Universidade Estadual de Londrina

ANA LUIZA FAVARÃO LEÃO

OBJECTIVE WALKABILITY MEASURES FOR BRAZILIAN TOWNS: A METHODOLOGICAL APPROACH

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Research submitted for the fulfilment of the requirements for the master's degree in Architecture and Urbanism from the Associated Master Program in Architecture and Urbanism from State University of Londrina and State University of Maringá.

Advisor: Profª. Drª. Milena Kanashiro
Co-Advisor: Profª.Drª. Mariana Ragassi Urbano

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2019

Para minha mãe, Alda.

“Amar e mudar as coisas me interessa mais”

Alucinação - Belchior

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ABSTRACT

The built environment has potential determinants for supporting more active lifestyles. However, regarding the large number of environmental variables that may influence physical activity (PA) and walking, composite walkability indices have been created. Notwithstanding, as social reality and PA are directly related (BAUMAN et al., 2012), walkability indices developed in larger cities and high-income countries may not be suited for Brazilian towns. Therefore, the main objective of this research was to evaluate the efficacy of objective walkability measures of the built environment in a Brazilian average-sized town. From the systematizing of spatial data and a subjective database from the Urban Mobility Plan (n=756) of a case study (Rolândia-PR), six different walkability indices and their variables were tested for six spatial units (200m, 400, 600m, 800m, 1000m buffers and census tracts). Walkability indices and variables were analyzed with self-reported walking (meter walked per area unit) through a machine learning approach, considering the Random Forest Algorithm. Perceptions of satisfaction with the built environment were tested with walking and walkability. Results indicated that the 1000m network-buffer scale best modeled the relationship. The most relevant walkability features were Entropy Z-score (FI= 0.609) and The Walkability Index considering Residential Density and Space Syntax at a Global Integration radius (FI= 0.408). No relation between objective walkability measures, walking and perceptions of satisfaction with the built environment were identified. These findings are of great implication to the operationalization of walkability in Brazilian towns, indicating that more traditional walkability indices might not be suited for our social, cultural and urban reality. Practical contributions of this work include the possibility to subsidize municipal regulations for the creation of evidence-centered, contextually-tailored urban policies.

Keywords: Walkability; Built environment; Walkability indices

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RESUMO

O ambiente construído possui determinantes de estilos de vida mais ativos. Dado o grande número de variáveis ambientais que podem influenciar a atividade física e a caminhada, fatores compostos para mensurar a caminhabilidade do bairro foram criados. No entanto, como a realidade social e a atividade física são diretamente relacionadas (BAUMAN et al., 2012), índices de caminhabilidade desenvolvidos para cidades maiores e em países de alta renda podem não ser adequados para cidades medias brasileiras. Portanto, o principal objetivo desta pesquisa foi avaliar a eficácia de medidas objetivas da caminhabilidade do ambiente construído em uma cidade média brasileira. A partir da sistematização de dados espaciais e de um banco de dados subjetivos do Plano de Mobilidade (n=756) de um estudo de caso (Rolândia-PR), foram testados seis índices de caminhabilidade e suas variáveis em seis escalas de vizinhança (buffers de rede de 200m, 400, 600m, 800m, 1000m buffers e setores censitário). Índices e suas variáveis foram analisados e cotejados com níveis de caminhada (metros caminhados por unidade de área) por meio de uma abordagem de aprendizado de máquina através do algoritmo *Random Forest*. Percepções de satisfação com o ambiente construído do bairro foram testadas em relação ao caminhar e a caminhabilidade. Os resultados indicam que a escala de buffer de rede de 1000 metros melhor modelou a relação. As variáveis da caminhabilidade mais relevantes foram o Escore-Z da medida de Entropia (FI= 0.609) e o Índice de Caminhabilidade considerando a Densidade Residencial e Sintaxe Espacial em um raio de Integração Global (FI= 0.408). Tais resultados são de grande implicação para a operacionalização da caminhabilidade em cidades brasileiras, indicando que índices mais tradicionais podem não ser adequados para nossa realidade social, cultural e urbana. Contribuições práticas deste trabalho incluem a possibilidade de subsidiar legislações municipais para a criação de políticas urbanas contextualizadas e baseadas em evidências.

Palavras-chave: Caminhabilidade; Ambiente Construído; Índices de Caminhabilidade

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BOARD INDEX

LIST OF ABBREVIATIONS AND ACRONYMS

ANTP	National Association of Public Transport (Associação Nacional de Transportes Públicos)
BE	Built environment
CTNP	North of Paraná Land Company (Companhia de Terras Norte do Paraná)
FAR	Floor area Ratio
GIS	Geographic Information Systems
IBGE	Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística)
ITEDES	Institute of Technology, Economic, and Social Development (Instituto de Tecnologia e Desenvolvimento Econômico e Social)
KNN	K nearest neighbor
ML	Machine Learning
NN	Nearest neighbor
NS	Neighborhood Satisfaction
OD	Origin - destinations
PA	Physical activity
RF	Random Forest
SES	Socioeconomic status

SUMMARY

1 INTRODUCTION

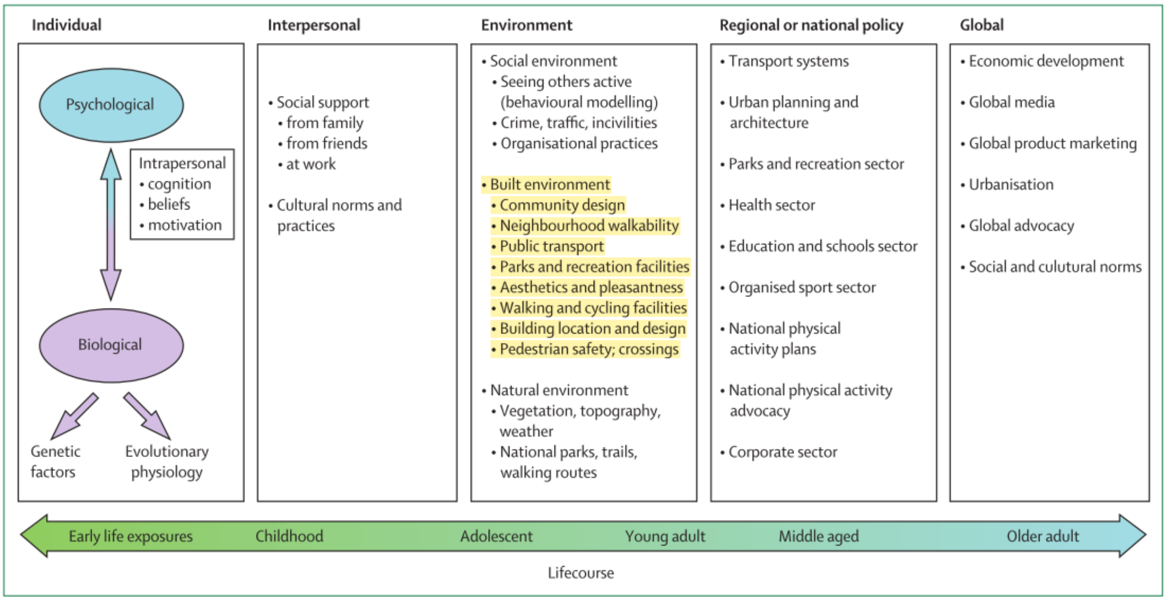
1.1 Background and Research Problem

According to the World Health Organization (WHO) non-communicable diseases (NCDs) such as cardiovascular diseases, hypertension and type 2 diabetes represent a threat to human development and the susceptibility to them increases due to physical inactivity (WORLD HEALTH ORGANIZATION, 2015). Therefore, regular physical activity (PA) is widely acknowledged for its capacity to prevent and treat an array of psychological and physical conditions (SALLIS et al., 2006; FITZSIMONS et al., 2008). Facing the prevalence of physical inactivity worldwide and its negative effects on health (DUMITH et al., 2011), understanding aspects that influence active behaviors is paramount.

Notwithstanding, PA is influenced by different factors, hence ecological models have been utilized in their analysis. These models are comprehensive approaches that propose many different scaled correlates of PA (Figure 1). According to this model, different levels of determinants and their interaction are responsible for the shaping of an individual's active behaviors (BAUMAN et al., 2012). Individual variables are widely studied (SALLIS et al., 2006) whereas environmental factors are less researched, despite their recognized effects on behavior (BAUMAN et al., 2012). Experimental evidence has identified direct environmental influence as a stronger determinant of walking behaviors than cognitively mediated behavioral choices (OWEN et al., 2004). Therefore, these findings indicate that the built environment (BE) may promote or hinder active behaviors.

The built environment (BE) is defined differently by many authors but is generally accepted as part of the environment, which is composed of social, natural, and built elements. "Social" refers to organizational practices, crime, traffic and seeing others active behaviors (BAUMAN et al., 2012) ; "Built" refers to what is constructed by human action (SALLIS et al., 2006) and "natural" to topography, vegetation, and climate (HINO, 2014). Hence, the following elements constitute the BE: organization and appearance of built elements, use patterns, distribution of activities through space, buildings, transportation system, the physical structure of streets, sidewalks, cycle paths, etc. (SAELENS; HANDY, 2008). Researchers that correlate BE aspects with health aim to understand the impact of contextual-physical factors on human behavior (PLIAKAS et al., 2017). The characteristics of the BE possibly correlated to PA may be grouped into seven categories: 1) Population Density; 2) Land use mix; 3) Places to practice physical activities; 4) Street pattern; 5) Sidewalks/cycle paths structures; 6) Public transport 7) Aesthetics and safety (HINO; REIS; FLORINDO, 2010).

Figure 1 – Adapted ecological model of the determinants of physical activity.



Source: Adapted from Bauman et al. (2012); Modified by the author, 2018.

Characteristics of the built environment can be quantified through objective and/or subjective measuring (HINO; REIS; FLORINDO, 2010). Most studies conducted on this topic (HANDY et al., 2002; MOUDON; LEE, 2003; SAELENS et al., 2003) show that several BE attributes, measured both objectively and subjectively, are related to levels of PA (LIN; MOUDON, 2010). Subjective measures have been commonly assessed via surveys asking about residents' perceptions. On the other hand, objective assessments of the BE have relied on field audits and geographic information system (GIS) (LEE et al., 2017). Many researchers recommend a combination of measurement approaches (TROPED et al., 2001; OWEN et al., 2004; HOEHNER et al., 2005; MCGINN et al., 2007; JANSUWAN; CHRISTENSEN; CHEN, 2014) to unveil the relationship of objective and perceptive data for a more accurate understanding of the influence of space in human behavior (SAELENS; SALLIS, 2002).

Consideration of residents' perceptions can be used for planning and designing healthy communities (LEE et al., 2017). Providing environmental features that support positive perceptions, and increase neighborhood satisfaction is desirable (LESLIE; CERIN, 2008). Neighborhood satisfaction is understood as influenced by two sets of variables: individual and neighborhood quality characteristics (BASOLO; STRONG, 2002). However, a possible low level of concordance confirms that perceptions should not be considered as proxies for objective measures (JAUREGUI et al., 2016a). According to Marans (2012) the urban quality of an environmental setting such as the neighborhood cannot be captured through a single measure; rather, it requires measures of multiple attributes of the environmental setting in question.

The advantages of objective measuring include (1) reduction in measurement errors, (2) easy standardization (3) facilitated translation into political actions (MOUDON; LEE, 2003) (4) and avoiding of bias associated with self-reports (KRAMER et al., 2013). Many reviews conducted on this theme (BROWNSON et al., 2009; FRANK et al., 2010; BAUMAN et al., 2012; SUGIYAMA et al., 2012) show a newfound emphasis for the understanding of the BE as an influence on active mobility (HOEHNER et al., 2005) pointing out that our cities play an important role to support healthier lifestyles (SALLIS; BAUMAN; PRATT, 1998; HUMPEL, 2002; DING; GEBEL, 2012).

With the growing burdens of motorized transportation (MURRAY; LOPEZ; CAMBRIDGE, 1996) urban qualities have lead researchers to gain understanding on the urban form's influence on travel behavior (CAMPOLI, 2012). It has been centered as an important emerging topic in the growing dialogue concerning neighborhood sustainability and as the core of city planning strategies of developed countries (GILDERBLOOM; RIGGS; MEARES, 2015). One of the strategies to evaluate the BE for supporting more active daily lives is walkability analysis, defined as the extent to which the BE supports and encourages walking (SOUTHWORTH, 2005, p. 258).

Walking is the most frequent type of PA (LIN; MOUDON, 2010). It is accessible, inexpensive and associated with a series of health benefits (DOESCHER et al., 2014). Walking can be categorized as commuting/functional and optional/recreational (CARMONA et al., 2010). Utilitarian walking – commuting to routine destinations – has been identified as a central element underpinning sustainable lifestyles (SAELENS; SALLIS; FRANK, 2003) and has proven effective in reaching recommended PA levels when incorporated into daily life (FRANK; ANDRESEN; SCHMID, 2004). Besides contributing to health, walking is at the core of sustainable mobility, it reduces motorized transportation minimizing environmental impacts. Walking demands fewer resources than other means of transportation, it is cheap, silent, and non-polluting (GEHL, 2013). Therefore, in low-income and middle-income countries, studies on environmental correlates of walking are urgently needed (BAUMAN et al., 2012) to attenuate the rapidly changing determinants of inactivity occurring due to urbanization, passive entertainment, and motorized transport.

In Brazil, According to Malta et al. (2014), 72.6% of NCDs cases are related to causes of death, mainly in the lower socioeconomic status population group. VIGITEL data (System of Surveillance of Risk Factors and Protection for Chronic Diseases by Telephone Inquiry) indicates that 45,4% of inhabitants living in capitals do not reach sufficient PA levels (BRASIL. MINISTÉRIO DA SAÚDE. SECRETARIA DE VIGILANCIA EM SAÚDE, 2011). These issues provide opportunities for urban planning to mitigate sedentary behaviors (REIS; HINO, 2013). Considering the Brazilian context, the economic burden of physical inactivity (WANG et al., 2004) and the recognized benefits of PA, studies on environmental factors that may positively influence active behaviors gain importance.

The existing literature on BE correlates of physical activity on Latin American countries points out that socioeconomic inequality within urban areas, highlights that different socioeconomic status (SES) groups live in very different epidemiological contexts, even within the same city (RYDIN et al., 2012). The social stratification that composes Brazilian cities usually possesses scale and complexity to generate alternative centers, reorienting centralities and further fragmenting the urban environment (KRAFTA, 2014). As a consequence of this scattered urban growth, infrastructure and public services become absent. The occupation of unsuitable areas through territorial sprawl results in peripheralization, environmental impacts, marginalized population and the occupation of fragile environments (FRACASSI; DE LOLLO, 2013).

This Brazilian scenario presents itself very differently from high-income countries, as there is a clear relationship between the spatial and physical characteristics of a city, and its functional, socio-economical and environmental qualities (CARMONA et al., 2010). Such differences emphasize the need for context-specific studies in designing and implementing environmental strategies to increase physical activity levels (SALVO et al., 2014).

There is ample evidence on the phenomenon of the BE as a support for walking in developed countries, even though existing data on active behavior determinants are eventually inconclusive (BAUMAN et al., 2012). However, even if this correlation is being addressed effectively through numerous studies, fewer aim to understand the dimensions of this relationship in low and middle-income countries (GOMES et al., 2011; PARRA et al., 2011). Such deficit of studies using objective walkability measures can be partly attributed to the difficulty to obtain Geographic Information System data (HINO et al., 2012) and to evaluate large areas through systematic observation (HINO; REIS; FLORINDO, 2010).

Such research interest is made even more relevant in towns where nonmotorized transportation is largely present and public transport is less used (*Associação Nacional de Transportes Públicos*, 2012). Brazil has most of its cities represented by an average of 5 to 100 thousand inhabitants (IBGE, 2015). According to ANTP (*Associação Nacional de Transportes Públicos*, 2012) active travel (by foot) is inversely proportional to the dimension of the city - the smaller the city, the higher the rates of active travel. Notwithstanding, there is a lack of studies on walkability in medium and small-sized towns. Considering these topics, the need for greater understanding of active travel patterns in Brazilian towns are evident for tailored mobility policies. Therefore, this study aims to fill the research gap, specifically for averaged sized towns, regarding built environment walkability measures and constructs in the unexploded context of the middle-income country of Brazil.

