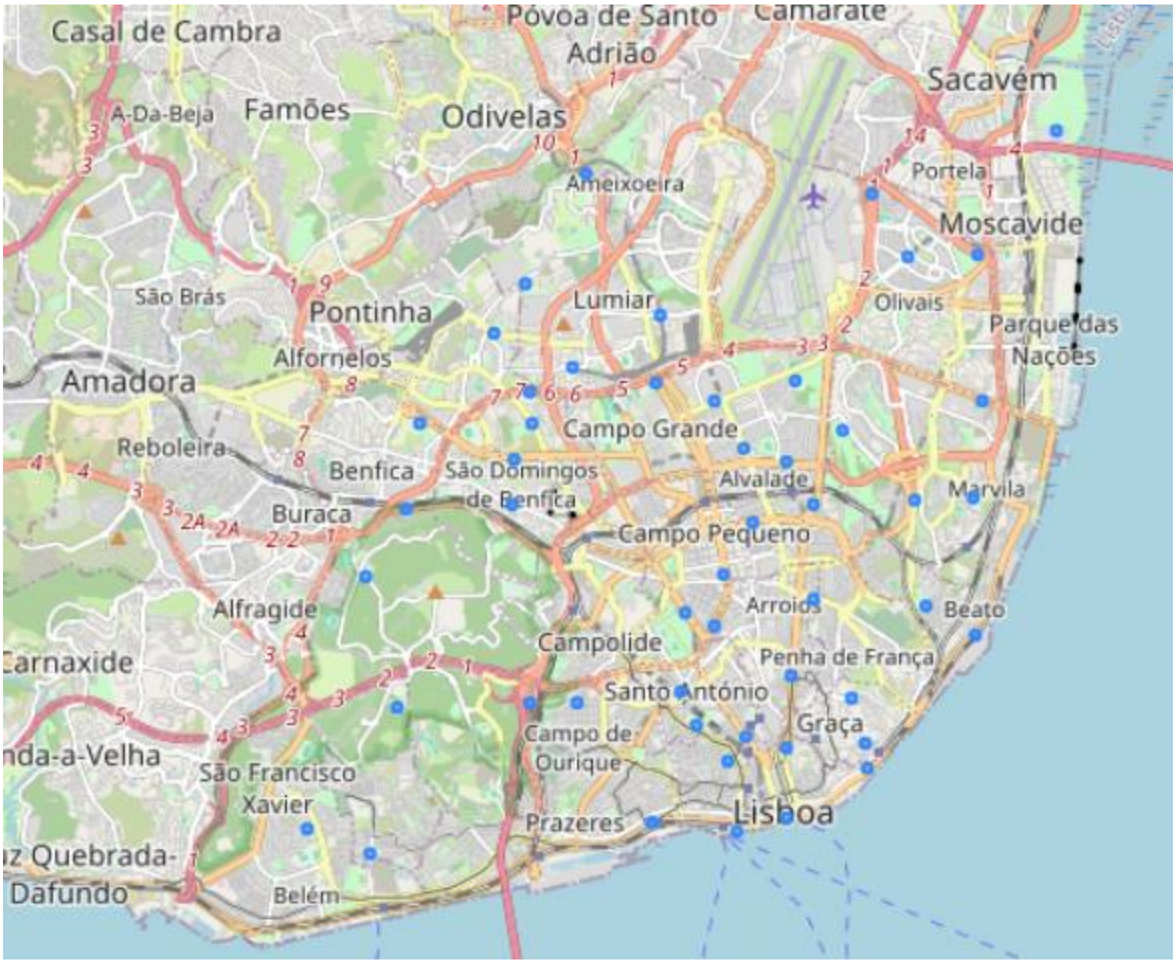


Figure 3 Air Quality Sensors Locations in Lisbon

3.3. DATA PREPARATION

This subchapter will detail what steps on data preparation were taken in order to have the data ready to be analyzed. This chapter will talk more in detail about how the geographic points were grouped by streets for the Amenities Accessibility Score dataset, how intersections were calculated from Waze dataset and the Amenities Accessibility Score dataset, and what kind of data aggregations and transformations were performed to account for the distance from the sensors to the locations in Parque das Nações. In order to perform this data preparation, the programming language Python 3.11 was used.

3.3.1. Amenities Accessibility Score Dataset:

Initially, the data was read from a CSV (Comma-Separated Values) file and streamlined by filtering out columns that wouldn't be necessary for this analysis. Following this, geometric data transformations were applied, converting WKT (Well-Known Text) formats into Shapely geometries, resulting in each point having a geometric representation that can be visualized in a map, as shown in Fig 4. WKT is a text markup language for representing vector geometry data, and Shapely is a Python library for set-theoretic analysis and manipulation of planar geometric objects. This conversion was crucial as it facilitated more complex spatial operations critical for detailed urban analysis.

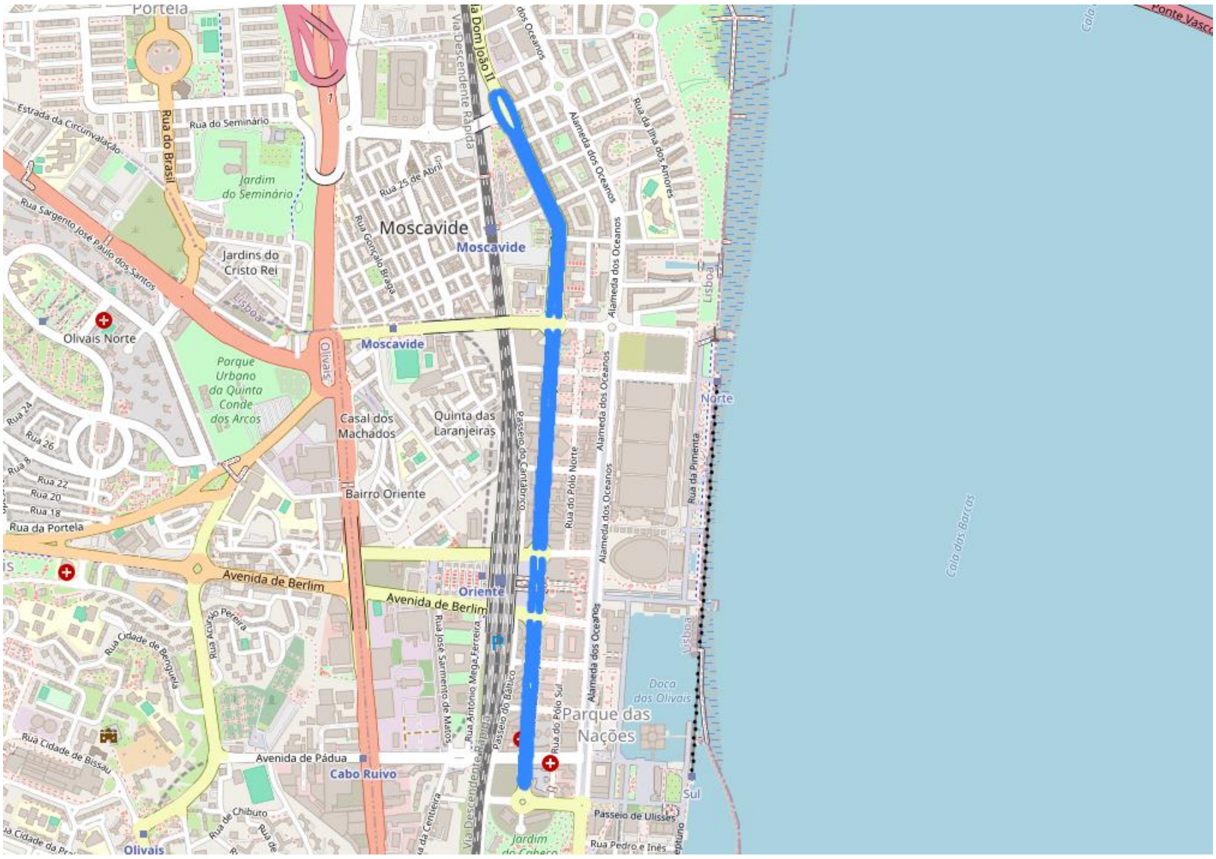


Figure 4 Representation of Latitude and Longitude geometric points in a map for “Avenida Dom João II”

The processed data were then organized by street names to construct LineStrings, which are a type of geometry in GIS (Geographic Information Systems) that represent a linear path composed of one or more line segments as illustrated in Fig 5. These LineStrings were then buffered into polygons that delineate the spatial extent of the streets, as shown in Fig 6. Buffering in GIS involves creating a zone around geometric shapes (in this case, LineStrings) that extends out to a specified distance, which is useful for including nearby spatial elements within a given radius.

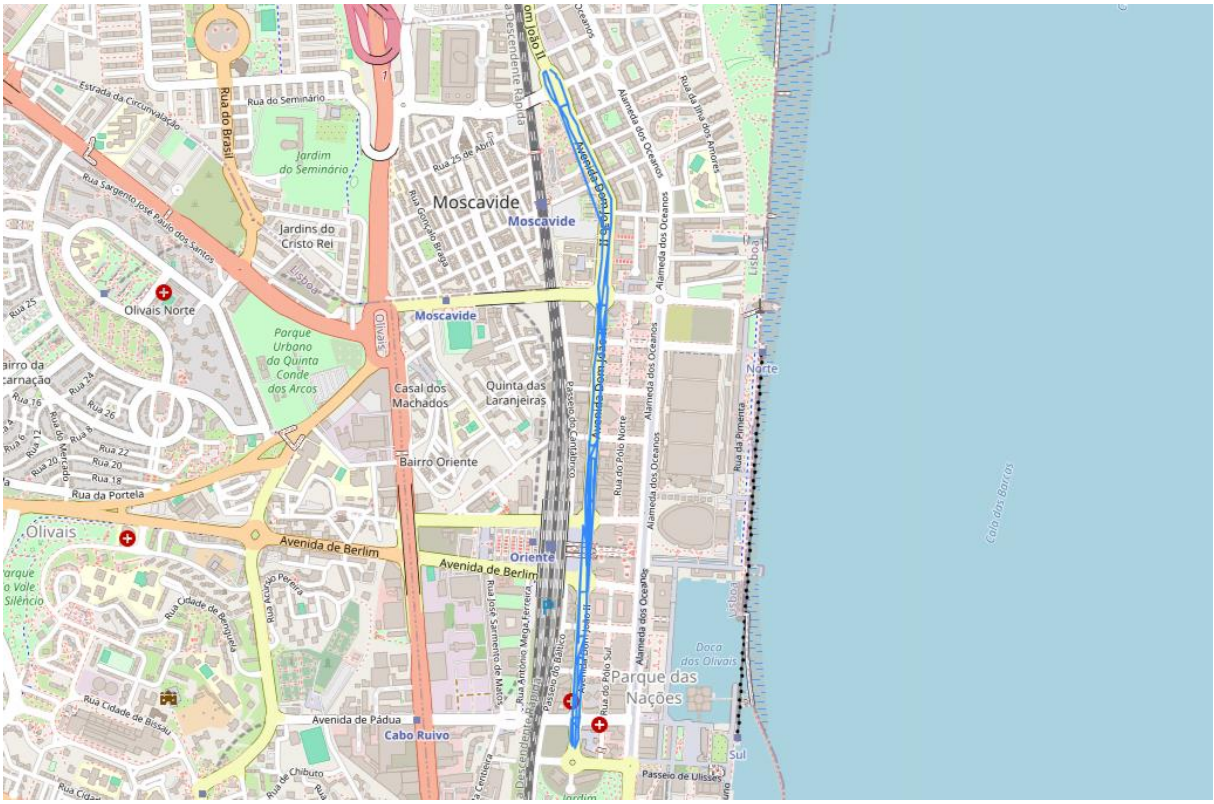


Figure 5 Illustration of LineString information for “Avenida Dom João II”