1.2 Research Objectives

In view of the above presented conceptual and methodological needs, this study analyzed the *phenomenon of the BE as a support for walking on Brazilian Towns.* To that end, objective walkability measures were verified through a comparison with self-reported travel behaviors. Such measures were also analyzed regarding their relationship to perceptions of neighborhood satisfaction.

A case study was conducted in the average sized Brazilian town of Rolândia-PR in reason of the real-life contemporary contextually of the BE as support for walking (YIN, 2001). We conjectured that the environmental variables related to walking behaviors were not the same in averaged-sized towns as the ones in larger Brazilian cities and high income developed countries. It was expected that some variables would exert a higher influence on behavior than others, demanding a specific approach to measuring the objective walkability-built environment effectively. This work had the theoretical assumption that when comparing objective walkability measures to travel behaviors on averaged-sized Brazilian towns it would be possible to uncover the specific variables that influence walking in Brazilian town~~s~~.

According to Bauman (2012), social reality and PA are directly related. In low- and middle-income countries active transportation can be intense, on the other hand, in high income countries leisure activity is dominant (BAUMAN et al., 2012). Therefore, we surmised that levels urban development, spatial patterns of urban sprawl, the urban form of the city as well as the socioeconomic and cultural reality would uncover unconventional correlations between the BE, behaviors, and perceptions.

Therefore, **the main aim** of this research was to:

- Evaluate the efficacy of walkability objective measures of the built environment in a Brazilian average-sized town.

The **specific aims** of the research were to:

- Analyze the urban form of Rolândia-PR/Brazil and how it relates to walkability;

- Identify the adequate spatial unit for capturing BE features on walkability assessment of average-sized Brazilian towns;

- Analyze the relationship between walking, walkability variables and walkability indices with perceptions of satisfaction with the built environment.

1.3 Research Outline

In order to achieve the research objectives, this study specifies the following structure:

- First, an introduction with contextualizing the research paradigm under investigation, and a general outline of the research;

- A second chapter containing a bibliographic and conceptual review that details walkability, walking and perceptions, as well as discusses aggregation strategies for such data;

- A third chapter regarding data and methods, that contains an integrative review for uncovering appropriate methodologies for quantifying walkability, walking levels and perceptions; the introduction of the case study; the units of analysis that were developed; the detailing of all correlational variables and objective walkability measures and lastly the delineation of the analytical strategy that was employed;

- A fourth chapter presenting the results and analysis of the relationships found between walking, walkability variables and walkability indices; and modeling of perception's relationship with the built environment, walking and time living in the neighborhood;

- A fifth chapter discussing data results and their implications; and analyzing walkability and the urban form of the case study;

- Finally, a sixth chapter concluding this work; indicating its strengths, contributions, limitations and future research possibilities.

The Correlational Research method was adopted (GROAT; WANG, 2002) due to the necessity to clarify patterns of relationship between two or more variables. The methodological strategy suited to our research problem is the Case Study, ideal to tackle contextual issues in a real-life contemporary phenomenon (YIN, 2001).

The methodological strategy of this research involves assessing the efficacy of objective walkability measures in the context of a Brazilian town. Methodologies for quantifying walkability, walking levels and perceptions were selected through the analysis of the scientific literature that utilizes combined subjective-perceived neighborhood-built environment and objectively measured neighborhood-built environment data to analyze walking behaviors. Objective walkability measures considered were a Walkability Index proposed by (FRANK et al., 2010), the Space syntax Walkability measure proposed by (KOOHSARI et al., 2016a) and some variations hypothesized to possibly be more adequate in the context of a Brazilian town. Those indices involve the following built environment constructs: (1) net residential density; (2) retail floor area ratio; (3) intersection density (4) land use mix and (5) space syntax metrics. Individual variables understood as related to walking levels and that possibly contribute to walkability measurement were also included: land parcel value and real estate value.

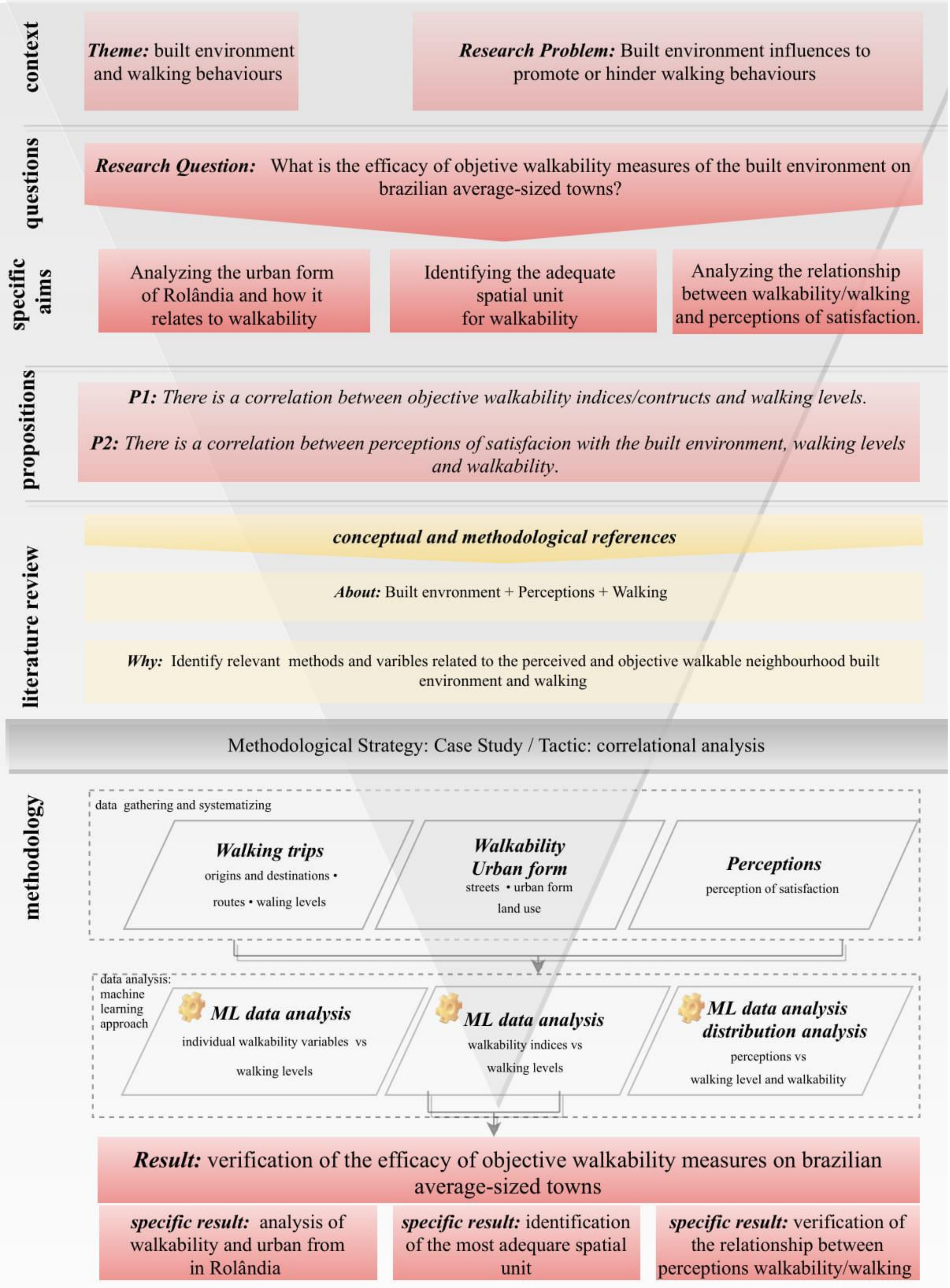
On account of database availability and populational representation of an average-sized Brazilian town the selected case study is Rolândia-PR. This town is currently in the processes of developing its mobility plan, therefore an extensive subjective database was provided by ITEDES. The available data includes self-reported travel behaviors and perceived neighborhood satisfaction. Perceived safety while walking, pleasure while walking, ease to walk and access to public transportation are some examples of the subjective aspects assessed (ATTACH A).

Objective data was collected in the field and geocoded by the researchers of the Environmental Design Research Group from the State University of Londrina. Data aggregation was undertaken in six different neighborhood representation scales: census tracts, 200-meter network buffers, 400-meter network buffers, 600-meter network buffers, 800-meter network buffers and 1000-meter network buffers around participants geocoded residential address.

Perceptions of satisfaction were dichotomized into two categories and walking levels were quantified in meters per unit area. The relationship between these variables, objective walkability measures and walkability constructs was analyzed through a Machine Learning approach. The Random Forest (RF) ensemble learning method for classification and regression proposed by Breiman (2001) was applied. RF is considered robust to errors and outliers as well as efficient in big data sets (BREIMAN, 2001), presenting itself as an ideal approach for this analysis.

First the analysis of the relationship between BE factors and self-reported walking data was conducted through a RF regression in three separate steps: Firstly, individual walkability related variables were tested and secondly walkability indices were evaluated. In sequence, the relationship between BE factors and self-reported perceptions of satisfaction was verified through a RF classification, aiming to investigate their concordance. Throughout these analyses the sensitivity of all results was explored by spatial scale, estimating separate models using BE factors aggregated at five buffer-based scales (200 m, 400 m, 600 m, 800 m, 1000 m) and census tract level. And lastly, urban form was discussed as to its relationship with walkability results. A research outline graphically explaining the development of the research is available in Figure 2

Figure 2 – Research Outline.



Source: Organized by the author, 2017

2 CONCEPTUAL AND BIBLIOGRAPHIC REVIEW

2.1 Urban form and walkability

The benefits of walking are widely recognized as it can be more than a utilitarian mean of transportation. It holds social, recreational and cultural values (SOUTHWORTH, 2005). Walking is the most equitable, accessible and available mean of transportation (ORELLANA; HERMIDA; OSORIO, 2016). It can promote mental and physical health, as well as enrich the community environment through social capital (LEYDEN, 2003). Given such benefits, several recent studies have dissected the domains involved in walking behaviors. Those researches aim to uncover evidence that can subsidize opportunities for cities to create health and wellbeing, making them people-centered (KLEINERT; HORTON, 2016).

The BE is an influence able to facilitate or constrain walking behaviors (SAELENS; HANDY, 2008). The character and qualities of streets and public open spaces impact the degree to which they are safe, comfortable, and attractive for walking (LEE; MOUDON, 2004). Such places that encourage walking possess the specific characteristics that make them walkable (SAELENS; HANDY, 2008). According to Southworth (2005), walkability is an urban quality widely referred to and operationalize but poorly defined. In this research the adopted concept of walkability follows the definition that proposed by Leslie and Cerin (2008): “the extent to which characteristics of the built environment and land use may or may not be conducive to walking for either leisure, exercise or recreation, to access services, or to travel to work”.

In terms of the scale of measurement, there are two types of walkability: micro- and meso-level walkability (PARK; CHOI; LEE, 2015). Micro-level walkability consists of the walking environment that is directly perceived by pedestrians. Specific street level characteristics comprise such walkability scale, such as the presence of trees, the shape of buildings, their arrangement, the width of sidewalks, the quality of streets, and, fundamentally, sidewalk quality. These features are thought to have a more instantaneous influence on pedestrian perception and can be improved in a short and medium time perspective (SAELENS et al., 2003). Testing micro-level walkability, as one of the determinants influencing walking travel behavior, could be very important for policy makers as improving micro-level walkability has great potential to be a cost-beneficial intervention tool to promote walking.

The quality of the “micro-scale” walking environment has long been of interest to urban designers and planners. Though the decades urban designers and theorist have introduced a variety of arguments that relate street-level walkability. Some examples are Jacob’s “eyes upon the street” (JACOBS, 1961), Alexander’s degree of “enclosure” (ALEXANDER et al., 1977), Appleyard’s “livable streets” (APPLEYARD; GERSON; LINTELL, 1981), and Jan Gehl’s “soft edges” concept (GEHL, 1986, 1987). Currently, there is an effort to objectively measure and quantify such qualitative design attributes in a comprehensive way, micro-scale walkability measurement tools have been developed (PIKORA, 2000; SAELENS; SALLIS, 2002; EWING et al., 2006; SALLIS, 2016).

On the other hand, there are “meso-level” aspects of general urban form that may be relevant to walking and subsequent positive health outcomes. This walkability scale has been evaluated by measuring urban form attributes such as density, land use mix, and street patterns. Cervero and Kockelman (1997) propose in their seminal work the concept of the 3Ds: Density, Diversity, and Design. According to these authors, neighborhoods with high population density, diverse land uses, and pedestrian-oriented design are more likely to facilitate active travel choices, which can contribute significantly to overall physical activity. The concept of the 3Ds encompasses following walkability components, often calculated as their sum: residential density (density), land-use mix (diversity), intersection density (design) and retail floor area ratio (design).

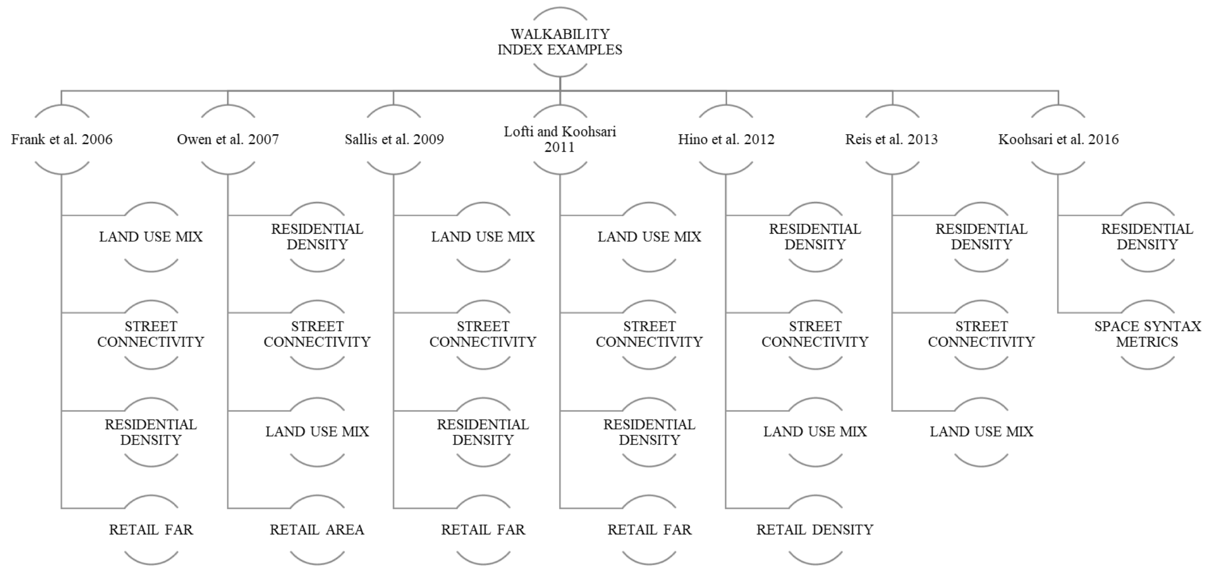
The ‘hierarchy hypothesis of walking needs' proposed by Alfonzo (2005) makes a case for meso-scale walkability. It suggests that micro-scale built environment features influence decisions to walk only after more basic needs are met, such as an individual’s ability, environmental accessibility and existence of destinations (ALFONZO, 2005). This argument is supported by empirical evidence, where micro-scale characteristics tend to minorly influence travel behavior when compared to meso-scale characteristics (e.g. destination proximity, density and connectivity) (CERVERO; KOCKELMAN, 1997; SAELENS; HANDY, 2008; ADKINS et al., 2015).

Meso-scale walkability has its measurement more effectively operationalized trough GIS applications, whereas developing objective and reliable measures of the micro-scale built environment is elusive and costly, leading to a heavy reliance on larger numbers of researchers dedicating more effort and time to collect sufficient data (KIM; PARK; LEE, 2014). Therefore, even though micro-level walkability has potential for cost-beneficial interventions and is relatively easy to "modify", many travel behavior studies on walking rely on meso-level urban form (PARK; CHOI; LEE, 2015).

There is a growing body of research that aims to create meso-scale composite walkability measures considering relevant urban form components that influence walking behaviors (CERVERO; KOCKELMAN, 1997; OWEN et al., 2007; LOVASI et al., 2008; FRANK et al., 2010; LOTFI; KOOHSARI, 2011; REIS et al., 2013; 2018; VAN CAUWENBERG et al., 2016). These objective environmental measures are usually operationalized using georeferenced data trough geographic information systems (GIS), optimizing the measuring of environmental attributes in large areas (HINO; REIS; FLORINDO, 2010).

The so-called Walkability indices, referred to as reduction tools (FRANK et al., 2010), have successfully described the walking environment in many cities, (MANAUGH; EL-GENEIDY, 2011). Walkability indices have been constructed considering a combination of different variables (Figure 3) and have, overall, found positive associations with walking (CHRISTIAN et al., 2011a).

Figure 3 – Walkability Index examples.



Source: Motomura (2017). Modified by the author (2018).

When it comes to the elements of a walkable urban form, one of the most prominent urban qualities is residential density. Density reveals the intensity of occurrence of an element or activity (CAMPOLI, 2012) and as a concept applies to any type of variable of the urban environment (people, parking, bus stops, jobs etc.) distributed over an unit of area. However, it is household density that is considered paramount for walking trips to be shorter and more convenient. Neighborhood residential density has been important as it is understood to have positive effects on utilitarian walking, land use balance and street connectivity (SAELENS; SALLIS; FRANK, 2003). The development of higher population densities is one of the factors that can reduce the number of motorized trips and increase the number of walking trips (CERVERO; KOCKELMAN, 1997). It has often been the basis of neighborhoods designed for sustainability with the purpose of housing enough people to be able to support urban services such as local shops, schools and public transport (CARMONA et al., 2010). Even though compact-high density development is encouraged in contemporary urban planning, it often conflicts with sociocultural contexts (CARMONA et al., 2010), especially in middle income countries. Seeking optimal densities for development thus remains one of the most challenging of the sustainable urban design principles.

Land-use mix can be seen as a complement to residential density (GRASSER, 2014. apud FRUMKIN et al., 2004;). This diversity measure of the built environment aims to quantify the heterogeneity of land uses (DUNCAN et al., 2010). Such built environment attribute has been shown to be associated with walking (FRANK, 2000) and other physical activity behaviors (FRANK et al., 2005). In an area where diverse land uses there are more non-residential destinations, being favorable to the increase of walking trips (CERIN et al., 2007). Neighborhoods with a greater mix of uses, utilitarian destinations are within a shorter reach from residences, increasing the convenience for walking (SAELENS; SALLIS; FRANK, 2003). The relevance of land use mix is so latent that evidences highlight the possibility that perceptions of land use mix may be relatively accurate, even if residents rely on motorized trips for daily activities (KOOHSARI et al., 2014).

Currently, land use mix is a walkability variable most often assessed (FRANK; ANDRESEN; SCHMID, 2004; GEBEL; BAUMAN; OWEN, 2009; LEE, 2010; GRASSER; TITZE; STRONEGGER, 2016) through a variation of the Shannon entropy equations which represent the extent of variation in the distribution of land uses (HAJNA et al., 2014). However, in some studies, land use mix has not been found to be associated to physical activity behaviors (FORSYTH et al., 2008; MCCORMACK; SHIELL, 2011; GRASSER et al., 2013). Such inconsistent findings may be partly due to lack of specificity in the land use categories considered (DUNCAN et al., 2010).

A walkability measure naturally connected to land use mix is retail floor area ratio (FAR) which is the ratio or the sum of commercial building floor area to the total commercially used land area (FRANK et al., 2010). It was created as a reflection of more options for destinations where goods and services may be purchased (LESLIE et al., 2007), but more importantly as a measure of pedestrian-oriented community design. Retail parcels with a high retail floor area ratio may be less likely to have the ‘pedestrian-unfriendly’ design (CERVERO; KOCKELMAN, 1997) with hostile large parking lots (LESLIE et al., 2007).

This measure is greatly linked to large retail chains and shopping malls from North American cities. It has even been considered only for large retail activities with three or more shops or a single shop of 250 square meters or larger (LESLIE et al., 2007). It can be interpreted as a derivation of the early metrics of parking ratios, that indicated the relationship between the space allotted for parking and the space occupied by retail buildings (GIBBS, 2012).

In this sense, zoning may seem as the greatest barrier to the development of neighborhoods that are denser, with a greater mixture of uses, more options for local destinations and local employment. Municipal Zoning may segregate residential and other land uses, restricting the possibility for developments capable of maintaining local retail and services (FRANK et al., 2006). However, land use mix, accessibility to goods and services are complex notions (HANSEN, 1959) intrinsically attached to the property market dynamics that operate across urban space at different spatial scales (CHIARADIA et al., 2012). Walkability has an important connection to the function of urban economies (HAMILTON, 2007). More walkable areas tend to be more developed and by consequence closer to more amenities. Such amenities only come to be in areas where their price is sufficiently valued (BOYLE; BARRILLEAUX; SCHELLER, 2014). Apart from the potential environmental, social benefits and individual improvements walkable neighborhoods have been linked to, there is a naturally occurring increase in residential and commercial property values (GUO; PEETA; SOMENAHALLI, 2017).

Therefore, an important aspect to be considered is the ample evidence that land values increase with walkability (MATTHEWS; TURNBULL, 2007; RAUTERKUS; MILLER, 2011; GUO; PEETA; SOMENAHALLI, 2017). Neighborhoods closer to centralities and established in older settlements have been found to be more walkable and more economically valued (RAUTERKUS; MILLER, 2011). When examining the degree to which property values are driven by land values, evidences also support the influence of walkability (RAUTERKUS; MILLER, 2011). According to Pivo and Fisher (2006) property types established in walkable communities generate higher income and, therefore, have the potential to generate returns as good as or better than properties less walkable. Taking such evidence into account, it is safe to conclude that land and property price are environmental/social variables intrinsically related to walkability and walkable characteristics, such as mix of uses (CHIARADIA et al., 2012).

Other characteristics, such as street connectivity can also be considered to have monetized value in the reduction in travel time, which is enabled by the grid geometry that increases the potential speed of the transport through the spatial network (CHIARADIA et al., 2012). As one fundamental walkability measure, street connectivity quantifies the linkage between destinations. It is argued that connectivity is an urban design measure that underpins a walkable neighborhood (KOOHSARI et al., 2016a). Urban travel occurs on streets, directly influencing travel patterns (GRASSER, 2014). Connected street networks provide more direct routes to destinations (FRANK et al., 2010), being a prerequisite for increasing pedestrian activity (ELLIS et al., 2015). Such importance is supported by several empirical findings that indicate consistent positive associations between walking, especially for transport, and street connectivity (OAKES; FORSYTH; SCHMITZ, 2007; BERRIGAN; PICKLE; DILL, 2010; SUGIYAMA et al., 2012).

Street connectivity is commonly operationalized as the quantification of urban features such as the number of intersections by unit area in the form of a density measure. It is often represented by the mean block size per area, indicating the average distance between intersection (ELLIS et al., 2015). Route directness or measures of accessibility based on the configuration of street elements, drawing from the space syntax theories, are also resorted to when representing street connectivity (KOOHSARI et al., 2016b).

The space syntax theory, developed primarily in the fields of Urban Design and Architecture, focuses on the spatial relationships between streets within a network. It aims to comprehend the morphological structure of urban environments (HILLIER; HANSON, 1984). Street connectivity, despite being a spatial construct, exerts influences on functional aspects of the urban form. The relationship between the movement of pedestrians and the urban configuration is described in several scientific works of space syntax theorists Hillier and Hanson (1984). Pedestrian movement is thought to be, to a large extent, dependent on the spatial arrangements produced by society. Space syntax analyzes the correspondence between the spatial structure and the social logic of space seeking to understand the logic that emerges from the urban configuration itself. Uncovering the correlation between these two elements may be, in a way, fundamental for understanding the social dynamics of cities themselves.

Hillier (1993) introduces the theory of Natural Movement, presenting evidences that the street network’s configuration and connectivity generates central areas with the potential for development of commercial activities and greater pedestrian movement. Hillier states in this seminal work that the configuration of streets is considered the "primary generator of pedestrian movement" (HILLIER et al., 1993). Where relationship between space syntax measures, i.e. integration, and pedestrian flow demonstrated high correlations. According to several empirical studies, even in Brazil, space syntax measures are positively correlated with pedestrian movement (ZAMPIERI; RIGATTI, 2006).

Researches involving space syntax measures have the potential to contribute with new insights on the relationship between urban form and walking behavior (KOOHSARI et al., 2014). These measurements have shown to be related to several urban spatial characteristics such as the price of land (SCHROEDER; SABOYA, 2015), the location of residential activities (CARVALHO; SABOYA, 2017) and commercial activities (LIMA, 2015). Although several studies have examined associations between street connectivity and walking levels (BARAN; RODRÍED;GUEZ; KHATTAK, 2008), only some international studies and no Brazilian researchers have investigated the role of space syntax as a walkability measure that influences walking behaviors.

2.2 Active travel behavior and perceived built environment

According to the ecological perspective proposed by Sallis and colleagues (2006), physical activity, walking behaviors and the adoption of a healthy lifestyle are complex actions. According to the authors, many domains influence PA, from personal, cultural, and socio-economic to environmental, that have been identified as important correlates of walking. However, these environmental attributes can be assessed in either an objective or subjective manner (DEWULF et al., 2012). It is not yet clear whether objective or perceived measures of walkability constructs are more or less related to actual physical activity behavior (DEWULF et al., 2012; LESLIE et al., 2005), but it is understood that both types of data don’t necessarily coincide as there are in different domains.

It is argued that human processing of information about environmental attributes is construed as cognitive maps; however, these may not precisely represent actual environment and could reflect cognitive distortions (GEBEL et al., 2011). On the other hand, according to Lin and Moudon (2010), most of the studies conducted in this approach showed that a number of built environment attributes, measured both objectively and subjectively are related to walking levels. Further Duncan, Spende and Mummery (2005) conducted a review that indicated that rates of walking are significantly supported by perceived environmental characteristics, as well as by objective characteristic. Incorporating both objective measures and perceptions of residents in research is important, as the impact of the objective environment on health depends on human perceptions, motivations, and deliberations (DEWULF et al., 2012).

In response to this potential disparity between the objective and perceived walkability environment, several studies have investigated their concurrence (MCGINN et al., 2007; SUGIYAMA et al., 2015a). Analyzing the scientific evidences on the literature that utilizes combined subjective-perceived and objective measures of the built environment to analyze walking behaviors is paramount, for a broad understanding of this inconclusive research paradigm.

Within this context, some studies aim to solely analyze the agreement between the objective and perceived built environment (HOEHNER et al., 2005; LESLIE et al., 2005; DING; GEBEL, 2012; JAUREGUI et al., 2016b). However, some focus to determine if there is an association between perceived and objective neighborhood environment variables considering neighborhood satisfaction (VAN DYCK et al., 2011; GRASSER; TITZE; STRONEGGER, 2016; LEE et al., 2017). Furthermore, others attempt to examine to what extent socioeconomic variations interfere (GILES-CORTI; DONOVAN, 2002; SUGIYAMA et al., 2015a; MACKENBACH et al., 2016) or even considerations of attitude toward walking (YANG; DIEZ-ROUX, 2017).

Earlier evidence indicates that those who walk more have more positive perceptions of their surrounding environments (CARNEGIE et al., 2002). Walking behavior is most commonly measured by self-reports, even though there are indications that there is possible bias and subjectivity in this type of assessment (CAPUTO et al., 2016). Several perceived environment characteristics have been found associated with walking (HUMPEL et al., 2004). To measure such perceptions instruments used vary greatly, however, the Neighborhood Environment Walkability Scale (NEWS), which is a self-report survey (SAELENS et al., 2003), is widely applied (LESLIE et al., 2005; MCCORMACK et al., 2008; DEWULF et al., 2012; SAELENS et al., 2012; JACK; MCCORMACK, 2014). Subscales of the survey are often used, such as safety from traffic (LESLIE et al., 2005; GEBEL et al., 2011; SAELENS et al., 2012; LEE et al., 2017); street connectivity (SALLIS et al., 2010; LEE et al., 2017); among others.

Neighborhood Built environment Satisfaction (NS) has been defined as an individual's evaluation of the neighborhood environment (HUR; NASAR; CHUN, 2010) that portrays evidence of the absence of complaints about the residential settings (LU, 1999). From a psychological aspect, it has been conceptualized as a ''positive affective'' state that one can have toward the residential environment (AMÉRIGO; ARAGONÉS, 1997). It has been widely studied as an indicator of resident's evaluations of the neighborhood environment (LESLIE;

CERIN, 2008; DYCK et al., 2011; GRASSER; TITZE; STRONEGGER, 2016; LEE et al., 2017).

NS concerns many different domains. An array of neighborhood features has received empirical support in relation to neighborhood satisfaction, such as physical features (traffic noise, access to services and destinations etc.), social features (poor social cohesion, safety etc.) and economic features (real estate values, neighborhood social economic status etc.) (SIRGY, M JOSEPH; CORNWELL, 2002). Evidences link dimensions of neighborhood satisfaction to mental health (LESLIE; CERIN, 2008), physical health (LEE et al., 2017) and better self-reported quality of life (ABASS; TUCKER, 2017). Policy, planning and the design of healthy communities should concern the provision of development patterns that induce higher NS (LESLIE; CERIN, 2008), which is understood as an important factor when analyzing residential mobility patterns and neighborhood stability. In light of these considerations, better understanding the built environment attributes linked to satisfaction is relevant (PERMENTIER; BOLT; VAN HAM, 2011).

Even though the influence of objective BE characteristics over NS is partly mediated by perceptions of neighborhood attributes, there is evidence of direct effects of objective neighborhood conditions on neighborhood satisfaction. (PERMENTIER; BOLT; VAN HAM, 2011). Objective walkability indicators have been found positively associated to active transportation and neighborhood satisfaction with infrastructure. (GRASSER; TITZE; STRONEGGER, 2016). Further, traffic load and congestion have been shown to be negatively correlated with neighborhood satisfaction (LESLIE; CERIN, 2008). In contexts of developing economies, results point out that many characteristics such as residential density, land use mix and access to public transportation are significant to positive NS outcomes (KIM; PARK; LEE, 2014).

Neighborhoods that include a mixture of retail/commercial and residential properties potentially promote the general well-being of the residents (RAUTERKUS; MILLER, 2011). However, evidences indicate that neighborhood socioeconomic level status confounds the association between walkability and neighborhood satisfaction (GRASSER; TITZE; STRONEGGER, 2016). Therefore it is important to emphasize that the relationship between walkability and neighborhood satisfaction is highly dependent on crime, esthetic-related problems, pollution and overall unsafety. (VAN DYCK et al., 2011)

Neighborhood satisfaction has been quantified using composite measures of various questions or individual questions regarding the physical and social neighborhood environment. Most surveys rely on 5-point Likert scales as indicators of a range of answers, from dissatisfied to satisfied. Five Likert-type formats have been questioned, however, current research indicates that the minimum number of response categories should be four, and the use of between four and seven is ideal. (LEE, 2010). Few studies regarding NS have been conducted in Brazil, however many neighborhood features that affect residents' quality of life through neighborhood satisfaction are noteworthy (SIRGY, M JOSEPH; CORNWELL, 2002). As a research variable NS is readily collected in social surveys but underused in the analysis (PARKES; KEARNS; ATKINSON, 2002).

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It is clear that individual factors of psychological, physical, social and cultural order determine different interpretations of the quality of space, influencing the cognitive processes that lead to travel decisions (VARGAS, 2015). Notwithstanding, perceived neighborhood characteristics, for the most part, are considered higher (more positive) in objectively-determined high walkable neighborhoods than in less walkable neighborhoods. However, this low level of concordance confirms that perceptions should not be considered as proxies for objective measures (JAUREGUI et al., 2016a).