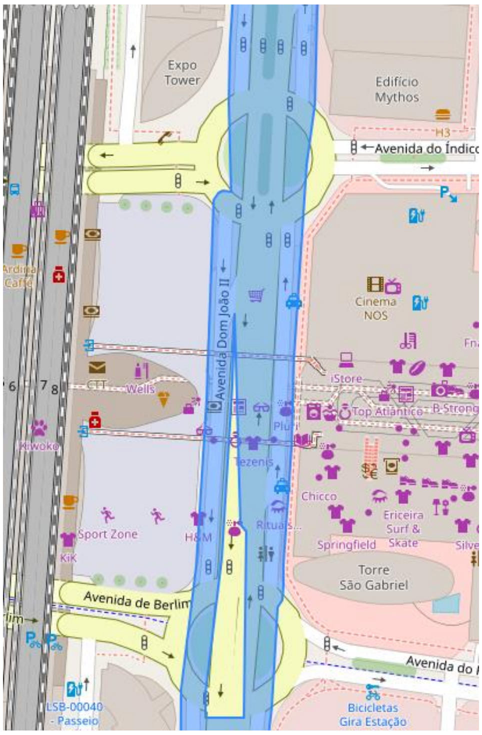


Figure 6 Buffered LineStrings into Polygons

Finally, these polygons were reprojected back to their original coordinate reference system, EPSG:4326, considered a global coordinate reference system for latitude and longitude used by the GPS satellite navigation system. The reprojection occurred after buffering within the projected CRS

(Coordinate Reference System) for Portugal, UTM (Universal Transverse Mercator) zone 29N. UTM is a system for assigning coordinates to locations on the surface of the Earth that is more suitable for regional maps. This meticulous process ensures that the data retains precision and relevance for urban planning analyses, providing accurate and actionable insights into the walkability of the area.

3.3.2. Car Traffic Dataset:

Vehicle traffic data from the Waze Maps application was already formatted as LineStrings, which represent continuous traffic flow along various streets, as shown in Fig 2. This pre-processed format facilitated straightforward integration with the amenities dataset.

By intersecting the Waze LineStrings with buffered LineStrings generated from the amenities distance scores, we were able to specifically quantify traffic congestion levels on streets linked with amenities data. Intersection is a spatial operation that identifies where different geometries overlap, allowing for the combination and comparison of data from those areas.

This method of data integration enables a targeted analysis of how traffic patterns intersect with pedestrian accessibility and the distribution of amenities. It allows for an examination of the relationships between vehicular traffic volumes and features that contribute to walkability, such as proximity to facilities and infrastructure.

3.3.3. Air Pollution Dataset:

To enhance analytical clarity and support longitudinal studies, this high-resolution data was aggregated to produce a six-month average for each pollutant. This longer-term aggregation provides a valuable annual snapshot, offering a comprehensive overview of air quality trends over time. Such data is crucial for environmental monitoring and assessing urban health impacts.

Due to the unavailability of air quality sensors on every street analyzed, we utilized the Inverse Distance Weighted (IDW) averaging method to estimate pollution levels.

The IDW method calculates the average air quality for each street by considering the measurements from the three nearest sensors. The influence of each sensor on the calculated average is inversely proportional to its distance from the street in question. This means that sensors located closer to a street exert a greater influence on the average pollution level calculated for that street. This approach ensures a spatially weighted assessment that more accurately reflects local air quality conditions, providing targeted insights into specific urban areas. This methodology is particularly effective in urban settings where environmental conditions can vary significantly over short distances.

3.4. MODELING

To investigate the association between the variables originally intended for constructing a walkability score and both car traffic and air pollution, we initiated our analysis with a linear regression model. In this model, car traffic counts and air pollution were chosen as the dependent variable, influenced by explanatory variables such as accessibility scores, sidewalk width, and slope level. The model is succinctly encapsulated by the equation:

$$y_i = \beta_0 + \sum_{m=1,n} \beta_m x_{im} + \epsilon_i$$

Equation 2 Linear (Gaussian) Regression

In this formulation, y_i denotes the dependent variable, representing car traffic counts and air pollution at location i; x_{im} signifies the values of the explanatory variables at i; ε_i is the error term; and β coefficients are the parameters estimated to minimize the sum of squared residuals. Traditional linear regression presupposes the independence of observations, an assumption often violated in spatial datasets due to the potential for spatial autocorrelation. This condition implies that the dependent variable's value at one location might be influenced by the explanatory variables' values at proximate locations, leading to biased and inefficient estimates of β parameters, characterized by enlarged standard errors.

Spatial autocorrelation and spatial heterogeneity present significant challenges in modeling spatial data. Spatial autocorrelation refers to the dependence among observations in space, suggesting that nearby locations may influence each other. Spatial heterogeneity, on the other hand, indicates that the relationship between explanatory and dependent variables varies across different geographic locations, contradicting the linear regression assumption of a constant relationship across space.

To address these spatial phenomena, the Geographically Weighted Regression (GWR) model is proposed as a more fitting approach. The GWR model extends the linear regression framework by allowing the parameter estimates to vary across space, thereby accommodating spatial heterogeneity:

$$y_i = \beta_{i0} + \sum_{m=1,n} \beta_{im} x_{im} + \epsilon_i$$

Equation 3 Geographically Weighted Regression (GWR)

Here, β_i are the location-specific coefficients, reflecting the spatial variation in the relationship between explanatory variables and the dependent variable. Prior to employing the GWR model, it is essential to specify parameters such as the kernel weighting function and the bandwidth. The bandwidth can be either fixed, setting a maximum distance for the weighting function, or adaptive, determining the number of neighboring points included in the estimation for each location. The optimal parameter combination for the GWR model, aimed at minimizing the Akaike Information Criterion (AIC), was identified through the Golden Section search method, selecting an adaptive bandwidth and the bisquare kernel function. These choices enhance the model's capacity to capture the nuanced spatial dynamics influencing pedestrian traffic.

To better model car traffic as a count variable, we advanced our analysis by implementing Poisson regression models. Poisson regression is suitable for modeling count data, particularly when the counts are over discrete intervals or regions.

First, we utilized a standard Poisson regression model, formulated as follows:

$$y_i \sim \text{Poisson}\left[N \exp\left(\beta_0 + \sum_k \beta_k x_k\right)\right]$$

Equation 4 Poisson Model

In this expression, y_i is the observed car traffic count at location i, x_{im} represents the explanatory variables (such as proximity to amenities, road conditions, etc.) at location i, and β_m are the parameters to be estimated. This model assumes a logarithmic link between the expected count of car traffic and the explanatory variables.

Recognizing the potential for spatial dependency in car traffic counts, we also developed a Poisson model that incorporates spatial information:

$$y_i \sim \text{Poisson}\left[N_i \exp\left(\beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{k,i}\right)\right]$$

Equation 5 Poisson GWR Model

Here, y_i remains the observed car traffic count, but $\beta_m(u_i, v_i)$ is adapted to be specific to location i reflecting the spatial dependency. The coordinates (u_i, v_i) represent the specific location, capturing spatial variations more accurately.

Both Poisson models offer a structured approach to analyze the counting process of car traffic, with the spatial model enhancing the accuracy by incorporating the geographical distribution of the data.

To conduct the regression analyses, we utilized the statsmodels package for implementing both Gaussian and Poisson regressions. For spatially adaptive regression models, specifically Gaussian and Poisson Geographically Weighted Regressions (GWR), we employed the mgwr module from the PySAL (Python Spatial Analysis Library) package. This allowed us to account for spatial heterogeneity in the relationships between the variables, providing more localized and accurate modeling outcomes.

To determine the optimal hyperparameters for Gaussian and Poisson Geographically Weighted Regression (GWR) models, we used the Sel_BW module from the PySAL package. This process involves searching for the ideal bandwidth for each model under specific conditions:

- Kernel Function:

We chose the Bi-Square kernel for the weighting function. This kernel assigns weights to data points that decrease to zero sharply beyond a certain distance, making it suitable for local regression.

- Adaptive Bandwidth:

We opted for an adaptive bandwidth, which adjusts based on the density of data points. This approach ensures that a consistent number of neighbors are considered for each local regression, making the model more flexible in areas with varying data density.

Adaptive bandwidth varies depending on the number of nearest neighbors, effectively adapting to local data density.

- Distance Metric:

Euclidean Distance was used as the distance metric for calculating distances between data points. Euclidean distance is the straight-line distance between two points in the coordinate system, and is commonly used due to its simplicity and efficiency in computation.

- Bandwidth Selection Criterion:

For the search of the optimal bandwidth, we used the Corrected Akaike Information Criterion (AICc). AICc adjusts the Akaike Information Criterion for small sample sizes, making it a more accurate measure for model evaluation when the number of observations is not large relative to the number of parameters.

3.5. EVALUATION

In the evaluation section, it will be discussed which metrics will be used to compare the models' performance on predicting car traffic and air pollution levels. Additionally, the section will cover how the significance of independent variables is assessed at a 95% confidence level and the interpretation of significant variables' effects depending on the model type.

- Model Performance Metrics:

To assess the efficacy of our models in predicting car traffic counts and air pollution levels, we employed several key performance metrics. The Akaike Information Criterion (AIC) and R-Squared values, or Pseudo R-Squared when traditional R-Squared is not suitable, were critical for this evaluation. These metrics help us understand the trade-off between a model's accuracy and its complexity. A model with a lower AIC is considered optimal as it effectively balances simplicity with the ability to accurately predict outcomes.

- Goodness of Fit:
  - Continuous Data Models: For linear regression models, R-Squared values indicate the percentage of variance in the dependent variables explained by the independent variables. This metric is essential for models based on continuous data.
  - Count Data Models: For models like Poisson regression, Pseudo R-Squared offers a more relevant measure by adjusting the R-Squared concept to accommodate non-linear relationships and discrete data typical in these models.

These measures collectively allow us to comprehensively evaluate model performance, ensuring our selected models not only fit the data well but also capture the essential spatial and non-spatial patterns affecting traffic and pollution.

- Variable Significance:

Upon selecting the best model, for each dependent variable, based on the lowest AIC and highest R-Squared/Pseudo R-Squared values, we tested the significance of each independent variable at a 95% confidence level. Variables with a p-value less than 0.05 were considered statistically significant, indicating a substantial impact on the model. In contrast, variables with a p-value above 0.05 were seen as not statistically significant.

- Interpretation of Significant Variables:

- Gaussian/Poisson Regression: For these models, we will interpret the implications of the significant variables using the beta coefficients, which reflect the strength and direction of each predictor's influence on the dependent variables.
- Geographically Weighted Regression (GWR): For GWR models, we will analyze the mean and standard deviation of the spatial beta coefficients. Since each geographic point has its unique beta coefficient in GWR, this approach allows us to understand the spatial variations in the data.

4. RESULTS AND DISCUSSION

This chapter presents and analyzes the findings from our statistical modeling of two critical urban issues: Car Traffic and Air Pollution. By organizing the discussion into two separate sections, we aim to provide a comprehensive review of the model performances, the insights they generate, and the broader implications of these results.

4.1. CAR TRAFFIC MODELS AND RESULTS

In the first section, we explore the outcomes from various regression models applied to car traffic data. The evaluation of these models involves detailed metrics such as AIC, R-Squared, and Pseudo R-Squared, enabling a nuanced discussion of how effectively these models capture the dynamics of traffic patterns and their influencing factors.