Therefore, the existing body of research conducted in lower and middle-income countries is still modest if compared to the extent of the evidence from high income. Some studies have found weak correlations between perceptions and the environment, highlighting the relevance of contextual factors. A different socio-economic gradient of behavior might be less apparent in high-income countries, where leisure-time activity predominates as social class and physical activity are directly related. Therefore, incorporating perceptions to walkability analysis in low-income and middle-income countries is urgently needed to guide the creation of contextually tailored interventions (BAUMAN et al., 2012).

2.3 Units of analysis

BE attribute studies have relied heavily on areas that only reflect homogeneity of socioeconomic attributes as guides for data aggregation (ROUX, 2002). These spatial units are considered of “convenience” for their availability (RIVA et al., 2008) and are represented mainly by census tracts or census wards (HOEHNER et al., 2005; GAUVIN et al., 2008; BORTONI et al., 2009; FRANK et al., 2010; FLORINDO; SALVADOR; REIS, 2013; GLAZIER; WEYMAN; CREATORE, 2013; etc.).It is argued that their boundaries may not match the BE areas that effectively influence behavior (FLOWERDEW; MANLEY; SABEL, 2008).

Census tracts have been defined by Hino (2014) as primary sampling units representing the smallest territorial unit possible, integrally contained in an urban or rural area, with a size and number of households that allow the survey by a census agent (IBGE, 2015). Census tracts lack spatial homogeneity; this might lead to artificial spatial patterns. In such case, environmental characteristics can be measured with error, internally invalidating the study (RIVA et al., 2008). Establishing units that better represent the variations of behavior influencing factors related to health and walking is paramount (DIEZ ROUX, 2001).

Alternative approaches for redefining census tracts are essential in light of the modifiable areal unit problem (MAUP). This concept exists in many studies where data is spatially aggregated and refers to the fact that analytical results are sensitive to the definition of spatial units in which data is aggregated (OPENSHAW, 1984). Results are directly influenced by the number of areas considered and the boundaries that define them. The MAUP is presented only when the units chosen are arbitrary regarding the specific BE characteristics considered in the research. Despite the relevance and implications of the MAUP for the comprehension of environmental influences on health, it has received little to no empirical attention in the literature (STAFFORD; DUKE-WILLIAMS; SHELTON, 2008).

It is clear that studies that disregard the specific definitions of an individual's exposure to the built environment may introduce measurement error, compromise statistical power of contextual analyses and come to spurious conclusions (SPIELMAN; YOO; LINKLETTER, 2013). Recent spatial analysis techniques and software capabilities have advanced on possible approaches for modeling individual walking neighborhoods, reducing the impact of the MAUP (FRANK et al., 2017). Alternative approaches to census tracts include automated zone design (SABEL et al., 2013), clustering (RIVA et al., 2008) and the most prominent technique of defining an individual’s neighborhood: buffers (LESLIE; CERIN; KREMER, 2010; SAELENS et al., 2012; SALLIS et al., 2016b; FLORINDO et al., 2017; GUNN et al., 2017). The buffering approach defines that an individual's environment is a personal territory represented as an area around their residence and not a discrete location (SPIELMAN; YOO; LINKLETTER, 2013).

Initially, many studies resorted to circular buffers (crow-fly buffers), that establish a circular area around an individual’s home at a given radius. However, it is probable that circular buffers don’t represent accurately relations between the built environment and walking (OLIVER; SCHUURMAN; HALL, 2007). Evidence from public health and built environment literature, starting with the work proposed by Oliver and colleagues (2007), show better associations in network buffers when analyzing built environment's relationships with walking (FRANK et al., 2017). This approach consists of creating a 'network buffer' polygon at a given distance from the participant's location based on the street network, better representing the area accessible to an individual.

When it comes to the area considered by the buffer, most studies indicate a radius metric. It must be considered that patterns observed using larger aggregation areas may mask meaningful differences observed at smaller geographic scales (MITRA; BULIUNG, 2012). Evidence suggests that restricting BE exposure classifications to within 1000 m may be appropriate given most walks are shorter than 600m and few exceed 1200 m (HOUSTON, 2014). Gehl (2013) indicated that considering people's perceptions 500-meter walk is an ideal size. According to Campoli (2012), a general transit planning rule is 450-800 meters, which generated roughly 50 hectares around one's residence. It can be concluded that those 400-meter buffers represent a median length of daily walking trips (CLARK; SCOTT, 2014 apud BOER et al., 2007), possibly being the ideal size for a buffer measure. Notably, there has been a call for more robust measures of the built environment at appropriate scales (CHRISTIAN et al., 2011b). Therefore, considering the presented methodological challenges and the lack of experimental evidence on most adequate units of analysis for the Brazilian town context, an exploration of the sensitivity of built environment measures to different neighborhood representations is needed.

3 DATA AND METHODOLOGY

The main objective of this research was to evaluate the efficacy of objective walkability measures on Brazilian averaged-sized towns. Considering the phenomenon under investigation as real-life and contemporary, dynamic and complex therefore indissociable from its contextuality, the most adequate research strategy is the case study (YIN, 2001). Rolândia-PR was chosen due to data availability and representation of an averaged-sized Brazilian town. For the development of this strategy, a Correlational methodology was adopted to identify spatial and behavioral patterns with many variables, using statistics (GROAT; WANG, 2002).

For the confirmation of research tendency and the appropriate methods to be applied, an integrative review, a method for gathering and synthesizing search results on a limited theme a systematic fashion was conducted (FERENHOF; FERNANDES, 2016). It had the objective of shedding light on methodologies for quantifying walkability, walking levels and perceptions through the analysis of the scientific literature that utilizes combined subjective-perceived neighborhood-built environment and objectively measured neighborhood-built environment data to analyze any category of walking behaviors in able-bodied, randomly selected adults. The specific literature review method utilized for this literature review is the SystemSearchFlow method (SSF) (FERENHOF; FERNANDES, 2016).

Initially, a research protocol was defined, with the objective of guiding the inclusion of quantitative studies on the associations of objective and perceived walkability-built environment. For such the following English language descriptors were used to compose a search strategy: ("built environment", "physical attributes", neighborhood); (walk*, “physical activity”); (measur*, perce*, objectiv*) were used to characterize the study’s dependent variable. The term (adult) and the excluded terms (older, elder, senior, disabled, patients, youth, children, adolescent*) delimitated the age group of interest and the physical condition of those included in the studies. The Boolean operators "OR” and "AND" were employed to combine words within and between the terms groups respectively and “NOT” to exclude the desired words from the search. Only article-type documents (of periodicals or conferences) were considered. The selection of articles was carried out without temporal restriction or research area.

The organization of the bibliographic portfolio, that allows for the consolidation and comparing of data, was conducted through a software that organizes bibliographies and references (Mendeley©), automating and streamlining the processes of searching, filtering, counting and storing. The standardization of the article selection was firstly based on the exclusion by duplicity. After the reading of all titles and abstracts, those that didn't adhere to the theme were excluded. The remaining papers were read in full and those that did fit the inclusion criteria were excluded.

A query in the scientific databases was conducted, applying the established protocol, through the Scopus, Web of Science®, PubMed® e and the TRID® database. The main inclusion criteria were: Studies that (a) objectively and subjectively (necessarily including neighborhood-built environment perceptions) examined the association of any of neighborhood environmental attribute and walking behaviors, and (b) had conducted analyses in a sample of adults. The exclusion criteria were (a) studies without quantitative analysis; (b) review studies; (c) studies that aim to elaborate or validate an objective or subjective analysis tool/audit; (d) studies that focus on minorities, elderly, adolescents and any type of health issue or disability; (e) studies conducted on or related to rural environments; (f) studies considering perceived safety from crime as the only environmental perception attribute.

The results were synthesized from 2269 papers that were identified in the standardized database query. From these 661 were excluded by duplicity and 1608 remained. Through the revision process, 1574 were excluded in the reading of titles and abstracts and 7 in the reading of the full texts. By the end of the selection process, 26 articles met the previously established criteria and were included in the review for the extraction of data in the application of the second phase of the SSF Method. To uphold reliability and reproducibility it is informed that the searches were conducted on 22 of September of the year 2017.

The results pointed out that among objective measuring of the neighborhood BE, walkability indices prevailed as the most present tool (n=12/46%) (Board 1). They are means to systematically measure urban form walkability variables and generate composite factors that combine multiple aspects of community design (FRANK et al., 2010).

When it comes to physical activity the researches relied heavily on self-reports (n=18). However, some studies did resort to accelerometers (n=3), pedometers (n=1) and even a combination of self-report with accelerometer use (n=1) to measure physical activity of the sample. Within those studies that assessed PA through self-report the instrument that was most applied were the International Physical Activity Questionnaire (IPAQ) and its variations, present in ten (n=10) studies.

Board 1 – Studies that applied Walkability indices and variables utilized.

AUTHOR	OBJ. TOOL	MEASURES
(LEE et al., 2017)	Walkability index	Net residential density; Retail FAR; Land use mix; Intersection density; Network distance to nearest park
(GRASSER; TITZE; STRONEGGER, 2016)	Walkability index	Gross population density, household unit density, entropy index, proportion of mixed land use, three-way intersection density, four-way intersection density,
(HANIBUCHI et al., 2015)	Walkability index	Population density, road density, access to parks, and access to retail areas
(SUGIYAMA et al., 2016)	Walkability index	Residential density, intersection density, land use mix, and retail FAR
(DEWULF et al., 2012)	Walkability index	Street connectivity, residential density, and land use mix
(GEBEL et al., 2011)	Walkability index	Dwelling density, street connectivity, land use mix, and retail FAR
(VAN DYCK et al., 2011)	Walkability index	Residential density, street connectivity and land use mix
(KERR et al., 2010)	Walkability index	Residential density, street connectivity, land use mix, and retail FAR
(GEBEL; BAUMAN; OWEN, 2009)	Walkability index	Dwelling density, street connectivity, land use mix, and retail FAR
(MCCORMACK et al., 2008)	Walkability index	Intersection density; dwelling density; and land-use mix + shortest road network distance in meters between the participant's home and previously mentioned destinations.
(OWEN et al., 2007)	Walkability index	Dwelling density, street connectivity, land-use mix, and, retail FAR
(LESLIE et al., 2005)	Walkability index	Intersection density, dwelling density, land-use mix

Source: Organized by the author, 2017

To measure perceptions of the neighborhood BE, the instruments used varied greatly. However, the Neighborhood Environment Walkability Scale (NEWS), which is a self-report survey previously found to be reliable and valid (SAELENS et al., 2003), was applied on 41% (n=11) of the studies analyzed (Board 2).

Board 2 – Studies that applied the NEWS survey and specific measures used.

AUTHOR	SUB. TOOL	MEASURES
(LEE et al., 2017)	(NEWS)	residential density, land use mix–diversity, land use mix–access, street connectivity, walking/cycling facilities, aesthetics, pedestrian/traffic safety, and safety from crime
(JAUREGUI et al., 2016)	(ANEWS) adapted for Latin America	land-use mix, intersection density, residential density, proximity to transit stops, proximity to parks, perceived neighborhood safety, and perceived park safety
(SUGIYAMA et al., 2015)	(NEWS)	access to destinations, neighborhood aesthetics, walking infrastructure, traffic/barriers not a problem, and crime safety
(JACK; MCCORMACK, 2014)	(NEWS-A)	safety from crime; neighborhood aesthetics; access to services; street connectivity; pedestrian infrastructure; motor vehicle traffic safety, and; physical barriers; recreation destination mix 15-minutes of home; utilitarian destination mix within 15-minutes of home
(KOOHSARI et al., 2014)	modified (NEWS)	street connectivity; land use mix
(DEWULF et al., 2012)	(NEWS)	estimates of walking times to various closest destinations
(SAELENS et al., 2012)	(NEWS)	neighborhood walking/cycling facilities, aesthetics, pedestrian/traffic safety, and safety from crime; reported on the proximity of 18 recreation facilities
(KERR et al., 2010)	(NEWS)	aesthetics, trees, hills, traffic speed, traffic safety, visibility of other people, crime safety, pedestrian facilities and number of destinations within a 20-min walk.
(GEBEL; BAUMAN; OWEN, 2009)	(NEWS)	perceived dwelling density, street connectivity, land use mix, net retail area
(MCCORMACK et al., 2008)	(NEWS)	estimates of perceived distances (EPD)
(LESLIE et al., 2005)	modified (NEWS)	residential density; land-use mix diversity; land-use mix access; street connectivity; walking facilities; aesthetics; traffic safety; safety from crime.

Source: Organized by the author, 2017

Considering the above-presented evidence, the use of walkability indices as large-scale reduction tools is justified for this research. It is clear that the environmental components of residential density; connectivity; and land use mix and Retail FAR are significant and should be taken into consideration when analyzing objective walkability. In attempting to replicate walkability indices in other contexts, modifications are often required due to differences in both contextual urban structure and availability of data for the study area (CHRISTIAN et al., 2011a). The greater amount of research conducted on this topic has been held in North America, further investigation of these relationships are required in varying urban, cultural and demographic environments (SALLIS et al., 2009).

The most adequate subjective measure of the perceived neighborhood environment is the Neighborhood Environment Walkability Scale (NEWS) (SAELENS; SALLIS, 2002). This easy to apply, valid, and peer approved tool measures the individual's perceptions, having subjectivity as a characteristic. Perceptions of satisfaction have been widely studied as an indicator of resident's evaluations of the neighborhood environment and can be considered a good proxy for peopled general perceptions of the neighborhood environment. Self-reported walking behavior is pointed out as a possibly biased dataset, however, alternatives remain unviable, especially in low-income contexts.

Therefore, walkability indices, the NEWS survey, and self-reported walking are measuring approaches relevant in the literature and were effectively adopted in this research. Objective urban form data was collected in the field by the researcher. Walkability indices were constructed using relevant walkability constructs in their most common combinations and proposed arrangements that could possibly better reflect the specific urban context at hand.

On account of database availability and populational representation of an average-sized Brazilian town, the selected case study is Rolândia-PR. This town is currently in the processes of developing its mobility plan, therefore an extensive subjective database was provided by ITEDES- Institute of Technology, Economic, and Social Development. The available data includes self-reported travel behaviors and perceived neighborhood satisfaction measured through the satisfaction subscale of NEWS survey. Perceived satisfaction of safety while walking, pleasure while walking, ease to walk and access to public transportation are some examples of the subjective aspects assessed (ATTACH A).

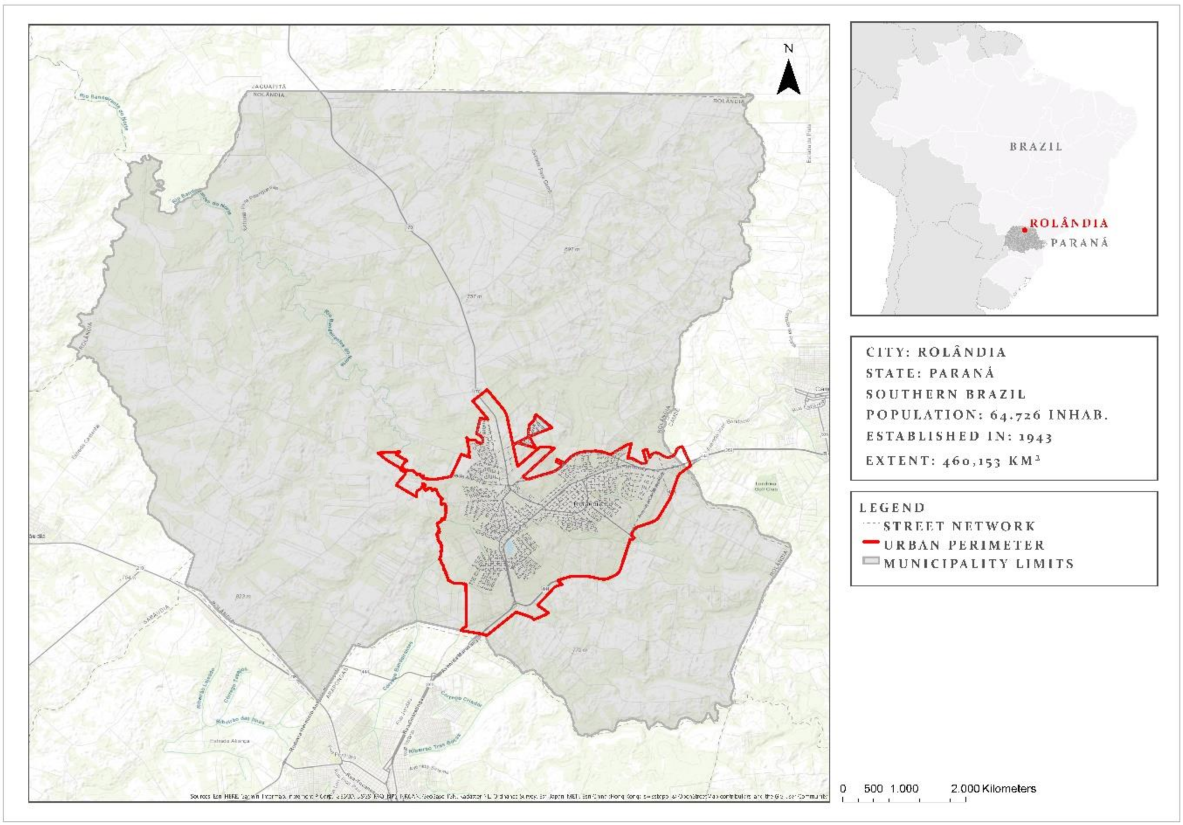
3.1 Case study: Rolândia, Paraná State, Brazil

Rolândia was chosen as a case study due to its representation of an average-sized Brazilian town and availability of subjective data. The municipality of Rolândia in the state of Paraná-Brazil has an extension of 454,174 km² and an estimated population in 2017 of 64,726 inhabitants (IBGE, 2018) (Figure 4).