From the results of the models (Table 1), Poisson GWR significantly outperformed other models, as indicated by its notably lower AIC score and higher Pseudo R-Squared value of 0.7872. This superior performance suggests that incorporating spatial information provides a more accurate representation of the variability in car traffic influenced by the analyzed variables. The Linear Regression model didn't achieve a necessary F-Score p-value below 5%, and for the other models, all of them had a F-Score p-value under 5%, making the other models statistically significant.

Model	**AIC**	**R2 / Pseudo-R2**
Linear Regression	27053.89	0.351
Gaussian GWR	26504.40	0.401
Poisson	28786.37	0.5142
Poisson GWR	21001.78	0.7872

Table 1 Car Traffic Models Comparison

The interpretation of β parameters within these models is crucial for understanding the influence of each variable on car traffic. The significance of these effects is further ascertained by examining the p-values associated with each β coefficient. Significant p-values indicate that the corresponding variables play a meaningful role in the model, thus providing actionable insights into factors that could be targeted to manage and mitigate traffic congestion effectively.

The global Poisson regression results for car traffic, as presented in Table 2, shows results for all of the 16 independent variables. Proximity to parking facilities, trees, health centers, and educational institutions strongly correlates with increased car traffic. Notably, areas near public transport also show higher car traffic. Conversely, proximity to crosswalks, sports facilities, financial and office districts, and entertainment zones is associated with reduced car traffic. Steeper slopes correlate positively with traffic, while wider sidewalks are linked to less car traffic. These findings, all statistically significant at $p < 0.05$ (except for water proximity, which is not significant), highlight the complex interplay between urban features and traffic patterns. While some relationships align with intuitive expectations, others, like the positive association between trees and traffic, present unexpected results.

Variable	**Coefficient**	**Standard Error**	**z-value**	**P-value**	**95% Confidence Interval**
Slope Degrees	3.40	0.36	9.44	0.000	(2.69, 4.10)
Food	-1.31	0.27	-4.82	0.000	(-1.84, -0.78)
Trees	5.04	0.31	16.40	0.000	(4.44, 5.64)
Parking	5.72	0.44	13.14	0.000	(4.87, 6.58)
Education	1.87	0.16	11.83	0.000	(1.56, 2.18)
Water	-0.32	0.17	-1.86	0.063	(-0.65, 0.02)
Finance	-2.44	0.26	-9.38	0.000	(-2.95, -1.93)
Office	-2.40	0.18	-13.34	0.000	(-2.75, -2.05)
Public Transport	2.42	0.16	15.25	0.000	(2.11, 2.74)
Government	-0.44	0.12	-3.62	0.000	(-0.67, -0.20)
Crosswalk	-5.02	0.29	-17.20	0.000	(-5.60, -4.45)
Health	4.09	0.18	22.56	0.000	(3.73, 4.44)
Entertainment	-1.43	0.12	-12.51	0.000	(-1.66, -1.21)
Leisure	-2.01	0.25	-8.07	0.000	(-2.49, -1.52)
Sport	-4.09	0.14	-30.06	0.000	(-4.36, -3.83)
Sidewalk Width	-0.80	0.06	-13.03	0.000	(-0.92, -0.68)

Table 2 Global Poisson Regression Results

The Geographically Weighted Poisson Regression (GWR) results (table 3) for car traffic reveals significant spatial variations in the effects of urban features on traffic patterns. Proximity to parking facilities exhibits the strongest positive mean effect on car traffic, followed by trees and health facilities. Conversely, crosswalks, food-related locations, and offices demonstrate the strongest negative mean effects. These relationships show considerable spatial heterogeneity, as evidenced by high standard deviations, particularly for crosswalks, trees, and slope. While some variables maintain consistent directional effects across locations, others, such as slope, health facilities, and leisure areas, show both positive and negative impacts depending on the specific area. Notably, certain findings diverge from the global model results, exemplified by public transport proximity's slight negative mean effect in the GWR model, contrasting with its positive effect in the global analysis.

Variable	**Mean**	**STD**	**Min**	**Median**	**Max**
slope_dg	-4.147	12.949	-32.367	-2.392	22.238
food	-11.293	6.920	-23.608	-10.364	6.887
trees	15.899	13.648	-0.248	15.687	47.406
parking	26.888	8.021	3.538	27.535	50.101
education	5.949	7.367	-4.245	2.596	26.404
water	-4.472	8.571	-21.146	-3.620	7.853
finance	-3.880	5.614	-17.440	-3.954	6.338
office	-8.311	8.535	-23.611	-4.980	3.117
public_transport	-3.484	6.351	-16.218	-3.947	10.032
government	-2.680	3.466	-11.253	-2.827	5.382
crosswalk	-12.592	16.436	-41.596	-5.510	7.343
health	6.948	10.656	-21.786	10.052	22.109
entertainment	3.196	5.553	-6.792	3.982	13.459
sport	-7.181	3.790	-16.360	-7.252	4.660
sidewalk_wd	-0.792	1.805	-6.138	-0.504	4.848
leisure	-7.107	6.420	-16.391	-9.802	11.026

Table 3 Poisson GWR Results

To illustrate the spatial variations in urban features' effects on car traffic, we focus on three key variables: trees, parking facilities, and crosswalks. These were chosen for their distinct and varied impacts across the city. Trees were selected due to their unexpected positive association with traffic and significant spatial variability. Parking facilities demonstrate a consistently strong positive effect on traffic, with interesting variations across different areas. Crosswalks show the highest spatial heterogeneity, with effects ranging from strongly negative to slightly positive, offering insights into the complex relationship between pedestrian infrastructure and traffic patterns. These variables provide a comprehensive view of how different urban elements influence car traffic, highlighting the importance of local context in urban traffic dynamics. While we highlight these three variables in detail, charts for all 16 independent variables examined in this study can be found in Appendix A, offering a complete overview of the spatial effects across all urban features analyzed.

The spatial analysis of trees, parking facilities, and crosswalks reveals distinct patterns in their relationships with car traffic across the area of Parque das Nações, as shown in Fig 7. Trees exhibit an intriguing south-to-north gradient, with a weak positive association in the south gradually intensifying to a strong positive correlation in the northern areas. This suggests that the presence of trees is more strongly linked to increased car traffic in the northern parts of the city, potentially reflecting differences in urban design or the nature of tree-lined streets in various neighborhoods.

Parking facilities demonstrate a similar but inverse pattern, with the strongest positive effect on car traffic in the north, gradually diminishing towards the south. This indicates that parking availability is more closely associated with higher traffic levels in the northern regions, possibly due to differences in land use or urban density. Crosswalks, conversely, show a strong negative association with car traffic in the north, transitioning to a weaker effect or even a slightly positive relationship in the south. This pattern suggests that crosswalks are more effective at reducing car traffic in the northern areas, perhaps reflecting differences in pedestrian infrastructure or urban core characteristics. These varied spatial patterns underscore the complex and location-specific nature of how urban features interact with traffic dynamics, highlighting the importance of considering local context in urban planning and traffic management strategies.

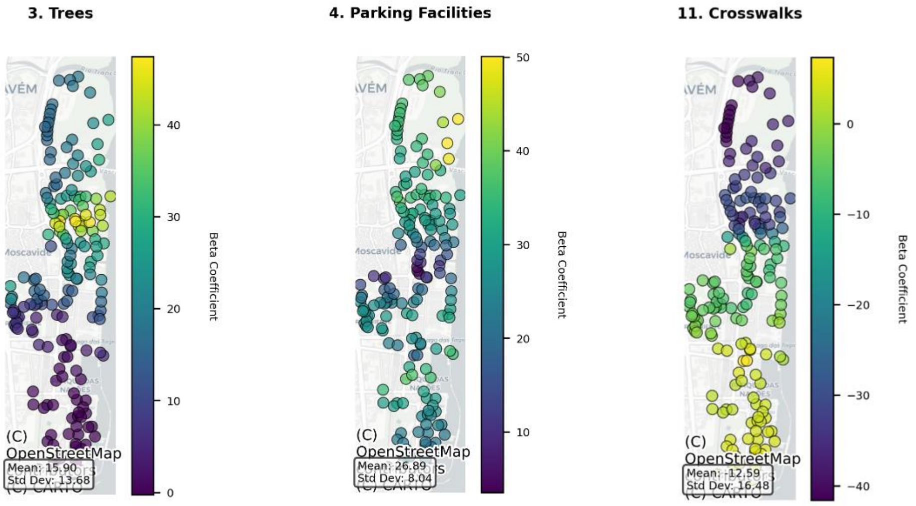


Figure 7 Map Chart for independent variables Trees, Parking and Crosswalks in Poisson GWR model

4.2. AIR POLUTION MODELS AND RESULTS

In this section, we examine the outcomes from different regression models applied to air pollution data, specifically comparing Linear Regression and Geographically Weighted Regression (GWR). Each model is evaluated using R-Squared and the Akaike Information Criterion (AIC) to assess their efficacy in capturing the variability in pollution levels across various pollutants.

Model	Poluent	R2	AIC
Linear Regression	CO	0.932	-983.0
GWR	CO	0.986	-1210.872
Linear Regression	NO	0.896	949.89
GWR	NO	0.981	709.872
Linear Regression	NO2	0.811	670.990
GWR	NO2	0.935	533.180

Table 4 Model Comparisons for Air Pollution

The comparative analysis of Linear Regression and Geographically Weighted Regression (GWR) across pollutants—CO, NO, and NO2—clearly shows that GWR consistently achieves higher R2 values and lower AIC scores compared to Linear Regression. Higher R2 values indicate that the model explains a greater proportion of the variance in pollution levels, suggesting a more accurate fit to the observed data. Simultaneously, lower AIC scores denote a model's better balance between fit and complexity, implying that GWR not only fits better but does so more efficiently without overfitting. All of those models were able to achieve a F-Score p-value under 5%, meaning that all of those models are statistically significant.

This consistent performance superiority of GWR supports its use in spatial analysis of environmental data, where capturing local variations and complex interactions is crucial for understanding and modeling air pollution effectively.

Firstly, we assessed the Gaussian global regression beta coefficients for each pollutant (Table 5) to determine which independent variables exerted a statistically significant influence. The results of all of three modes reveal that proximity to various urban features significantly influences air pollution levels (CO, NO, and NO2) in cities. Closeness to trees emerges as a key factor, with areas nearer to green spaces showing reduced levels of both CO and NO2. This underscores the importance of accessible urban greenery for air quality. Proximity to financial districts shows mixed effects, with nearby areas experiencing lower NO levels but slightly higher CO and NO2 concentrations, highlighting the complex relationship between business centers and air quality. Areas closer to entertainment zones show increased levels of all three pollutants, particularly NO, suggesting potential air quality challenges in these vicinities. Other factors, including nearness to offices, public transport, water features, and changes in terrain slope, also play roles, though their impacts vary across pollutants. These findings demonstrate the intricate nature of urban air quality management and emphasize the need for nuanced, location-specific approaches in city planning to effectively reduce air pollution.

	CO		NO		NO2	
Variable	Beta Coefficient	p-value	Beta Coefficient	p-value	Beta Coefficient	p-value
Slope Degrees	-0.091	0.166	-26.194	0.028	-13.692	0.014
Food	0.043	0.170	9.426	0.100	-1.214	0.651
Trees	-0.353	0.000	-9.837	0.076	-26.019	0.000
Parking	0.029	0.638	20.480	0.065	9.782	0.060
Education	-0.037	0.095	-2.988	0.457	1.654	0.379
Water	0.131	0.000	-8.094	0.125	6.402	0.010
Finance	0.113	0.006	-34.754	0.000	7.864	0.023
Office	-0.072	0.001	-20.166	0.000	4.103	0.029
Public Transport	0.036	0.225	17.667	0.001	-6.017	0.018
Government	-0.003	0.836	-6.910	0.021	0.299	0.831
Crosswalk	0.041	0.354	2.249	0.779	-2.764	0.462
Health	-0.009	0.742	18.450	0.000	-3.480	0.132
Entertainment	0.050	0.009	26.888	0.000	3.614	0.025
Sport	0.012	0.490	1.835	0.563	-1.532	0.302
Sidewalk Width	-0.006	0.601	-1.907	0.323	0.747	0.408
Leisure	0.065	0.082	2.687	0.691	5.951	0.060

Table 5 Global Linear Regression results for Air Pollution

The Geographically Weighted Regression (GWR) analysis (Table 6) reveals complex spatial variations in how urban features affect air pollutants (CO, NO, and NO2). Proximity to trees consistently shows a negative effect across all pollutants, with the strongest impact on NO2, reinforcing the importance of urban greenery in reducing air pollution. Financial districts demonstrate a mixed influence, generally increasing CO and NO2 levels but decreasing NO, highlighting their complex impact on air quality. Areas closer to parking facilities tend to have higher levels of NO and NO2, suggesting these spaces may contribute to increased pollution. Water proximity shows varied effects, generally reducing NO levels but slightly increasing CO. Entertainment zones tend to increase levels of all three pollutants, indicating potential air quality challenges in these areas. Interestingly, proximity to public transport appears to reduce NO2 levels while having minimal impact on CO and NO.

The analysis reveals significant spatial heterogeneity in these effects, as indicated by high standard deviations for many variables. This means that the impact of urban features on air quality can vary considerably across different locations within the city. Some findings align with the global model results, while others differ, emphasizing the importance of considering local contexts in urban air quality management.

	CO		**NO**		**NO2**	
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Slope Degrees	0.048	0.113	-2.990	9.473	-2.024	7.928
Food	-0.011	0.079	2.467	11.560	-2.948	4.278
Trees	-0.133	0.104	-3.836	26.831	-14.443	9.128
Parking	0.030	0.102	13.426	21.233	8.420	11.062
Education	-0.006	0.034	0.198	13.519	4.371	4.769
Water	0.041	0.032	-8.069	7.617	-0.420	4.843
Finance	0.119	0.083	-4.520	9.442	6.028	8.990
Office	-0.017	0.028	-7.582	14.689	0.591	6.598
Public Transport	-0.027	0.028	0.283	8.931	-5.209	8.232
Government	0.001	0.018	-3.713	4.743	-1.335	1.971
Crosswalk	-0.004	0.034	0.844	8.702	0.583	6.614
Health	-0.011	0.035	6.863	12.844	0.193	5.800
Entertainment	0.040	0.024	3.504	8.429	3.255	3.597
Sport	0.172	0.297	18.766	50.763	3.125	9.353
Sidewalk Width	-0.001	0.007	-1.017	1.956	1.243	1.591
Leisure	-0.001	0.035	-5.241	20.837	-0.994	6.046

Table 6 Gaussian GWR results for Air Pollution

To illustrate the spatial variations in how urban features affect air pollutants, we focus on three key variables: trees, parking facilities, and sport areas. Trees were selected for their consistent negative effect across all pollutants, particularly strong for NO2, highlighting the importance of urban greenery in air quality management. Parking facilities demonstrate a consistently positive effect on pollutant levels, especially for NO and NO2, providing insights into the environmental impact of car-centric infrastructure. Sport areas were chosen due to their striking spatial variability, particularly for NO, where they show the highest mean effect and standard deviation among all variables.

The behavior of the beta coefficients of the independent variable Trees (proximity to trees) differs depending on the pollutant across Parque das Nações, as shown in Fig 8. For CO, the strongest negative associations occur in the south of the location of study, with weaker effects in the north and central parts. This indicates trees may be most effective at reducing CO levels in southern Parque das Nações. NO displays the most complex spatial variability, with positive coefficients predominant in the north (suggesting higher NO levels near trees) and a mix of positive and negative associations in central and southern areas. This implies that local factors in Parque das Nações, such as traffic patterns and others, may be influencing the tree-NO relationship differently across the location.

NO2 shows the most consistent negative relationship with tree proximity throughout Parque das Nações, though the intensity varies. The strongest negative associations are found in the central and south-central parts of the location of study, with moderately strong effects in the north and weaker (but still negative) associations in the far south. This pattern suggests that trees generally reduce NO2 levels across Parque das Nações, but their effectiveness may vary due to local environmental conditions. These spatial variations highlight the importance of considering location-specific factors within Parque das Nações when evaluating the impact of urban trees on air quality, as their effects can differ significantly across pollutants and geographic areas within the same location of study.

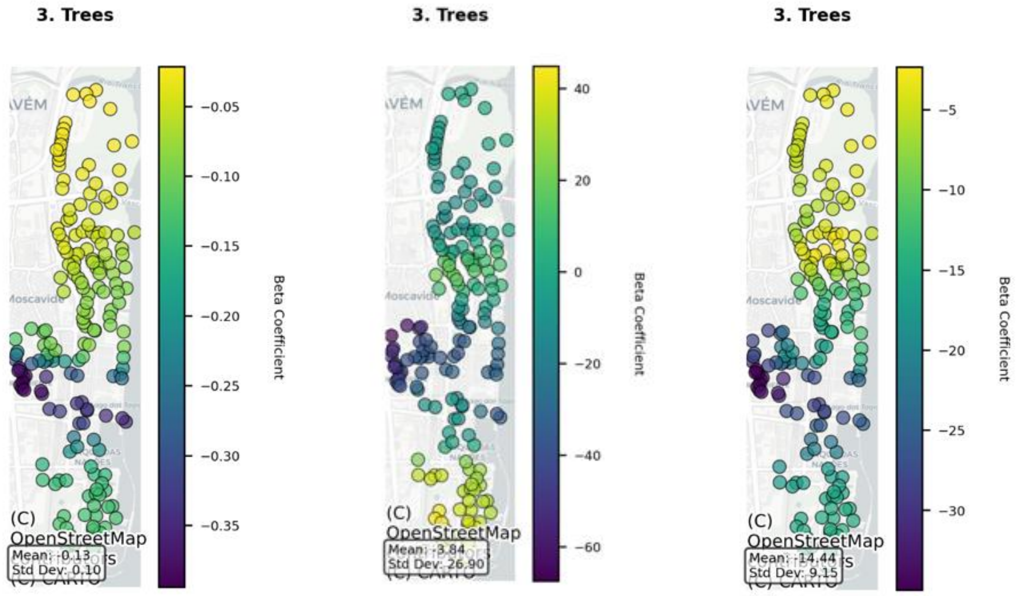


Figure 8 Map chart for Trees betas coefficients for CO, NO and NO2 respectively.

For the independent variable proximity to Parking facilities, the beta coefficients show a slightly different behavior compared to Trees, as shown in Fig 9. For CO, there's a clear north-south divide: the northern and central areas show positive associations, while the southern part displays negative relationships. This pattern suggests that parking facilities in the north and center may be linked to higher CO levels, while in the south, they're associated with lower CO concentrations. NO exhibits the most extreme variability, with strong positive coefficients (up to 60) predominant in the central and southern areas, and negative associations in the north. This implies that local factors in Parque das Nações significantly influence the parking-NO relationship across different parts of the area.

NO2 shows a more moderate range of associations, with the strongest positive relationships in the central and south-central parts of the study area, and a mix of positive and negative associations in the far south. The northern region displays weaker positive to neutral associations for NO2.

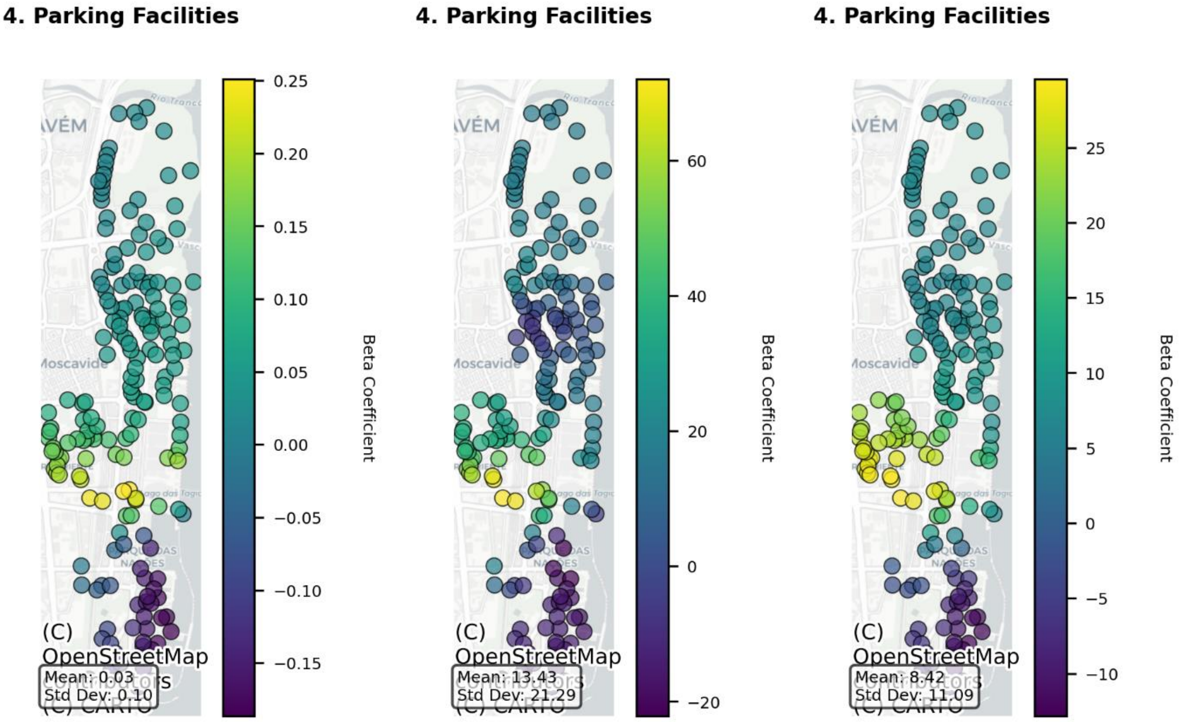


Figure 9 Map chart for Parking Facilities betas coefficients for CO, NO and NO2 respectively.

The distribution of the beta coefficients of proximity to Sport Facilities shows the opposite behavior to the one from Parking Facilities, across Parque das Nações, as shown in Fig 10. For CO, the relationship is generally weak and positive throughout the area, with slightly stronger positive associations in the south. This suggests that proximity to sports facilities may be linked to minor increases in CO levels, particularly in southern Parque das Nações. NO exhibits the most pronounced spatial variability, with a clear north-south gradient. Negative coefficients dominate the north, indicating that sports facilities might be associated with lower NO levels in this area. However, strong positive associations emerge in the south, implying that proximity to sports facilities correlates with higher NO concentrations there. This stark contrast suggests that local factors in Parque das Nações, such as traffic patterns or facility usage, may significantly influence the sports facility-NO relationship.

NO2 displays a similar north-south pattern to NO, but with less extreme values. Negative coefficients in the north suggest that sports facilities may help reduce NO2 levels in this area, while positive coefficients in the south indicate the opposite effect. It's interesting to note that in the northern part of Parque das Nações, there's almost no effect from sports facilities, which is consistent with their location predominantly in the southern part of the area.