Rolândia is included in the metropolitan region of Londrina. Its economy is based on the agriculture of corn, wheat, sugar cane and orange, and more predominantly soybean. The municipality has most of its area categorized as rural (410,144 km²), and a modest urban perimeter area (44,03 km²). The local economy also contains an industrial complex (IPARDES, 2018).

The Human Development Index (HDI) is 0.739, considered medium to high (IBGE, 2018). However, due to the lack of administrative infrastructure, georeferenced spatial data is almost never available. Therefore, the Georeferencing of data of the city of Rolândia-PR was conducted by the researchers.

Figure 4 – Rolândia's municipal perimeter.



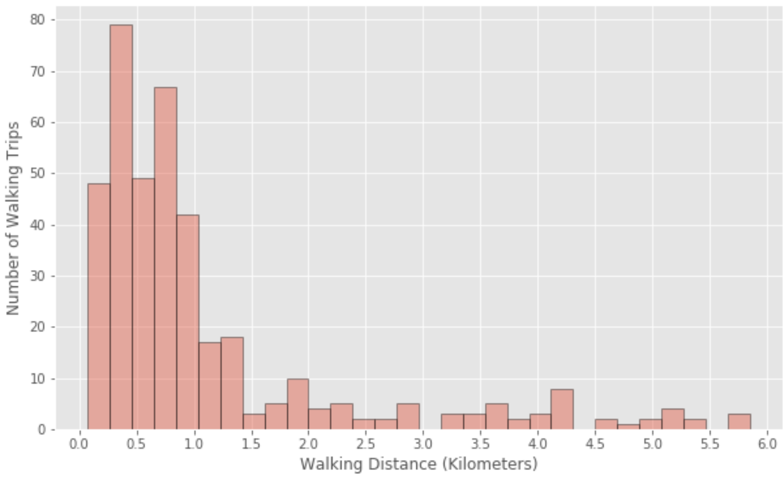
Source: ESRI (2018a). Organized by the author, 2018.

Rolândia is historically a German colony established through the *Companhia de Terras Norte do Paraná (CTNP)*, that in the mid-twentieth century executed the commercialization of land in northern Paraná. Most of the cities colonized by *CTNP* followed the railway line, having their origin at the stops along the extension of the train line and took a euclidian orthogonal street network design (REGO e MENEGUETTI, 2006). Rolândia followed such characteristics and was the sixth colony to be established. The first immigrants to arrive at the site were of Jewish-German origin in the years of 1932-1933 (DUARTE et al, 2004). In 1934 the first house inside this perimeter was built giving rise to local urban growth was expansive and fast.

3.2 Units of analysis

This study has conducted all analysis in six different spatial unit operationalizations: census tracts and five buffer scales. The 'sliding scale' units of analysis (GEHRKE; CLIFTON, 2014) were based on three network buffers of 200, 400, 600, 800 and 1000 meters extending along the street network of around the households of respondents (Figure 6). These radii follow literature tendencies that consider BE exposure classifications to within 1000 meters, as most walks are shorter than 600m and few exceed 1200 m (HOUSTON, 2014). Further, the available data regarding self-reported travel behaviors, as represented in the histogram (Figure 5), shows a majority of walking trips restricted within the 1000-meter distance range. The 6 selected radii metrics reflect walking patterns present in the case study considered here.

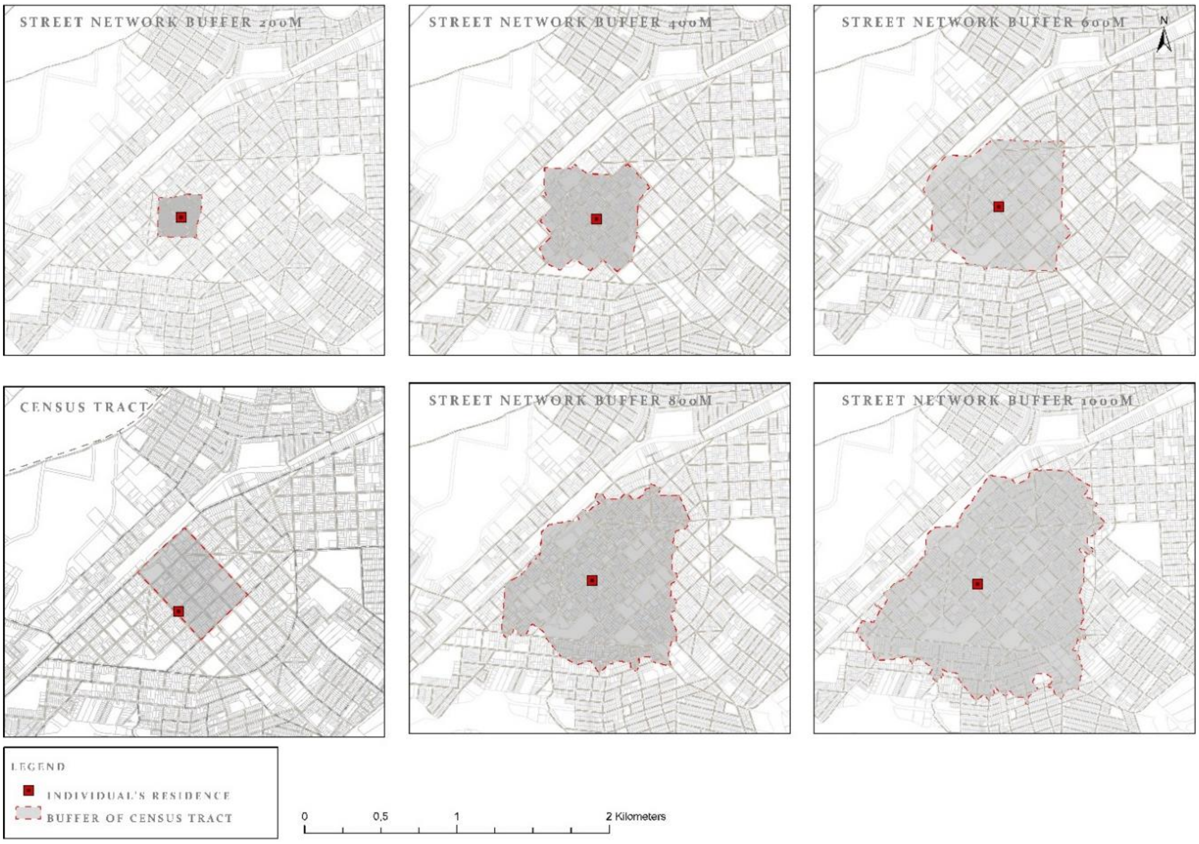
Figure 5 – Rolândia's walking trips versus walking distance histogram.



Source: Organized by the author, 2018.

All compared buffers sizes were generated using the ESRI ArcGIS 10.4.1 software and the Service Area Solver within the Network Analyst extension. The 'detailed' polygon generation option was enabled. Figure 6 depicts a size comparison between the five different buffer sizes and census tract.

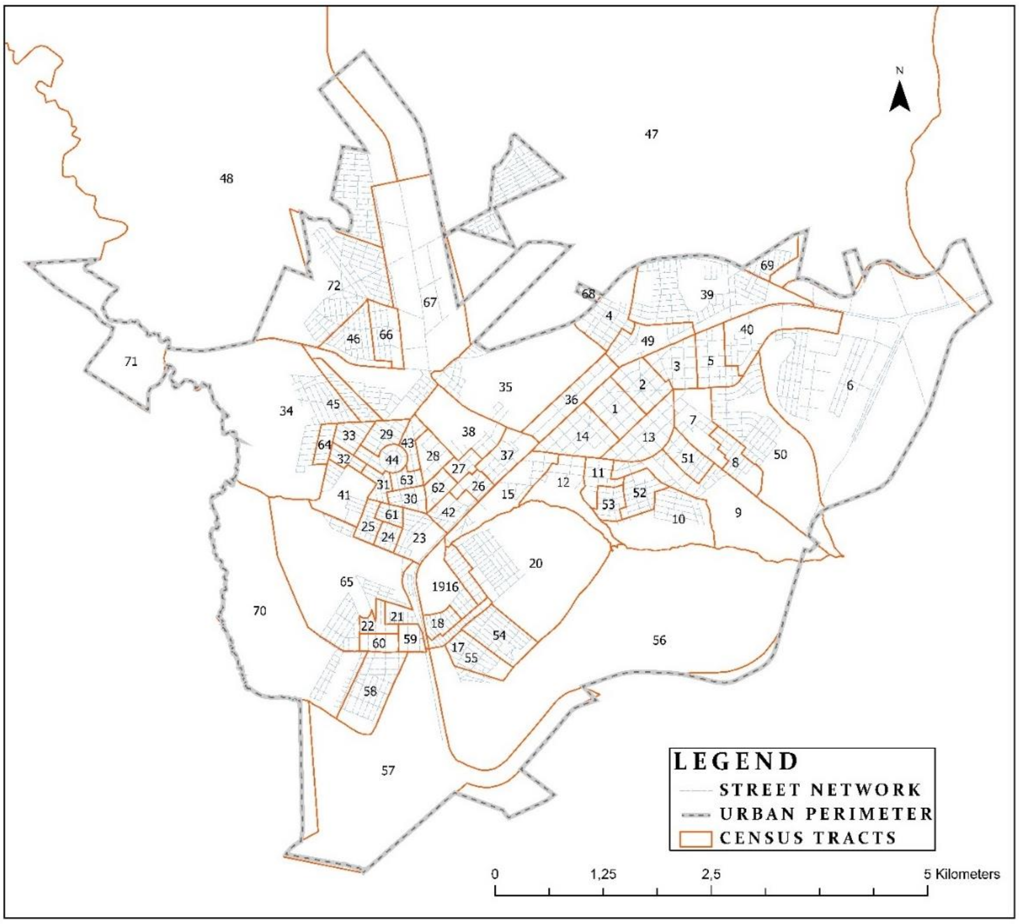
Figure 6 – Scales of units of analysis considered.



Source: Organized by the author, 2018.

The fixed scale units of analysis (GEHRKE; CLIFTON, 2014) were based on Rolândia's administrative division, obtained from IBGE available data. Rolândia is currently divided in 74 urban census tracts, however, four of these are characterized as rural areas. On the other hand, sector #47 is classified as rural although it is included in the urban perimeter and has a large inhabitant settlement. Sectors #48 and #57 were disregarded in the walkability calculations and statistical correlations as they represent a new unoccupied allotment area with only limiting streets and no internal network, making the calculations unfeasible. Therefore, the final sample considered were 69 census tracts included in the urban perimeter of the municipality of Rolândia (Figure 7).

Figure 7 – Considered census tracts.



Source: IBGE (2016). Organized by the author, 2017

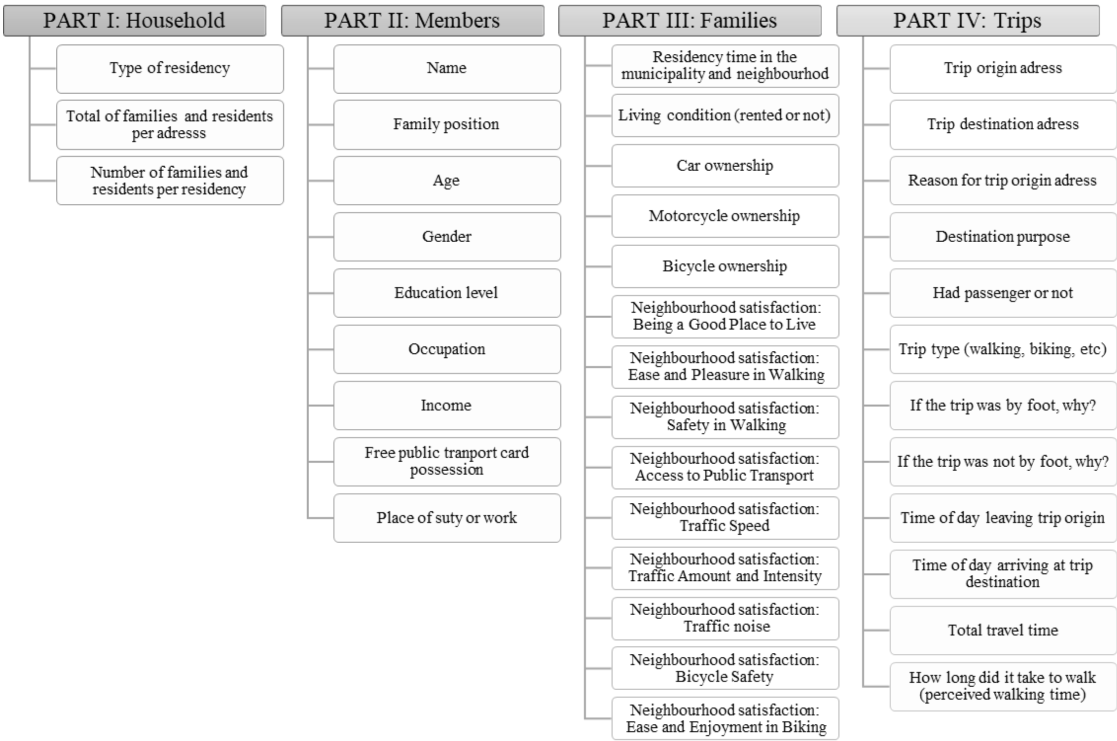
3.3 Correlational variables

This research's correlational variables were based on secondary data from the Rolândia Urban Mobility Plan (PlanMob). This document was prepared in 2017 and 2018 under the responsibility of ITEDES. An Urban Mobility Plan consists of understanding people and cargo movements in an urban environment, analyzing and directing planning measures to guarantee more efficient transit systems. They are currently necessary to comply with the national guidelines of the Federal Law n. 12,587 / 2012 related to the National Policy on Urban Mobility.

The Origin-Destination (OD) survey is one of the main researches used in Traffic Engineering and was the basis for Rolândia's Mobility Plan. The OD research conducted in Rolândia-PR was household-based, with a sample related to the total of permanent private households. The questionnaire (ATTACH A) was organized into different and specific sections (Figure 8), relating to household data, family data and individual data from members of the families which includes the trips made by them the day before. From each section of the survey, it was possible to select the correlational variables for the current study, which are: walking levels, perceptions of satisfaction with the neighborhood environment and individual variables.

Initially, publicity work was conducted to inform the population of the field work that would be done by the researchers. Personnel was trained for standardization and correct application of the research (ITEDES, 2018). Next, a pilot trial was carried out, in order to detect possible problems in data tabulation. The person in charge of the selected domicile was interviewed on household characteristics, family member characteristics and each trip made the previous day by each household resident. The surveyed days were set from Tuesday to Friday. Thus, there were no trips made on atypical days, such as the weekends. Holidays were also disregarded (ITEDES, 2018).