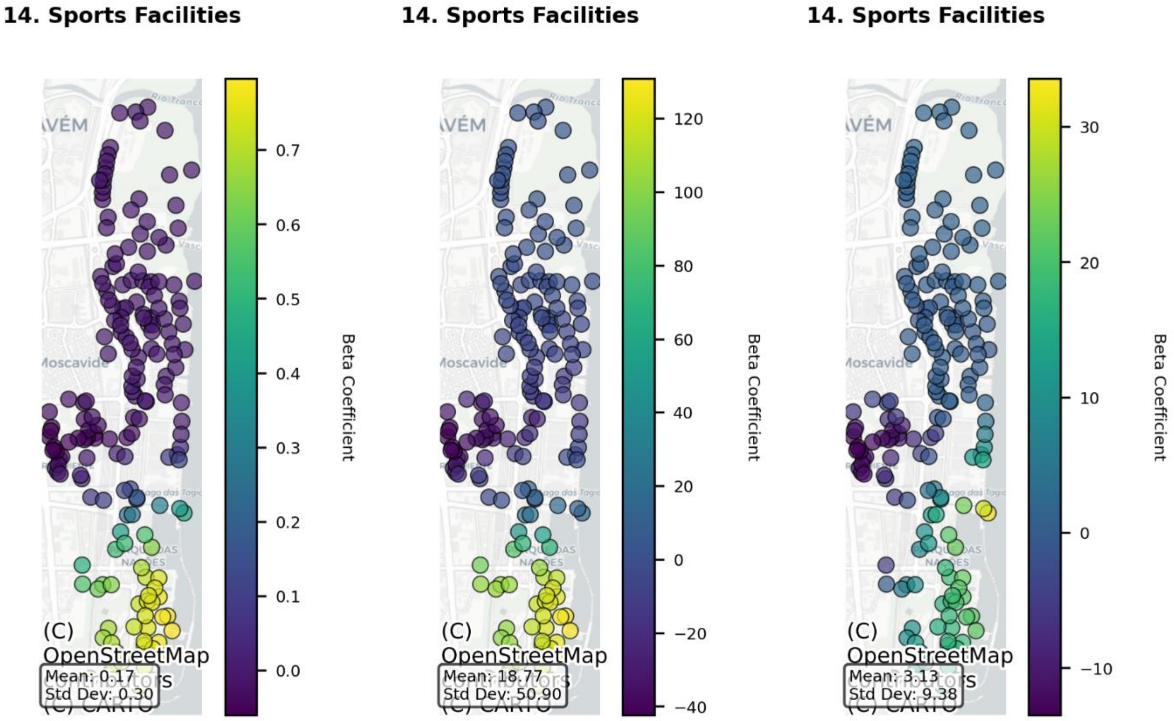


Figure 10 Map chart for Sport Facilities betas coefficients for CO, NO and NO2 respectively.

5. CONCLUSION AND FUTURE WORKS

This study provides a nuanced understanding of the complex relationships between urban features, car traffic, and air pollution in city environments. Through the application of advanced statistical models, particularly Geographically Weighted Regression (GWR), we have uncovered significant spatial variations in these relationships that are not captured by traditional global models.

In the analysis of car traffic, the Poisson GWR model demonstrated superior performance, highlighting the importance of considering spatial heterogeneity in traffic patterns. Key findings include the unexpected positive association between trees and traffic, possibly due to tree-lined boulevards in high-traffic areas, and the strong influence of parking facilities on increasing traffic. The varied effects of crosswalks across different city areas underscore the need for location-specific urban planning strategies to manage traffic effectively.

Notably, wider sidewalks were associated with reduced car traffic, suggesting that improved pedestrian facilities not only encourage physical activity and support local commerce but also contribute to traffic reduction. This finding emphasizes the importance of pedestrian-friendly urban design in creating more livable and less congested cities.

For air pollution, the Gaussian GWR models consistently outperformed linear regression across all pollutants (CO, NO, NO2), emphasizing the spatial variability in air quality determinants. Trees appeared as a crucial factor in reducing pollution levels, particularly for NO2, reinforcing the importance of urban green spaces. Parking facilities were associated with increased pollution, especially NO and NO2, highlighting the environmental impact of car-centric infrastructure.

The positive association between public transport proximity and air pollution, particularly NO, raises questions about the current public transit system. This could indicate an over-reliance on diesel buses rather than lower-emission alternatives like electric buses, trams, or light rail. It suggests a need for cities to transition to cleaner public transportation options to fully realize the air quality benefits of mass transit.

The striking spatial variability in the effects of sport areas on air pollution, particularly NO, reveals the complex dynamics of urban air quality and possibly reflects differences in accessibility and transport modes used to reach these facilities.

These findings have significant implications for urban planning and environmental management

1. Spatial context: One-size-fits-all approaches are likely to be ineffective. Urban planners and policymakers should consider local variations when designing strategies for traffic management and air quality improvement.
2. Green infrastructure: While trees show complex relationships with traffic, their consistent negative association with air pollution underscores their importance in urban environmental strategies.
3. Transportation infrastructure: The varied effects of parking facilities and public transport on both traffic and pollution suggest a need for balanced, context-sensitive approaches to transportation planning. This includes transitioning to lower-emission public transit options and creating more pedestrian-friendly spaces.

4. Pedestrian-friendly design: The positive impact of wider sidewalks on reducing car traffic highlights the potential of pedestrian infrastructure to reshape urban mobility patterns.

For future works, even more precise insights can be achieved conducting the analysis at individual street points—rather than aggregating data by street—could provide deeper understanding of the effects of urban features. While this approach demands greater computational resources, it offers potential for more detailed exploration of the influence coefficients of various variables, thereby enhancing the specificity and applicability of urban planning interventions.

In conclusion, this study provides a robust foundation for understanding the spatial complexities of urban environments, offering valuable insights for creating more sustainable, livable, and environmentally friendly cities. It underscores the need for nuanced, data-driven approaches to urban planning that consider local contexts and the interplay between various urban elements to effectively manage traffic, improve air quality, and enhance overall urban well-being.

BIBLIOGRAPHICAL REFERENCES

Abdelfattah, D., & Nasreldin, R. (2019). Perceptional Dimension Towards More Walkable Communities: An Assessment Tool Approach. *Journal of Urban Research*, *33*(1). https://doi.org/10.21608/jur.2019.86917

An, R., & Zheng, J. (2014). Proximity to an exercise facility and physical activity in China. *Southeast Asian Journal of Tropical Medicine and Public Health*, *45*(6).

Ariffin, R. N. R., & Zahari, R. K. (2013). Perceptions of the Urban Walking Environments. *Procedia - Social and Behavioral Sciences*, *105*. https://doi.org/10.1016/j.sbspro.2013.11.062

Arifin, M., Rasyid, A. R., & Osman, W. W. (2020). Walkability index of real estate housing in Makassar. *IOP Conference Series: Earth and Environmental Science*, *419*(1). https://doi.org/10.1088/1755-1315/419/1/012107

Beshears, J., Choi, J. J., Laibson, D. I., Madrian, B. C., & Reynolds, G. I. (2016). Vaccination rates are associated with functional proximity but not base proximity of vaccination clinics. *Medical Care*, *54*(6). https://doi.org/10.1097/MLR.0000000000000523

Bielik, M., König, R., Schneider, S., & Varoudis, T. (2018). Measuring the Impact of Street Network Configuration on the Accessibility to People and Walking Attractors. *Networks and Spatial Economics*, *18*(3). https://doi.org/10.1007/s11067-018-9426-x

Biswal, A., Singh, V., Malik, L., Tiwari, G., Ravindra, K., & Mor, S. (2023). Spatially resolved hourly traffic emission over megacity Delhi using advanced traffic flow data. *Earth System Science Data*, *15*(2). https://doi.org/10.5194/essd-15-661-2023

Biswas, S., & Roychowdhury, K. (2022). Perception of the Impact of Heavy Vehicle Movement on Walkability in Krishnanagar Municipality, India. *GIS Ostrava 2022 Earth Observation for Smart City and Smart Region*. https://doi.org/10.31490/9788024846026-3

Blackwood, J., Suzuki, R., Shah, S., & Webster, N. (2021). Neighborhood Walkability and Physical and Mental Health among Older Adults Living in a Deprived Community. *Innovation in Aging*, *5*(Supplement_1). https://doi.org/10.1093/geroni/igab046.2361

Blečić, I., Canu, D., Cecchini, A., Congiu, T., & Fancello, G. (2016). Factors of perceived walkability: A pilot empirical study. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9789*. https://doi.org/10.1007/978-3-319-42089-9_9

Blecic, I., Canu, D., Cecchini, A., Congiu, T., & Fancello, G. (2017). Walkability and street intersections in rural-urban fringes: A decision aiding evaluation procedure. *Sustainability (Switzerland)*, *9*(6). https://doi.org/10.3390/su9060883

Blečić, I., Congiu, T., Fancello, G., & Trunfio, G. A. (2020). Planning and design support tools for walkability: A guide for Urban analysts. In *Sustainability (Switzerland)* (Vol. 12, Issue 11). https://doi.org/10.3390/su12114405

Brown, B. B., Werner, C. M., Amburgey, J. W., & Szalay, C. (2007). Walkable route perceptions and physical features: Converging evidence for en route walking experiences. *Environment and Behavior*, *39*(1). https://doi.org/10.1177/0013916506295569

Campisi, T., Ignaccolo, M., Inturri, G., Tesoriere, G., & Torrisi, V. (2021). Evaluation of walkability and mobility requirements of visually impaired people in urban spaces. *Research in Transportation Business and Management*, *40*. https://doi.org/10.1016/j.rtbm.2020.100592

Carr, L. J., Dunsiger, S. I., & Marcus, B. H. (2011). Validation of Walk Score for estimating access to walkable amenities. *British Journal of Sports Medicine*, *45*(14). https://doi.org/10.1136/bjsm.2009.069609

Cerin, E., Frank, L. D., Sallis, J. F., Saelens, B. E., Conway, T. L., Chapman, J. E., & Glanz, K. (2011). From neighborhood design and food options to residents' weight status. *Appetite*, *56*(3). https://doi.org/10.1016/j.appet.2011.02.006

Cerin, E., Leslie, E., Toit, L. du, Owen, N., & Frank, L. D. (2007). Destinations that matter: Associations with walking for transport. *Health and Place*, *13*(3). https://doi.org/10.1016/j.healthplace.2006.11.002

Cerin, E., Saelens, B. E., Sallis, J. F., & Frank, L. D. (2006). Neighborhood environment walkability scale: Validity and development of a short form. *Medicine and Science in Sports and Exercise*, *38*(9). https://doi.org/10.1249/01.mss.0000227639.83607.4d

Colley, R. C., Christidis, T., Michaud, I., Tjepkema, M., & Ross, N. A. (2019). An examination of the associations between walkable neighbourhoods and obesity and self-rated health in Canadians. *Health Reports*, *30*(9). https://doi.org/10.25318/82-003-x201900900002-eng

Corseuil Giehl, M. W., Hallal, P. C., Brownson, R. C., & D'Orsi, E. (2017). Exploring Associations between Perceived Measures of the Environment and Walking among Brazilian Older Adults. *Journal of Aging and Health*, *29*(1). https://doi.org/10.1177/0898264315624904

Cubukcu, E. (2013). Walking for Sustainable Living. *Procedia - Social and Behavioral Sciences*, *85*. https://doi.org/10.1016/j.sbspro.2013.08.335

da Silva, O. H., Pitilin, T. R., Gobbo, C. A. R., Caxambu, M. G., Sanches, S. da P., & Neto, G. D. A. (2020). Accessibility index for urban walkable spaces. *Acta Scientiarum - Technology*, *42*(1). https://doi.org/10.4025/actascitechnol.v42i1.45181

Dannenberg, A. L., Cramer, T. W., & Gibson, C. J. (2005). Assessing the walkability of the workplace: A new audit tool. *American Journal of Health Promotion*, *20*(1). https://doi.org/10.4278/0890-1171-20.1.39

Darmawan, A. M., & Rahmi, D. H. (2021). Quality of Walkability in Peunayong, Banda Aceh. *Built Environment Studies*, *2*(2). https://doi.org/10.22146/best.v2i2.2039

De Paiva Neto, F. T., Arins, G. C. B., D'Orsi, E., & Rech, C. R. (2021). Are changes in walking for transportation in Brazilian older adults associated with attributes of the neighborhood environment? *Journal of Aging and Physical Activity*, *29*(4). https://doi.org/10.1123/JAPA.2020-0120

Ding, D. (2003). Scoring for the Neighborhood Environment Walkability Scale – Youth (NEWS-Y). *American Journal of Public Health*, *93*.

Domeneghini, J., Macke, J., & Sarate, J. A. R. (2022). Walkability Drivers for Sustainable Cities: a Pedestrian Behavior Survey. *Journal of Sustainable Architecture and Civil Engineering*, *30*(1). https://doi.org/10.5755/j01.sace.30.1.29756

Duncan, D. T., Aldstadt, J., Whalen, J., Melly, S. J., & Gortmaker, S. L. (2011). Validation of Walk Score® for estimating neighborhood walkability: An analysis of four US metropolitan areas. *International Journal of Environmental Research and Public Health*, *8*(11). https://doi.org/10.3390/ijerph8114160

Ertz, O., Fischer, A., Ghorbel, H., Hüsser, O., Sandoz, R., & Scius-Bertrand, A. (2021). CITIZEN PARTICIPATION & DIGITAL TOOLS to IMPROVE PEDESTRIAN MOBILITY in CITIES. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *46*(4/W1-2021). https://doi.org/10.5194/isprs-archives-XLVI-4-W1-2021-29-2021

Eynard, E., Melis, G., & Tabasso, M. (2020). Walkable Urban Environments for Wellbeing. *International Journal of Urban Planning and Smart Cities*, *1*(2). https://doi.org/10.4018/ijupsc.2020070102

Fernandes, P., Sousa, C., Macedo, J., & Coelho, M. C. (2019). How to evaluate the extent of mobility strategies in a university campus: An integrated analysis of impacts. *International Journal of Sustainable Transportation*, *14*(2). https://doi.org/10.1080/15568318.2018.1531183

Forsyth, A. (2015). What is a walkable place? The walkability debate in urban design. *Urban Design International*, *20*(4). https://doi.org/10.1057/udi.2015.22

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association*, *72*(1). https://doi.org/10.1080/01944360608976725

Fry, R., Akbari, A., Mah, S., & Ross, N. (2018). Measuring Active Living Environments: An international comparison between Canada and Wales. *International Journal of Population Data Science*, *3*(2). https://doi.org/10.23889/ijpds.v3i2.523

Fujiwara, D., Tsuchiya, K., & Okuro, T. (2018). Evaluation of perceived walkability and streetscape attractiveness in different types of width and street plantings in sidewalks. *Reports of the City Planning Institute of Japan*, *16*(4). https://doi.org/10.11361/reportscpij.16.4_383

Gallagher, M., & Morris, D. (2016). Assessing Usability of Active Infrastructure on a College Campus. *Medicine & Science in Sports & Exercise*, *48*. https://doi.org/10.1249/01.mss.0000487299.49411.44

Gilderbloom, J. I., Riggs, W. W., & Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities*, *42*(PA). https://doi.org/10.1016/j.cities.2014.08.001

Giles-Corti, B., Macaulay, G., Middleton, N., Boruff, B., Bull, F., Butterworth, I., Badland, H., Mavoa, S., Roberts, R., & Christian, H. (2014). Developing a research and practice tool to measure walkability: A demonstration project. *Health Promotion Journal of Australia*, *25*(3). https://doi.org/10.1071/HE14050

Giles-Corti, B., Wood, G., Pikora, T., Learnihan, V., Bulsara, M., Van Niel, K., Timperio, A., McCormack, G., & Villanueva, K. (2011). School site and the potential to walk to school: The impact of street connectivity and traffic exposure in school neighborhoods. *Health and Place*, *17*(2). https://doi.org/10.1016/j.healthplace.2010.12.011

Glazier, R. H., Creatore, M. I., Weyman, J. T., Fazli, G., Matheson, F. I., Gozdyra, P., Moineddin, R., Shriqui, V. K., & Booth, G. L. (2014). Density, destinations or both? A comparison of measures of walkability in relation to transportation behaviors, obesity and diabetes in Toronto, Canada. *PLoS ONE*, *9*(1). https://doi.org/10.1371/journal.pone.0085295

Halonen, J. I., Stenholm, S., Kivimäki, M., Pentti, J., Subramanian, S. V., Kawachi, I., & Vahtera, J. (2015). Is change in availability of sports facilities associated with change in physical activity? A prospective cohort study. *Preventive Medicine*, *73*. https://doi.org/10.1016/j.ypmed.2015.01.012

Hankey, S., Marshall, J. D., & Brauer, M. (2012). Health impacts of the built environment: Within-urban variability in physical inactivity, air pollution, and ischemic heart disease mortality. *Environmental Health Perspectives*, *120*(2). https://doi.org/10.1289/ehp.1103806

Herrmann, T., Gleckner, W., Wasfi, R. A., Thierry, B., Kestens, Y., & Ross, N. A. (2019). A pan-Canadian measure of active living environments using open data. *Health Reports*, *30*(5). https://doi.org/10.25318/82-003-x201900500002-eng

Hirsch, J. A., Moore, K. A., Evenson, K. R., Rodriguez, D. A., & Roux, A. V. D. (2013). Walk score® and transit score® and walking in the multi-ethnic study of atherosclerosis. *American Journal of Preventive Medicine*, *45*(2). https://doi.org/10.1016/j.amepre.2013.03.018

Hua, Y., & Yang, E. (2014). Building spatial layout that supports healthier behavior of office workers: A new performance mandate for sustainable buildings. *Work*, *49*(3). https://doi.org/10.3233/WOR-141872

Jano Reiss, M., Rotem, A., Gridinger, O., Tzur, Y., Reichman, G., Berenbaum, R., & Tziraki, C. (2022). Health and wellbeing (SDG3) in urban design and spatial planning–a retrospective roadmap towards the collective impact model. *Cities and Health*, *6*(5). https://doi.org/10.1080/23748834.2022.2147469

Jardim, B., de Castro Neto, M., & Barriguinha, A. (2023). A street-point method to measure the spatiotemporal relationship between walkability and pedestrian flow. *Computers, Environment and Urban Systems*, *104*, 101993. https://doi.org/10.1016/J.COMPENVURBSYS.2023.101993

Jensen, W. A., Brown, B. B., Smith, K. R., Brewer, S. C., Amburgey, J. W., & McIff, B. (2017). Active transportation on a complete street: Perceived and audited walkability correlates. *International Journal of Environmental Research and Public Health*, *14*(9). https://doi.org/10.3390/ijerph14091014

Jia, S., & Wang, Y. (2021). Effect of heat mitigation strategies on thermal environment, thermal comfort, and walkability: A case study in Hong Kong. *Building and Environment*, *201*. https://doi.org/10.1016/j.buildenv.2021.107988

Jing, Y., Ma, D., Liu, Y., Cui, J., Zhang, S., & Chen, Y. (2021). Decoding the street-based spatiality of urban gyms: Implications for healthy city planning. *Land*, *10*(2). https://doi.org/10.3390/land10020175

Kaczynski, A. T., Robertson-Wilson, J., & Decloe, M. (2012). Interaction of perceived neighborhood walkability and self-efficacy on physical activity. *Journal of Physical Activity and Health*, *9*(2). https://doi.org/10.1123/jpah.9.2.208

Keats, M. R., Cui, Y., Declercq, V., Grandy, S. A., Sweeney, E., & Dummer, T. J. B. (2020). Associations between neighborhood walkability, physical activity, and chronic disease in Nova Scotian adults: An Atlantic path cohort study. *International Journal of Environmental Research and Public Health*, *17*(22). https://doi.org/10.3390/ijerph17228643

Kim, S., Choi, J., & Kim, Y. (2011). Determining the sidewalk pavement width by using pedestrian discomfort levels and movement characteristics. *KSCE Journal of Civil Engineering*, *15*(5). https://doi.org/10.1007/s12205-011-1173-1

Knuiman, M. W., Christian, H. E., Divitini, M. L., Foster, S. A., Bull, F. C., Badland, H. M., & Giles-Corti, B. (2014). A longitudinal analysis of the influence of the neighborhood built environment on walking for transportation: The RESIDE study. *American Journal of Epidemiology*, *180*(5). https://doi.org/10.1093/aje/kwu171

Koohsari, M. J., Sugiyama, T., Shibata, A., Ishii, K., Hanibuchi, T., Liao, Y., Owen, N., & Oka, K. (2018). Walk Score® and Japanese adults' physically-active and sedentary behaviors. *Cities*, *74*. https://doi.org/10.1016/j.cities.2017.11.016

Lajeunesse, S., Ryus, P., Kumfer, W., Kothuri, S., & Nordback, K. (2021). Measuring pedestrian level of stress in urban environments: Naturalistic walking pilot study. In *Transportation Research Record* (Vol. 2675, Issue 10). https://doi.org/10.1177/03611981211010183

Li, M., Sheng, H., Irvin, J., Chung, H., Ying, A., Sun, T., Ng, A. Y., & Rodriguez, D. A. (2023). Marked crosswalks in US transit-oriented station areas, 2007–2020: A computer vision approach using street view imagery. *Environment and Planning B: Urban Analytics and City Science*, *50*(2). https://doi.org/10.1177/23998083221112157

Li, X., Li, Y., Xia, B., & Han, Y. (2021). Pathways between neighbourhood walkability and mental wellbeing: A case from Hankow, China. *Journal of Transport and Health*, *20*. https://doi.org/10.1016/j.jth.2021.101012

Li, Y., Yatsuya, H., Hanibuchi, T., Ota, A., Naito, H., Otsuka, R., Murata, C., Hirakawa, Y., Chiang, C., Uemura, M., Tamakoshi, K., & Aoyama, A. (2020). Positive association of physical activity with both objective and perceived measures of the neighborhood environment among older adults: The aichi workers' cohort study. *International Journal of Environmental Research and Public Health*, *17*(21). https://doi.org/10.3390/ijerph17217971

Lindsey, G. (2021). Review: Within Walking Distance: Creating Livable Communities for All by Philip Langdon . *Journal of Planning Education and Research*, *41*(1). https://doi.org/10.1177/0739456x18803152

Liu, X., Couloigner, I., & Bertazzon, S. (2017). Walk the Less Trodden Path, or Rather, the Less Driven: Mapping Pedestrian Paths and Local Air Pollution for Selective Walking in Cleaner Air (breakout presentation). *Journal of Transport & Health*, *7*. https://doi.org/10.1016/j.jth.2017.11.053

Lund, H. (2003). Testing the Claims of New Urbanism. *Journal of the American Planning Association*, *69*(4).