Figure 8 – Origin-Destination questionnaire structure.



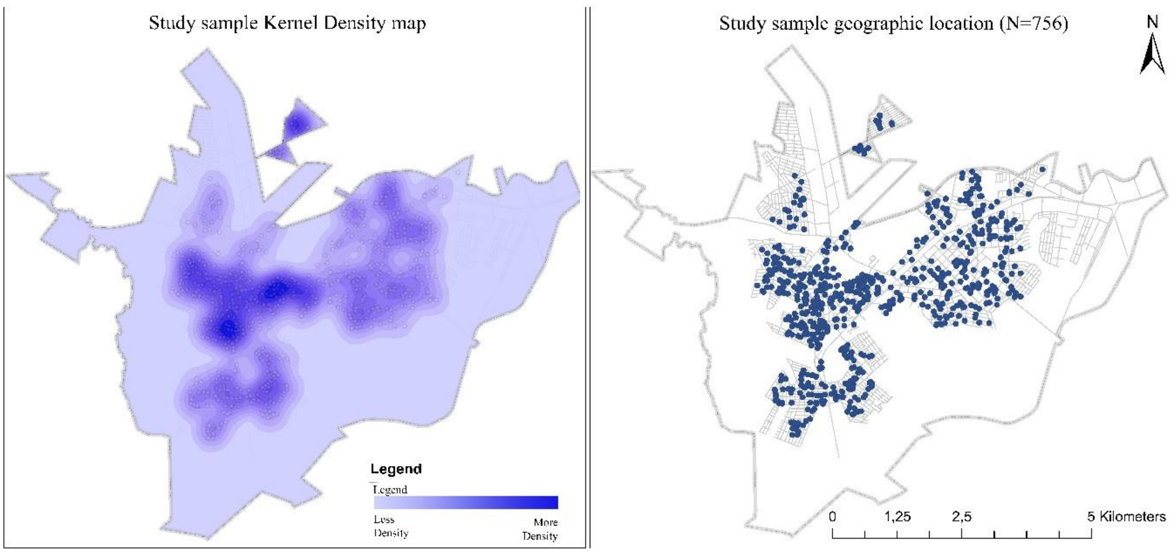
Source: ITEDES (2018). Organized by the author, 2018.

The households considered in the OD survey were selected according to an income criterion. For this, the list of residencies from SANEPAR (Sanitation Company of Paraná) was used, where the tax paying units were classified. Sample was conducted in a probabilistic manner, in this case, trough Stratified Random Sampling. A total of 756 valid questionnaires was applied, representing 3.76% of the of 20.065 Permanent Private homes (IPARDES, 2018). Considering 10% margin of error and 95% level of confidence the sample is well over the necessary sample size (approximately 380 households).

The population (N) of tax paying units was first divided into subpopulations/strata according to income. These subpopulations were nonover-lapping, and together comprise the whole of the population. After strata had been determined, a random sample was drawn from each stratum. Such strategy ensures each subgroup within the population receives proper representation within the sample providing better coverage of the population (COCHRAN; WILEY, 1977). The households were distributed through census tracts and municipal sectors, guaranteeing uniform stratification across the territory (ITEDES, 2018).

For the visual representation of the sampled population considered and its coverage of the territory a Kernel Density map was constructed. This mapping method represents a study area through the point density of a variable. The points, in the case, are the geographical location of the residences that comprise the selected sample weighted in a specific method of interpolation (the Kernel Function) (HART; ZANDBERGEN, 2014). The patterns of distribution of the sample can be observed in Figure 9, next to the study case's residential density kernel density map. It can be noticed that all permanent private residence areas of the territory are contemplated by the selected sample. Areas of the urban grid such as the extreme north (an un-occupied residential area) and the extreme east (an industrial site) are not included in the extent of the sample for the inexistence of residents.

Figure 9 – Household sample Kernel density map and geographic location.



Source: ITEDES (2018). Organized by the author, 2018.

3.3.1 Active travel in Rolândia Paraná: Walking for any purpose

The OD survey collects detailed travel behavior data by asking participants to describe all trips made the day before. The precise addresses of each trip's origin and destination were collected, along with purpose, mode, time of day and duration. A trip was established as any time you went from one address to another in a vehicle, by walking or biking (BOER et al., 2007). Each trip made was accounted for, providing data on pedestrian, bicycle and traffic movement. Two thousand seven hundred thirty-one (2731) trips were registered in the OD survey conducted in Rolândia. Due to inconsistencies in the research's output, such as the misspelling of street names and missing information, a total of 2097 trips were geocoded.

The survey question "What modal of transport did you use to arrive at your destination?" was used to indicate the mode of transportation. The possible answers were (1) bus (2) private bus (3) school bus (4) van (5) motorcycle (6) driving automobile (7) passenger automobile (8) taxi (9) bicycle (10) by foot (11) others. Table 1 shows the number of trips related to each possible transport mode.

Table 1 – Number of trips collected from each modal

Type of Trip	Number of trips		Definition
Automotive	1311	62.5%	Automotive car, Motorcycle, Taxi, Bus, Van
Walk	394	18.8%	Walk
Bike	392	18.7%	Bike
Total	2097	100%	-

Source: ITEDES (2018). Modified by the author, 2018.

The walking trips considered in this research were the ones which the participant replied with the answer "by foot" (10), 394 trips were computed. Table 2 shows the average length of walking trips and the sum of the kilometrage of walking trips. A prevalence home and study walking trips can be observed, as well as the fact that most are mainly under 1 km long.

Table 2 – Number, the sum and average length of walking trips by purpose.

Type of walking trip	Number of trips	Sum walking route lengths (km)	Average length (km)
Work-industry	3	9,93	3,31
Work-retail	5	7,36	1,47
Work- services	15	14,26	0,95
Study	81	109,67	1,35
Shopping	18	16,43	0,91
Health Care	13	12,33	0,95
Leisure	20	21,00	1,05
Return home	196	211,96	1,08
Other	42	35,77	0,85
Total	394	438,71	11,94

Source ITEDES (2018). Modified by the author, 2018.

Respondents were also asked the following questions "If you did walk, why?" and "If you did not walk, why?". The possible answers for reasons for walking were: (1) Inefficient public transportation; (2) Small distance; (3) Other motives (Table 3). As for not walking the possibilities were: (1) Excessive distance; (2) Unsafety; (3) Fear of being run over by car (4); Climate (5); Topography (6); Other reasons. Most respondents reported choosing walking because of "small distances" and most reported not walking for "excessive distances" (Table 3).

Table 3 – Reasons for walking and reasons for not walking.

Reason for walking	Number of trips	Percentage	Reasons for not walking	Number of trips	Percentage
Inefficient Public Transport	57	14.47%	Excessive distance	999	76.20%
			Unsafety	23	1.75%
Small distance	314	79.9%	Fear of being run over	2	0.155%
			Climate	0	0%
Other motives	21	5.33%	Topography	6	0.45%
			Other reasons	171	13.04%
Total	394	100%	Total	1311	100%

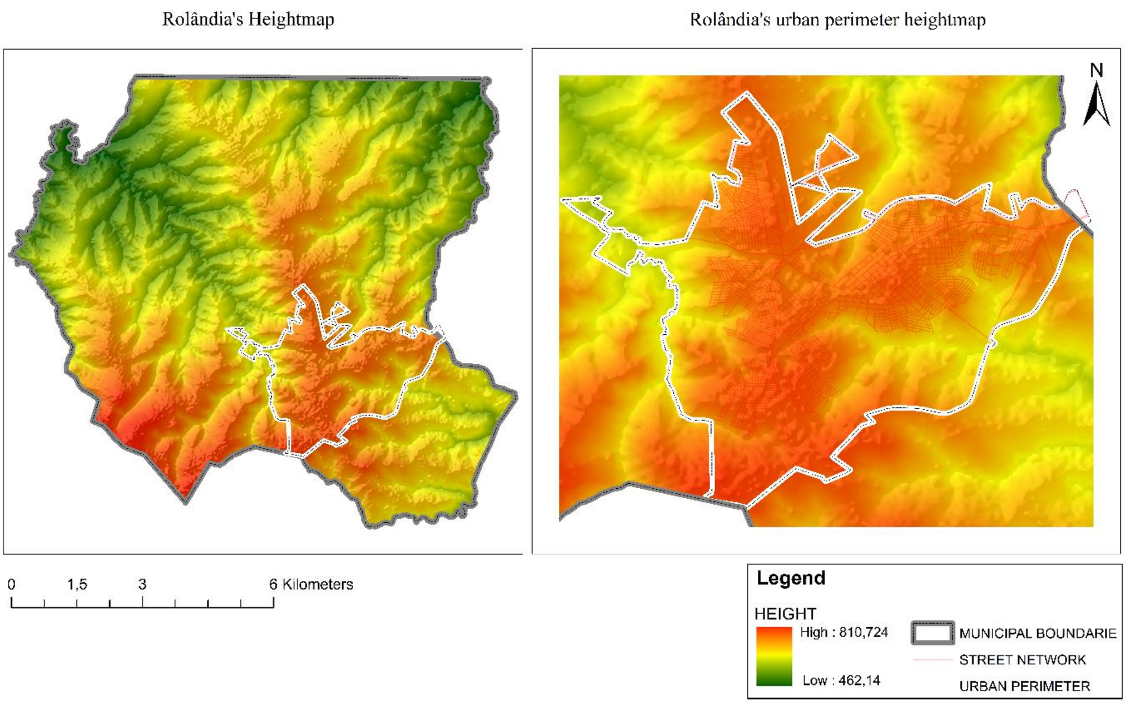
Source: ITEDES (2018). Modified by the author, 2018.

To more precisely correlate urban form measures to walking behavior, trips registered through the OD research were spatialized in geoprocessing procedures that connect geocoded origins and destination trough georeferenced routes. Geoprocessing is the connection of data through spatial operations, connecting objects in their actual location (DRUCK et al., 2005).

It is important to emphasize that in the present study the constructed routes considered only the preliminary choice of route, coarsely depicting the minimization travel cost (e.g. the effort or difficulty associated with a particular route) of a walked trip (BORST et al., 2009). Here the shortest distance between origin and destination of the route is accounted for in the software's automatic route generating procedure. Also, terrain slope is a controlled variable as the case study presents minimum slope overall. The urban grid of Rolândia has developed on a high plane, or plateau, a flat terrain raised significantly above the surrounding area (Figure 10 – Rolândia's municipal boundary and urban perimeter heightmap.).

Many studies investigate the particular criteria that influence pedestrian choice of a specific route. Even though such field of study is dense and complex, general evidences indicate that pedestrians often seem to choose the shortest route, however other factors considered as important encompass domains of the street network itself (e.g straightness) (BRUNYÉ et al., 2015); street characteristics (e.g. sidewalk width) (CZOGALLA; HERRMANN, 2017); urban form (e.g. land use/retail; open spaces) (GUO, 2009; GUO; LOO, 2013); terrain slope (e.g. hilly topology) (GUO, 2009); among others.

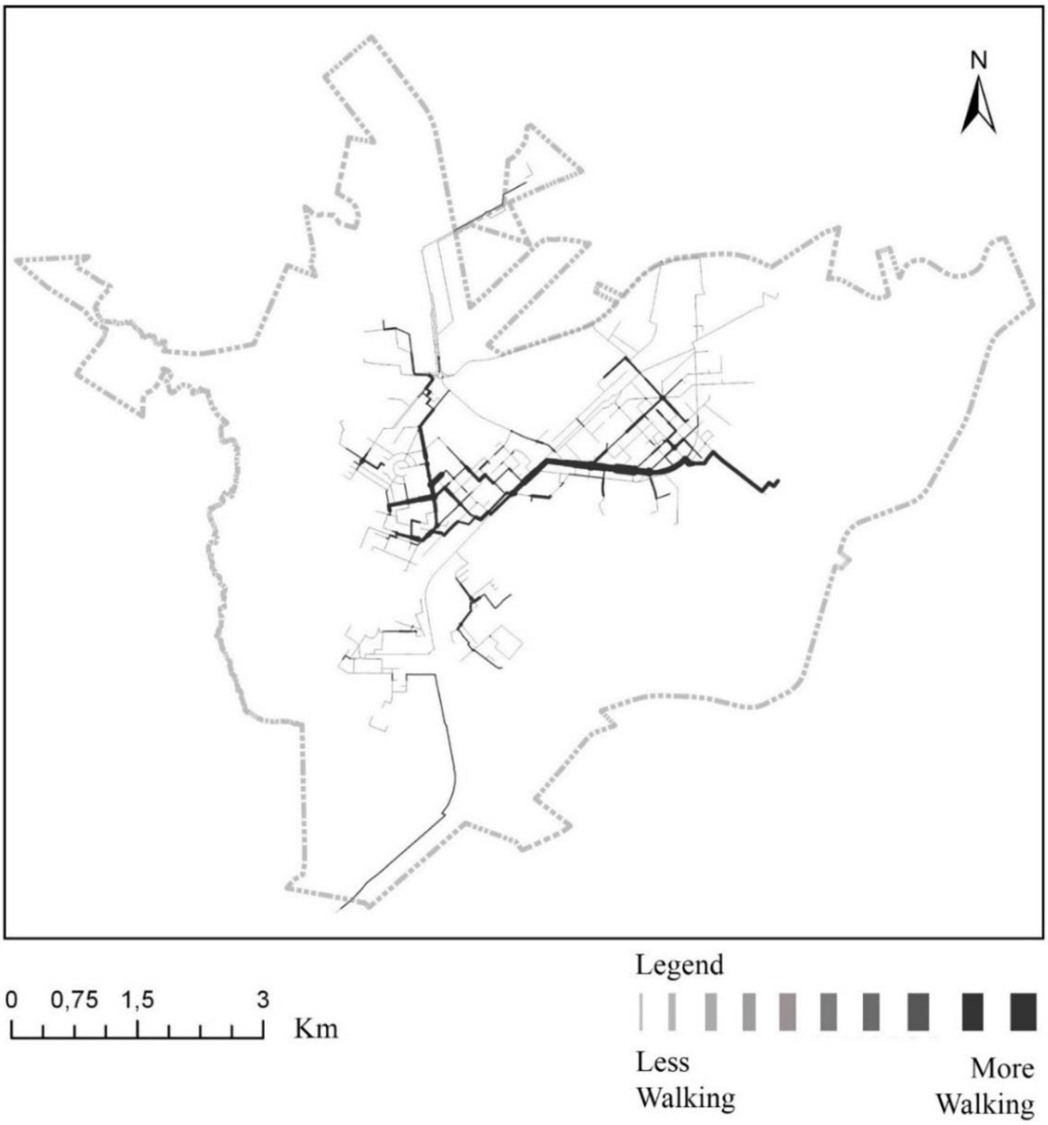
Figure 10 – Rolândia's municipal boundary and urban perimeter heightmap.



Source: IBGE (2016). Organized by the author, 2017

The 756 Respondent's and the 2097 origin and destination address from all transport modes were spatialized using the Geocoding Tools toolbox and Geocode Addresses feature from ArcGIS 10.4.1 (ESRI, Inc). Through the ArcGIS On line's Spatial Analyst toolbox and Connect Origins to Destinations tool (ESRI, 2018b), routes were geocoded. This tool measures the distance between pairs of points using travel modes. It follows paths and roads from the street network that allow pedestrian transit, optimizing travel time by considering the shortest possible path. A geodesic method is set to account for the actual shape of the earth (ESRI, 2018b). From the geocoded routes it was possible to model street loads for all modes of transportation. Figure 11 indicates the locations and intensity of the 394 walking trips as a street load map (Figure 11).