Macdonald, L., Mccrorie, P., Nicholls, N., & Olsen, J. R. (2019). Active commute to school: does distance from school or walkability of the home neighbourhood matter? A national cross-sectional study of children aged 10-11 years, Scotland, UK. *BMJ Open*, *9*(12). https://doi.org/10.1136/bmjopen-2019-033628

Mavoa, S., Boulangé, C., Eagleson, S., Stewart, J., Badland, H. M., Giles-Corti, B., & Gunn, L. (2018). Identifying appropriate land-use mix measures for use in a national walkability index. *Journal of Transport and Land Use*, *11*(1). https://doi.org/10.5198/jtlu.2018.1132

McCormack, G. R., Giles-Corti, B., & Bulsara, M. (2008). The relationship between destination proximity, destination mix and physical activity behaviors. *Preventive Medicine*, *46*(1). https://doi.org/10.1016/j.ypmed.2007.01.013

McCormack, G. R., Koohsari, M. J., Vena, J. E., Oka, K., Nakaya, T., Chapman, J., Martinson, R., & Matsalla, G. (2023). Associations between neighborhood walkability and walking following residential relocation: Findings from Alberta's Tomorrow Project. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.1116691

Moin, J. S., Glazier, R. H., Kuluski, K., Kiss, A., & Upshur, R. (2021). Impact of neighbourhood walkability on the onset of multimorbidity: A cohort study. *BMJ Open*, *11*(4). https://doi.org/10.1136/bmjopen-2020-045890

Mu, T., & Lao, Y. (2022). A Study on the Walkability of Zijingang East Campus of Zhejiang University: Based on Network Distance Walk Score. *Sustainability (Switzerland)*, *14*(17). https://doi.org/10.3390/su141711108

Napier, M. A., Brown, B. B., Werner, C. M., & Gallimore, J. (2011). Walking to school: Community design and child and parent barriers. *Journal of Environmental Psychology*, *31*(1). https://doi.org/10.1016/j.jenvp.2010.04.005

Nigro, M., Petrelli, M., Ušpalytė-Vitkūnienė, R., & Žilionienė, D. (2018). Understanding the walkability propensity. *Baltic Journal of Road and Bridge Engineering*, *13*(2). https://doi.org/10.7250/bjrbe.2018-13.408

Nykiforuk, C. I. J., McGetrick, J. A., Crick, K., & Johnson, J. A. (2016). Check the score: Field validation of Street Smart Walk Score in Alberta, Canada. *Preventive Medicine Reports*, *4*. https://doi.org/10.1016/j.pmedr.2016.09.010

Owen, N., Cerin, E., Leslie, E., duToit, L., Coffee, N., Frank, L. D., Bauman, A. E., Hugo, G., Saelens, B. E., & Sallis, J. F. (2007). Neighborhood Walkability and the Walking Behavior of Australian Adults. *American Journal of Preventive Medicine*, *33*(5). https://doi.org/10.1016/j.amepre.2007.07.025

Ozawa, H., Fukuda, A., Malaitham, S., Vichiensan, V., Luathep, P., & Numa, H. (2021). Evaluation of walking environments around urban railway stations in Bangkok and consideration of improvement plans. *Asian Transport Studies*, *7*. https://doi.org/10.1016/j.eastsj.2021.100038

Park, S., & Ko, D. (2020). Investigating the factors influencing pedestrian-vehicle crashes by age group in Seoul, South Korea: A hierarchical model. *Sustainability (Switzerland)*, *12*(10). https://doi.org/10.3390/su12104239

Pelclová, J., Frömel, K., & Cuberek, R. (2013). Gender-Specific associations between perceived neighbourhood walkability and meeting walking recommendations when walking for transport and recreation for Czech inhabitants over 50 years of age. *International Journal of Environmental Research and Public Health*, *11*(1). https://doi.org/10.3390/ijerph110100527

Piracha, A., & Chaudhary, M. T. (2022). Urban Air Pollution, Urban Heat Island and Human Health: A Review of the Literature. *Sustainability (Switzerland)*, *14*(15). https://doi.org/10.3390/su14159234

Pivo, G., & Fisher, J. D. (2011). The walkability premium in commercial real estate investments. *Real Estate Economics*, *39*(2). https://doi.org/10.1111/j.1540-6229.2010.00296.x

Rafiemanzelat, R., Emadi, M. I., & Kamali, A. J. (2017). City sustainability: the influence of walkability on built environments. *Transportation Research Procedia*, *24*. https://doi.org/10.1016/j.trpro.2017.05.074

Rogers, S. H., Halstead, J. M., Gardner, K. H., & Carlson, C. H. (2011). Examining Walkability and Social Capital as Indicators of Quality of Life at the Municipal and Neighborhood Scales. *Applied Research in Quality of Life*, *6*(2). https://doi.org/10.1007/s11482-010-9132-4

Rohrer, J., Pierce, J. R., & Denison, A. (2004). Walkability and self-rated health in primary care patients. In *BMC Family Practice* (Vol. 5). https://doi.org/10.1186/1471-2296-5-29

Rosso, A. L., Harding, A. B., Clarke, P. J., Studenski, S. A., & Rosano, C. (2021). Associations of Neighborhood Walkability and Walking Behaviors by Cognitive Trajectory in Older Adults. *Gerontologist*, *61*(7). https://doi.org/10.1093/geront/gnab005

Rubaszek, J., Gubański, J., & Podolska, A. (2023). Do We Need Public Green Spaces Accessibility Standards for the Sustainable Development of Urban Settlements? The Evidence from Wrocław, Poland. *International Journal of Environmental Research and Public Health*, *20*(4). https://doi.org/10.3390/ijerph20043067

Sallis, J. F., Bowles, H. R., Bauman, A., Ainsworth, B. E., Bull, F. C., Craig, C. L., Sjöström, M., De Bourdeaudhuij, I., Lefevre, J., Matsudo, V., Matsudo, S., Macfarlane, D. J., Gomez, L. F., Inoue, S., Murase, N., Volbekiene, V., McLean, G., Carr, H., Heggebo, L. K., … Bergman, P. (2009). Neighborhood Environments and Physical Activity Among Adults in 11 Countries. *American Journal of Preventive Medicine*, *36*(6). https://doi.org/10.1016/j.amepre.2009.01.031

Sarroeira, R., Henriques, J., Sousa, A. M., Ferreira da Silva, C., Nunes, N., Moro, S., & Botelho, M. do C. (2023). Monitoring Sensors for Urban Air Quality: The Case of the Municipality of Lisbon. *Sensors*, *23*(18). https://doi.org/10.3390/s23187702

Shafray, E., & Kim, S. (2017). A study of walkable spaces with natural elements for urban regeneration: A focus on cases in Seoul, South Korea. *Sustainability (Switzerland)*, *9*(4). https://doi.org/10.3390/su9040587

Shigematsu, R., Sallis, J. F., Conway, T. L., Saelens, B. E., Frank, L. D., Cain, K. L., Chapman, J. E., & King, A. C. (2009). Age differences in the relation of perceived neighborhood environment to walking. *Medicine and Science in Sports and Exercise*, *41*(2). https://doi.org/10.1249/MSS.0b013e318185496c

Sirjani, A. H., & Szabó, Á. (2021). Perceiving Liveability through the Diverse Aspects of Walkability. *Periodica Polytechnica Architecture*, *52*(1). https://doi.org/10.3311/ppar.16449

Slater, S. J., Nicholson, L., Chriqui, J., Barker, D. C., Chaloupka, F. J., & Johnston, L. D. (2013). Walkable communities and adolescent weight. *American Journal of Preventive Medicine*, *44*(2). https://doi.org/10.1016/j.amepre.2012.10.015

Stockton, J. C., Duke-Williams, O., Stamatakis, E., Mindell, J. S., Brunner, E. J., & Shelton, N. J. (2016). Development of a novel walkability index for London, United Kingdom: Cross-sectional application to the Whitehall II Study. *BMC Public Health*, *16*(1). https://doi.org/10.1186/s12889-016-3012-2

Sukor, N. S. A., & Fisal, S. F. M. (2020). Safety, Connectivity, and Comfortability as Improvement Indicators of Walkability to the Bus Stops in Penang Island. *Engineering, Technology and Applied Science Research*, *10*(6). https://doi.org/10.48084/etasr.3849

Sun, Z., Scott, I., Bell, S., Zhang, X., & Wang, L. (2021). Time distances to residential food amenities and daily walking duration: A cross-sectional study in two low tier chinese cities. *International Journal of Environmental Research and Public Health*, *18*(2). https://doi.org/10.3390/ijerph18020839

Talaat, Y., & Emad, M. (2022). Enhancing Walkability in pedestrian oriented gated communities Case Study: Arabia’s Gated Community-New Cairo City. *Engineering Research Journal*, *175*(0). https://doi.org/10.21608/erj.2022.258295

Tiwari, R. (2015). Designing a safe walkable city. *Urban Design International*, *20*(1). https://doi.org/10.1057/udi.2013.33

Van Dyck, D., Cerin, E., Conway, T. L., De Bourdeaudhuij, I., Owen, N., Kerr, J., Cardon, G., Frank, L. D., Saelens, B. E., & Sallis, J. F. (2012). Perceived neighborhood environmental attributes associated with adults’ transport-related walking and cycling: Findings from the USA, Australia and Belgium.

International Journal of Behavioral Nutrition and Physical Activity, *9*. https://doi.org/10.1186/1479-5868-9-70

Vilhelmson, B., & Elldér, E. (2021). Realizing proximity in times of deregulation and densification: Evaluating urban change from a welfare regime perspective. *Journal of Transport Geography*, *94*. https://doi.org/10.1016/j.jtrangeo.2021.103098

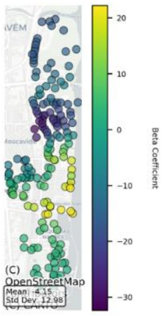
Watson, K. B., Whitfield, G. P., Thomas, J. V., Berrigan, D., Fulton, J. E., & Carlson, S. A. (2020). Associations between the National Walkability Index and walking among US Adults — National Health Interview Survey, 2015. *Preventive Medicine*, *137*. https://doi.org/10.1016/j.ypmed.2020.106122

Zumelzu, A., Barría, T., & Barrientos-Trinanes, M. (2019). EFECTOS DE LA FORMA URBANA SOBRE LA ACCESIBILIDAD PEATONAL EN BARRIOS DEL SUR DE CHILE. *Arquitetura Revista*, *16*(1). https://doi.org/10.4013/arq.2020.161.01

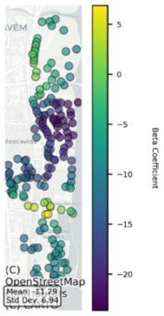
APPENDIX A

a) Poisson GWR Beta Coefficients for significant variables for Car Traffic

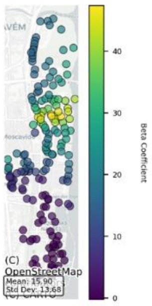
1. Slope (degrees)



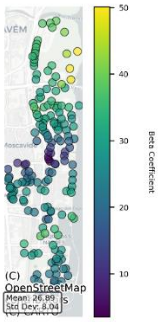
2. Food Establishments



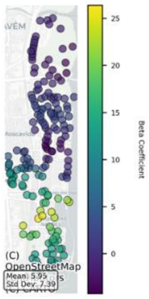
3. Trees



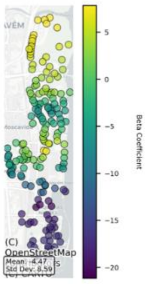
4. Parking Facilities



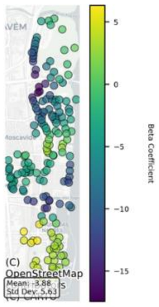
5. Educational Institutions



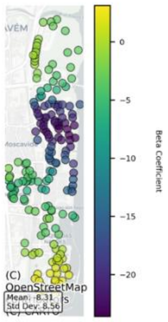
6. Water Features



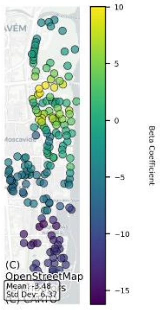
7. Financial Services



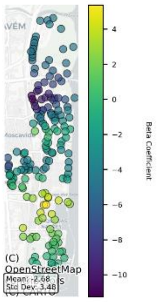
8. Office Buildings



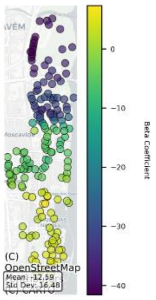
9. Public Transport



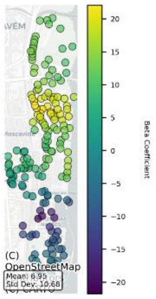
10. Government Buildings



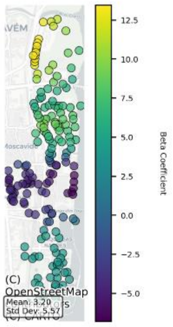
11. Crosswalks



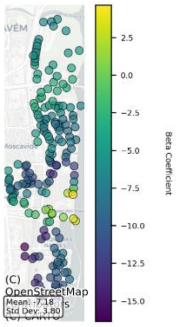
12. Healthcare Facilities



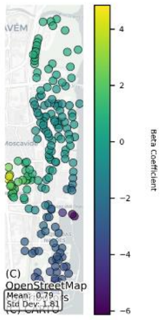
13. Entertainment Venues



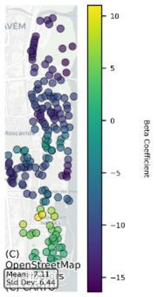
14. Sports Facilities



15. Sidewalk Width

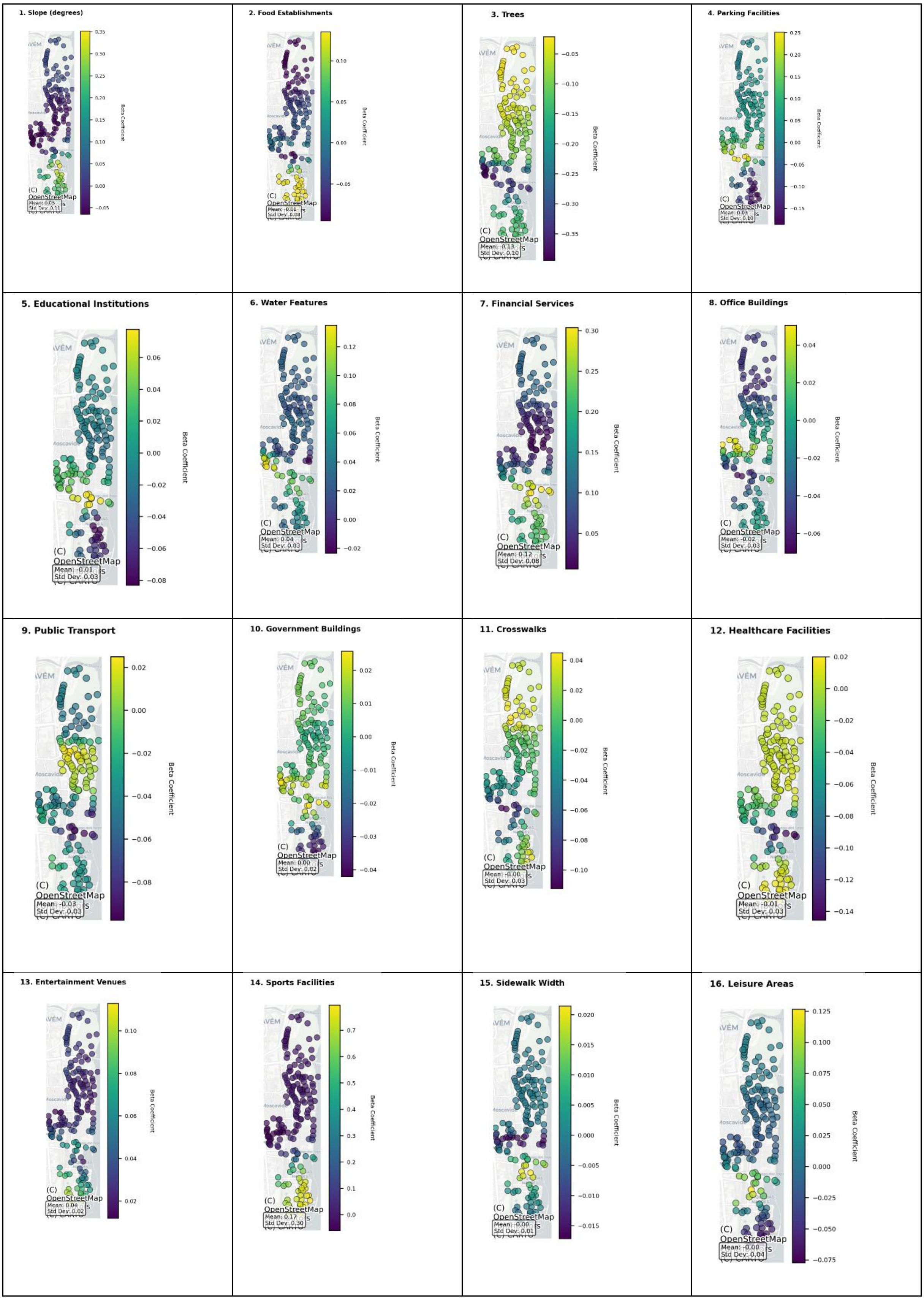


16. Leisure Areas



APPENDIX B

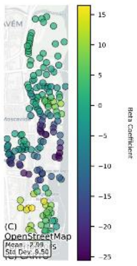
GWR Beta Coefficients for CO



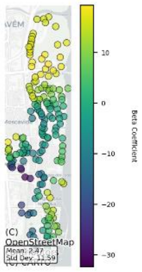
APPENDIX C

GWR Beta Coefficients for NO

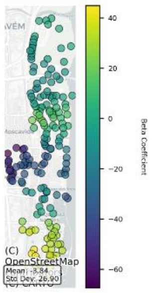
1. Slope (degrees)



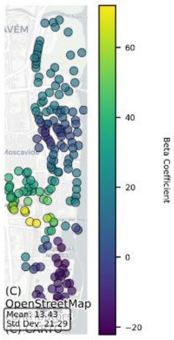
2. Food Establishments



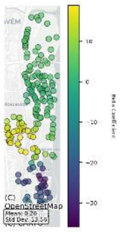
3. Trees



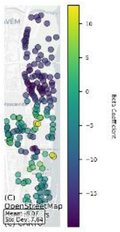
4. Parking Facilities



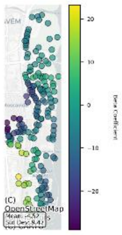
5. Educational Institutions



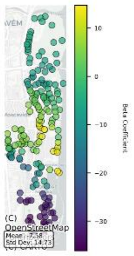
6. Water Features



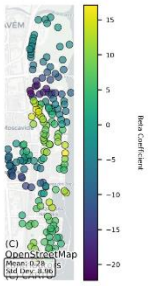
7. Financial Services



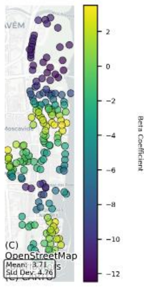
8. Office Buildings



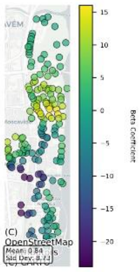
9. Public Transport



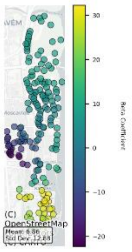
10. Government Buildings



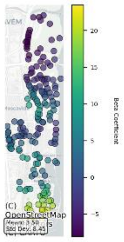
11. Crosswalks



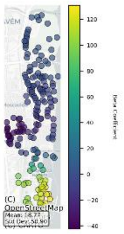
12. Healthcare Facilities



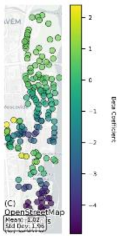
13. Entertainment Venues



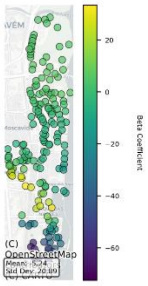
14. Sports Facilities



15. Sidewalk Width



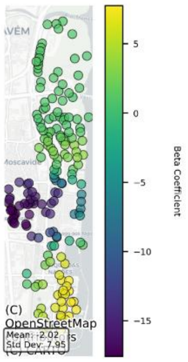
16. Leisure Areas



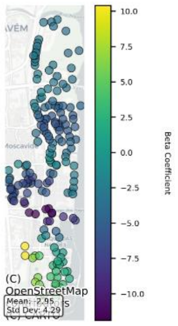
APPENDIX D

GWR for NO2

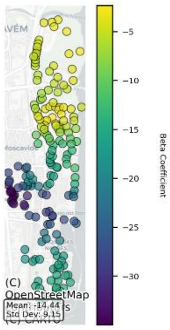
1. Slope (degrees)



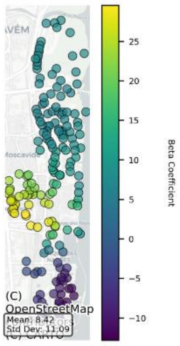
2. Food Establishments



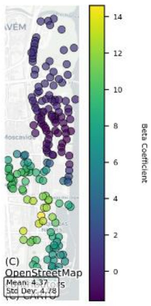
3. Trees



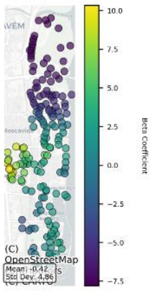
4. Parking Facilities



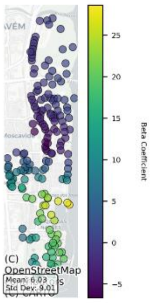
5. Educational Institutions



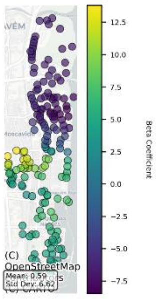
6. Water Features



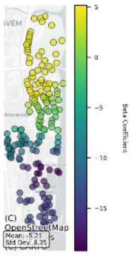
7. Financial Services



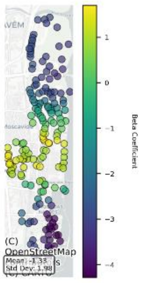
8. Office Buildings



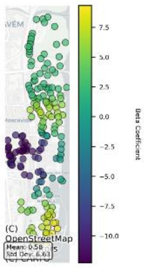
9. Public Transport



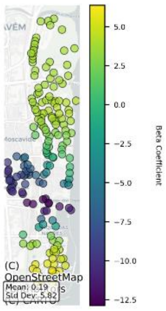
10. Government Buildings



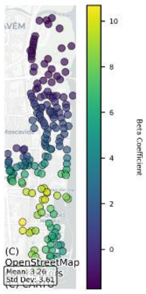
11. Crosswalks



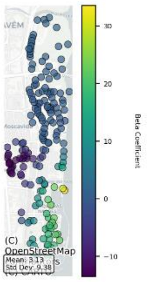
12. Healthcare Facilities



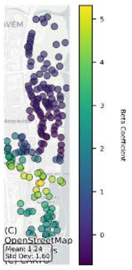
13. Entertainment Venues



14. Sports Facilities



15. Sidewalk Width



16. Leisure Areas