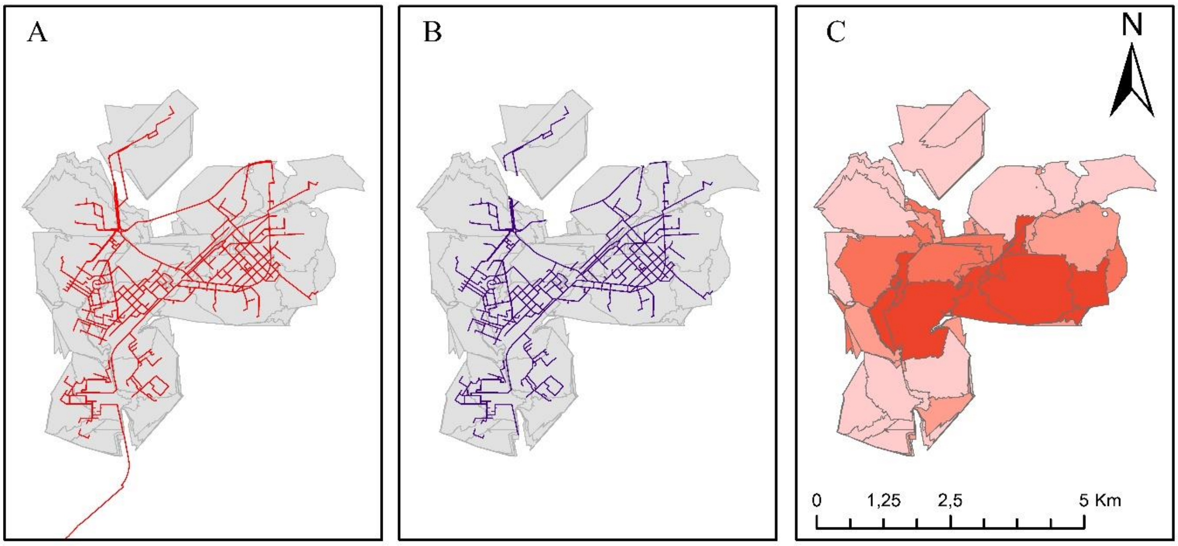
Figure 11 – Walking street load.



Source: ITEDES (2018); Organized by the author, 2018.

Such routes were quantified per unit area, census tracts and buffers. Route information was overlapped with unit areas through the *intersect* ArcGIS tool which computes a geometric intersection of the input features, in this case routes and unit areas (Figure 12"A"). Features or portions of features which overlap are written to an output feature class (Figure 12"B"). In sequence, after the routes had been attributed to each individual unit area, the *summarize* feature from the table of attributes, which calculates summary statistics for fields in a feature class, was used for obtaining the sum of walking meters per unit area. The output of the summarize procedure is a table which in sequence is *joined* through the *join tables* tool to a shapefile containing all information on urban form walkability and respondent's characteristics. The final composed data is a measure of meters walked per unit area (Figure 12"C"). This is the base for the final correlational data that was used to verify the efficacy of objective walkability measures and their constructs in Rolândia-Pr.

Figure 12 – A: input features, in this case routes and unit areas; B: the routes attributed to each individual unit area; C: final composed data is a measure of meters walked per unit area.



Source: ITEDES (2018); Organized by the author, 2018.

3.3.2 Quantifying neighborhood perception of satisfaction

Self-reported neighborhood satisfaction was employed as a proxy for walkability in this present study. The OD survey (ATTACH A) included questions based on the Neighborhood satisfaction subscale from the Neighborhood Environment Walkability Scale (NEWS) (SAELENS et al., 2003). Originally, the OD survey applied considered 9 question derived from the NEWS satisfaction subscales, however two of these were related to bikeablity therefore were excluded from the present analysis.

Walking and cycling are functionally different in that they fulfill different daily purposes for individuals and pose different problems for facility planning and community design (KRIZEK; HANDY; FORSYTH, 2009). In the same sense, dimensions of the built environment influencing each mode may differ (MOUDON; LEE, 2003), therefore there are differences between a measure for walkability and one for bikeability. (WINTERS et al., 2013). Therefore, neighborhood satisfaction was defined by the answers of seven relevant question on aspects of *Travel Network*; *Safety and Walkability*; and Traffic *and Noise* (Table 4).

Table 4 – Survey questions for neighborhood satisfaction assessment.

Satisfaction Factor	Survey Instrument Items
Travel Network	• The access to public transportation in your neighborhood
Safety and Walkability	• How easy and pleasant it is to walk in your neighborhood • Safety in walking • Your neighborhood as a good place to live. • Access
Traffic and Noise	• The amount and intensity of traffic in your neighborhood. • The speed of traffic in your neighborhood. • The noise from traffic in your neighborhood.

Source: ITEDES (2018); Organized by the author, 2018.

It must be emphasized that the construction and application of questionnaires is a complex methodological task, from planning, structuring, writing and asking survey questions, including avoiding ambiguity and how the actual questionnaire should look

(BRACE, 2005). Specific methods and procedures make questionnaire design a scientific activity (SARIS; GALLHOFER, IRMTRAUD, 2014). In the case study under investigation, questions from the perception of satisfaction subscale from NEWS were aggregated to the traditional OD survey. This adjustment could possibly have compromised the quality of the data. The original selection of questions initially broke the sequence and linguistic of the source NEWS questionnaire.

The data considered in the quantification of neighborhood satisfaction are those sourced from the households that reported walking trips. The 394 walking trips were surveyed from 142 households. Only the person in charge of the household was interviewed, therefore, perceptions trace back only to one person. Due to such misconnection of data, it is unfortunately impossible to connect perception to walking trips, neither is it possible to connect the perception data to individual characteristics as the person in charge of the household is not indicated in the member section of the survey. Coarse generalizations from each household can be made, such as mean age, mean income and mean degree of education.

Likert scales have been ubiquitously employed to measure levels of neighborhood satisfaction among respondents (LEE, 2010). Each of the questions surveyed was rated by the respondents using a 5-point Likert scale from 'very dissatisfied' (1) to 'very satisfied' (5). Such categories of answers were dichotomized into positive and negative: null, 1 (very dissatisfied) 2 (dissatisfied) and 3 (neither satisfied nor dissatisfied) were classified and negatives and 4 (satisfied) and 5 (very satisfied) as positives.

The distribution of data can be observed in Figure 13 to Figure 19. It is very clear that some of the responses are not well distributed, such as in “Being a Good Place to Live”. The possible reason for such unevenness is the psychological perspective of NS where there is a ‘‘positive affective’’ state toward the environment (AMÉRIGO; ARAGONÉS, 1997), possibly inciting an unwillingness to rate it as a bad place to live. Similarly, in “Access to public transport” there is an evident response unevenness, probably due to actual lack of such urban infrastructure and services.

Figure 13 – Categorization distributions: Satisfaction with Access to public transport.

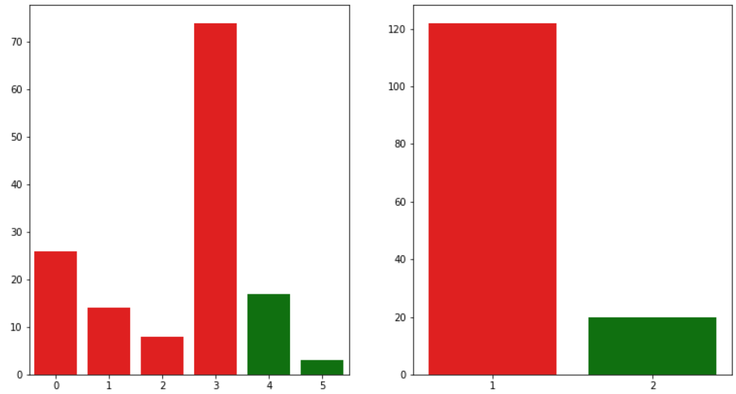


Figure 14 – Categorization distributions: Satisfaction with *Ease and pleasure in walking*

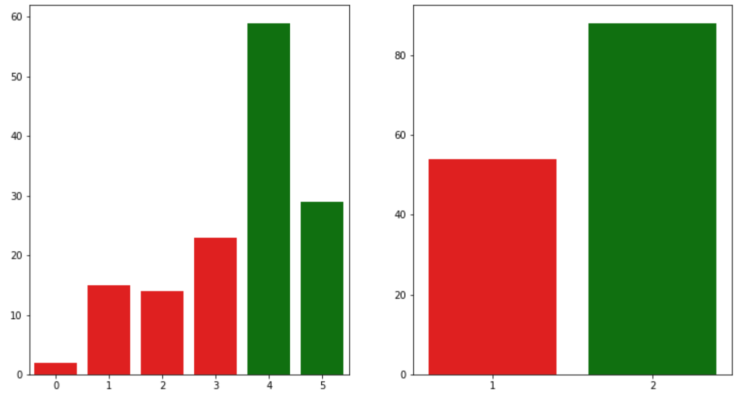


Figure 15 – Categorization distributions: Satisfaction with *Safety in walking*

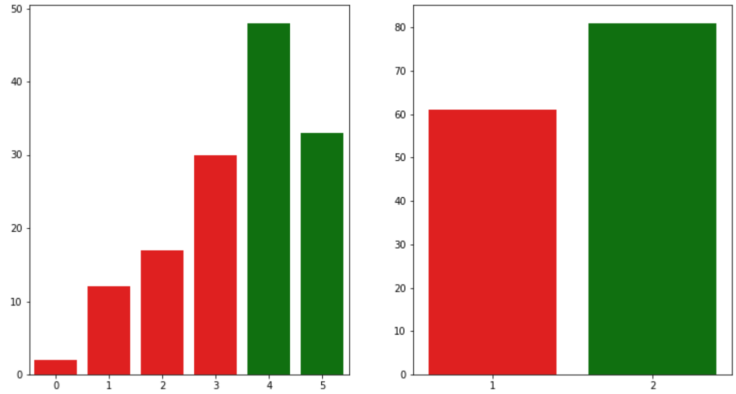


Figure 16 – Categorization distributions: Satisfaction with *Traffic amount/ intensity*

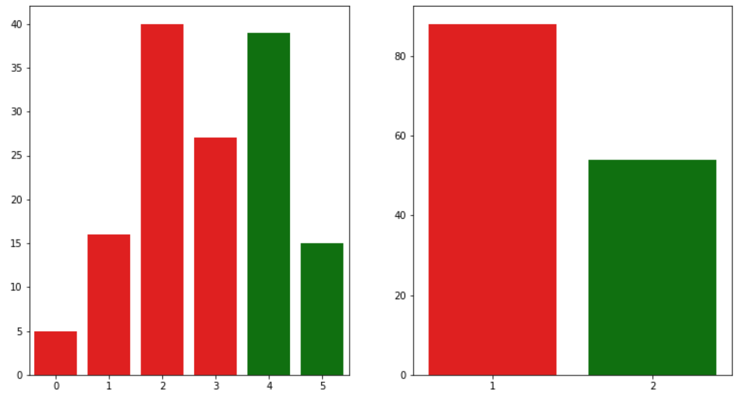


Figure 17 – Categorization distributions: Satisfaction with *Traffic Speed*

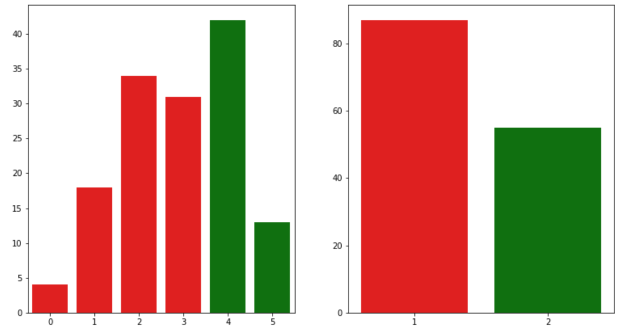


Figure 18 – Categorization distributions: Satisfaction with *Traffic Noise*

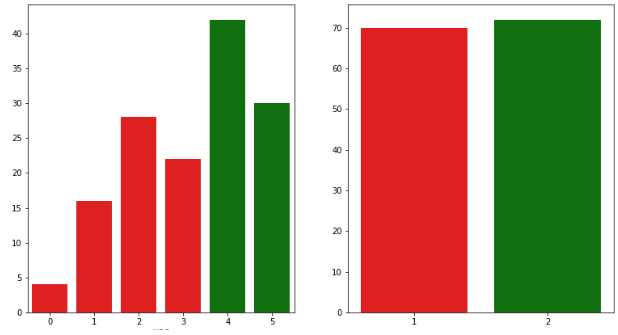
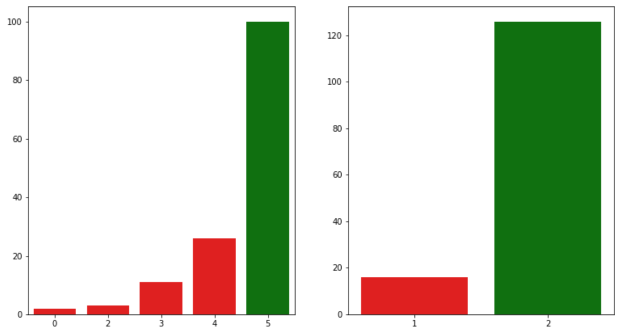


Figure 19 – Categorization distributions: Satisfaction with *Being a good place to live*



Source: ITEDES (2018). Organized by the author, 2018.

The dichotomized perceptions were quantified per unit area, census tracts or buffers. The product of this juxtaposition of data was a measure of positive and negative perceptions. This was the final data utilized in the analysis of the relationship between perceptions of satisfaction, objective walkability measures and walking.

3.4 Objective measurement

Considering the evidence presented in the previous chapter, the use of walkability indices as large-scale reduction tools is justified and in line with the type of analysis, this research proposes. Also following literature tendencies, the individual walkability constructs to be considered are residential density, street connectivity, retail floor area ratio, land use mix, space syntax, and parcel/real estate price.

Regarding residential density, it is clear that this environmental component is consistently related to physical activity and walking (REIS et al., 2013 apud PANTER et al., 2011) and, in the present work, is taken into consideration when analyzing walkability.

According to Sugiyama and colleagues (2012), street connectivity has been substantially associated with walking, indicating that there is solid evidence for considering this feature. Street connectivity is most usually represented by intersection density. Within common walkability indices, such as on the prominent walkability study proposed by Frank (2010), this metric is often weighted by a factor of two. This study is one of the pioneering walkability index propositions. It was conducted with data from American cities, Baltimore and Seattle, where there are large distances between intersections justifying the double weight given attributed to the measure. This methodological choice was based on prior simulations of alternative weighting schemes (FRANK et al., 2010). However, this environmental feature is, in general, very different in Brazil (REIS et al., 2013), applied walkability analysis to some census tracts in Curitiba reducing the weight given to intersection density. Motomura (2017) also pointed out that a higher intersection density was found in Brazilian outskirts, locus of social housing as these areas are mostly characterized by small lots and long-narrow blocks.

It can be inferred that such spaces are most likely not walkable, and their residents possibly have more negative perceptions of the built environment (Figure 20). It must be considered that intersection density might propose a setback when it comes to Brazilian town. New simulations of alternative weighting schemes on intersection density for Brazilian towns should be considered. Initially, the reduction of the weight given to the calculation of intersection density was made in an attempt to lessen its representation for our specific context.

The greater amount of research conducted on this topic has been held in North America, further investigation of these relationships are required in varying urban, cultural and demographic environments (SALLIS et al., 2009). In attempting to replicate walkability indices in diverse settings, modifications are often required due to differences in both contextual urban structure and availability of data for the study area (CHRISTIAN et al., 2011a). Retail FAR is linked to larger retail and shopping malls, a type of development that is rare in medium and small Brazilian towns. It can be considered a context-specific characteristic that might require simulations and validations to be tested.

Figure 20 – Social housing development San Tiago in Rolândia PR - example of the impact of street connectivity.

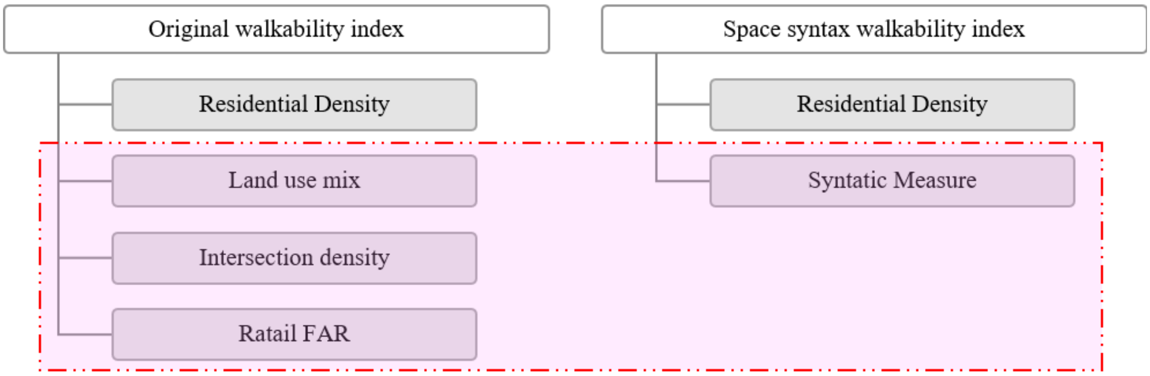
Source: ESRI (2018a).

Several studies have concluded that increased land use mix is associated with reduced levels of automobile-based travel (FRANK, 2000). Further, mixed-land use communities are thought of as more livable and presenting higher levels of satisfaction with physical character (KWEON et al., 2010). Land use mix is a critical element for the development of more compact, sustainable (STEVENSON et al., 2016) and walkable cities, therefore was taken into consideration in this research. However, land use mix involves the ability to properly describe land use diversity at the neighborhood level (GEHRKE; CLIFTON, 2014). There is evidence that the most common land use mix measure, based on the Shannon (1948) entropy formula, may be leading many studies to spurious results (HAJNA et al., 2014).

Current research has associated to measures of Space Syntax (KOOHSARI et al., 2016a) to walkability analysis, relying on the premises that space syntax substitutes calculations related to land use mix, retail FAR and intersection density (Figure 21). This strategy is based on the fundamentals of the space syntax theory where Hillier and Hanson (1984) argue that street layout is the “primary generator of pedestrian movement”. According to Hillier (1996), the urban grid's structure is the 'most powerful single determinant' of urban movement”. Movement is a key aspect of spatial behavior and space is more than a static background in which people move, but an active element of movement behavior (ORELLANA; HERMIDA; OSORIO, 2016).

Following this approach, space syntax is understood to explain destinations. How a street segment is “integrated” within a larger street network may explain its accessibility to other areas possibly increasing pedestrian activities (KOOHSARI et al., 2014). Consequently, movement is drawn to more integrated streets that in turn attract more commercial destinations (HILLIER, 1999). Such assumptions have been addressed in several studies that indicate that more integrated areas have a higher land-use mix (KIM; SOHN, 2002) and that space syntax has the potential to explain retail spatial patterns in a city (TSOU; CHENG, 2013). In essence, the basic assumption is that the street network, could influence pedestrian movement through the differential distribution of commercial land uses (KOOHSARI et al., 2016a). While street connectivity itself is a spatial construct, it may have implications on functional aspects of urban form. Considering such possibility, space syntax measures might be an appropriate substitute for both street connectivity and land use measures, for instance, land use mix and retail FAR. Taking into account such evidence, space syntax was an objective measurement considered in this analysis.

Figure 21 – Conceptual diagram of Space Syntax walkability.



Source: LEÃO; OLAK; KANASHIRO (2018). Modified by the author, 2017

Land price and real estate property price are aggregate elements of environmental features, as consequences of urban form attributes. They have never been included in walkability indices per se, however, they are proven to be related to walkability characteristics. In this study, a first approach to such data was conducted through individual simulations, not included in indices but considered as walkability constructs. Land price and real estate price are represented as mean scores of the properties included in each unit of analysis.

In light of the evidence on the relevance and possible mischiefs of walkability constructs on Brazilian town settings presented above, six simulations were conducted of objective walkability indices considering: residential density; land use mix, intersection density, retail FAR, space syntax measures and parcel/real estate price. The implied relationship to walking for each of the measures considered are summarized in Table 5.

Table 5 – Environmental characteristics and relationships to walking behavior.

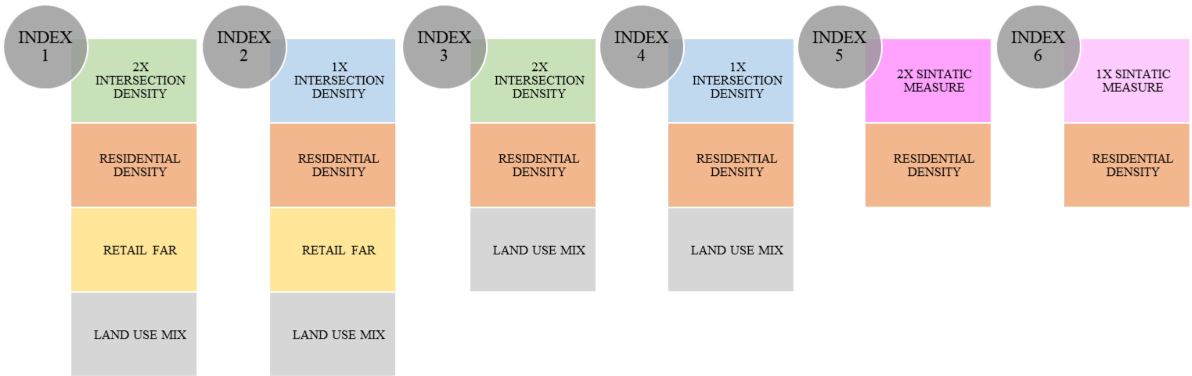
Environmental component	Implied Relationship with Walkability	GIS Databases component
Residential density	• Density Improves accessibility to complementary uses • Associated with increases in retail and service variety, • Results in shorter distances between destinations	Residential location data
Connectivity	• Higher intersection densities provide people with a greater variety of potential routes • Higher connectivity provides easier access to major roads where public transport is available • Shorter times to get to destinations	Road center line and intersections data
Land Use	• People who live near multiple and diverse retail opportunities tend to make more frequent, more specialized and shorter shopping trips, many by walking • People who live farther away from retail are more likely motorized transportation for every-day purchases • land use mix generates more interesting built- form increasing esthetic value making routes more conducive to walking	Land use data and number of floors/units per parcel
Net area retail	• More options for destinations where goods and services may be purchased • More local employment opportunities that can be reached by walking	Retail location data and Retail building projections
Space Syntax Integration and Choice	• More integrated areas have the potential for development of commercial activities • More integrated areas support of land use mix trough pedestrian movement	Axial lines from street centerline data
Land price and Real estate price	• More development and by consequence more amenities • Support of mixed uses • More quality of the micro-scale urban environment	Tax valuation and cadastral (parcel) data

Source: Based on Leslie et al. (2007a). Modified by the author, 2017

The starting point for the index simulations is the index organized by Frank et al. (2010a). It is part of the NQLS (Neighborhood Quality of Life Study) and it is associated with measurements of active transportation and physical activity. The built environment can influence transportation mode choices and studies involving characteristics of community design have gained attention (Frank et al., 2010a). The second simulation utilizes the same equation but removes the double weight attributed to the intersection density measure, as justified previously. Thirdly, the original index is maintained, without the retail FAR measure, in order to analyze its relevance in a Brazilian average-sized town. The same proposition was done in the fourth simulation, however also considering the removal of the double weight given to the intersection density measure.

Simulations number five and six are related to the experimentation with space syntax measures. First, the index proposed by Koohsari (2016) was tested, where residential density was analyzed with syntactic measures weighted twice as much. And lastly, a measure of the same index is made with both residential density and space syntax measures being weighted only once. All indices proposed can be observed in the diagram presented in Figure 22.

Figure 22 – Diagram of objective walkability indices proposed.



Source: Organized by the author, 2018.

Initially, land use data was collected from the Google Earth and the Street View tool and operationalized on ArcGIS 10.4 software. This type of technique is suitable for studies conducted in several locations or in a large geographical area, providing fast, convenient, cheap and reliable data (TAYLOR et al., 2011). Land use data, number of floors and units were collected by researchers between December 2017 and January 2018. A dataset was constructed within GIS at the census tract and buffers level. This method allowed mapping the location of all existing residences and retail in the city. Other data stem from tax valuation, cadastral (parcel) data, building projections and street centerline data. Such information was obtained from Rolândia's city hall. The following sections describe how each specific measure and its constructs were quantified.

3.4.1 Walkability indices construction

For this research, the starting point for the index simulations proposed is the index organized by Frank et al. (2010a). This measure, referred to as index #1, can be expressed through the following equation:

$$\text{Walkability index \#1} = [\,(2\times \text{z-intersection density}) + (\text{z-residential density}) + (\text{z-retail floor area ratio}) + (\text{z-entropy})\,]$$

The second simulation utilizes the same equation but removes the double weight attributed to the intersection density measure, as used by Hino et al. (2012b), can be expressed through the following equation:

$$\text{Walkability index \#2} = [\,(1\times \text{z-intersection density}) + (\text{z-residential density}) + (\text{z-retail floor area ratio}) + (\text{z-entropy})\,]$$

Thirdly the original index is maintained with the removal of the retail FAR measure, to analyze its relevance in the Brazilian medium and small-town context. It can be expressed through the following equation:

$$\text{Walkability index \#3} = [\,(2\times \text{z-intersection density}) + (\text{z-residential density}) + (\text{z-entropy})\,]$$

The same is done in the fourth iteration, however, it is also proposing the removal of the double weight given to the intersection density measure. It can be expressed through the following equation:

$$\text{Walkability index \#4} = [\,(1\times \text{z-intersection density}) + (\text{z-residential density}) + (\text{z-entropy})\,]$$

From the systematization of each variable by census tract and buffers, the method proposes normalization by z-score, exemplified in Table 6. For all calculations (APPENDIX B) the software used was Excel 2013. The construction of the indices was carried out in a georeferenced environment through the software ArcGIS 10.4. The calculations of these four initial walkability index components are further detailed in the next four subchapters.

Table 6 – Walkability index calculation example.

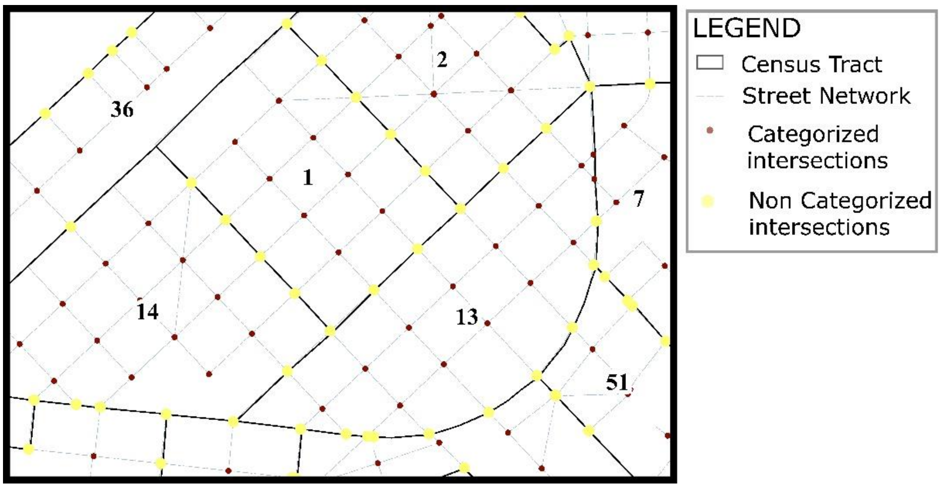
Tract or buffer	Intersection Density		Residential density		Retail FAR		Land use mix		Final Walkability score
	Crude Value	Normalized Value (z-score)	Crude Value	Normalized Value (z-score)	Crude Value	Normalized Value (z-score)	Crude Value	Normalized Value (z-score)	
1	0,267	-0,340	6,569	0,257	0,672	0,502	0,731	2,700	2,779
2	0,360	0,113	5,301	-0,098	0,654	0,435	0,453	1,068	1,632
3	0,343	0,032	5,214	-0,122	0,573	0,124	0,412	0,827	0,893
4	0,409	0,350	6,856	0,337	0,527	-0,055	0,223	-0,276	0,706
5	0,323	-0,065	4,508	-0,320	0,516	-0,097	0,288	0,100	-0,447
6	0,073	-1,279	0,060	-1,563	0,242	-1,150	0,447	1,032	-4,239

Source: Organized by the author, 2018.

3.4.1.1 Methodological approach for Intersection Density

Intersection density is a measure related to the connectivity of the street network, represented by the ratio between the number of true intersections (between three or more roads) and the areal extension of the unit being considered (FRANK et al., 2010). This measure is, therefore obtained by the division of *N* true intersections contained in a unit and the area in squared meters of that same unit. Such calculation can be easily made for buffers; however, census tracts have their boundaries delimitated by the street network, therefore many intersections are located over boundaries of adjacent census tracts (Figure 23).

Figure 23 – Intersections are located over boundaries of adjacent census tracts.

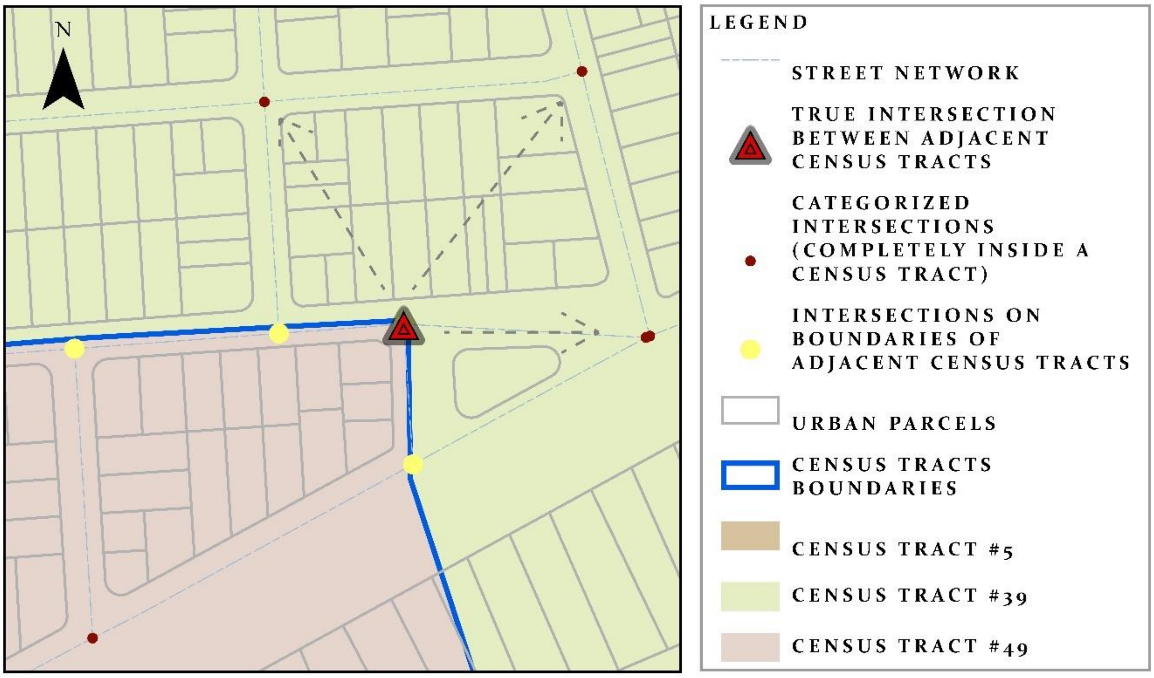


Source: Elaborated by the author, 2018.

This situation raised a problem in the calculating the intersection density measure for census tracts. After an exploratory analysis of the literature on this type of calculation a solution from walkability literature was not found. Therefore, a methodology was proposed: the k-Nearest Neighbor (kNN) classification approach was used to define to which census tract the intersections over boundaries belonged to. The Nearest Neighbor (NN) rule, initially proposed by Fix and Hodges (1951), is one of the oldest and simplest pattern classification algorithms. The basic reasoning is intuitive: nearby instances in space probably belong to the same class (WANG; NESKOVIC; COOPER, 2007). From the basic principle that a point (instance) is often a member of the same class as most of its closest neighbors, where k is a fixed number for all points to be classified, the algorithm tries to classify an unknown sample based on the known class of its neighbors (KIBANOV et al., 2018).

Considering intersections located over boundaries of adjacent census tracts, the parameter k was set to 3, so that the closest three samples are considered for classification. This parameter was set based on a cross-validated grid search (PEDREGOSA et al., 2012). The Euclidean rather than the geodesic distance between neighbors was used. Figure 24 provides a sketch of the k-NN algorithm application, where three of the closest intersections belong to the same class and the unclassified instance is then classified as belonging to their class.

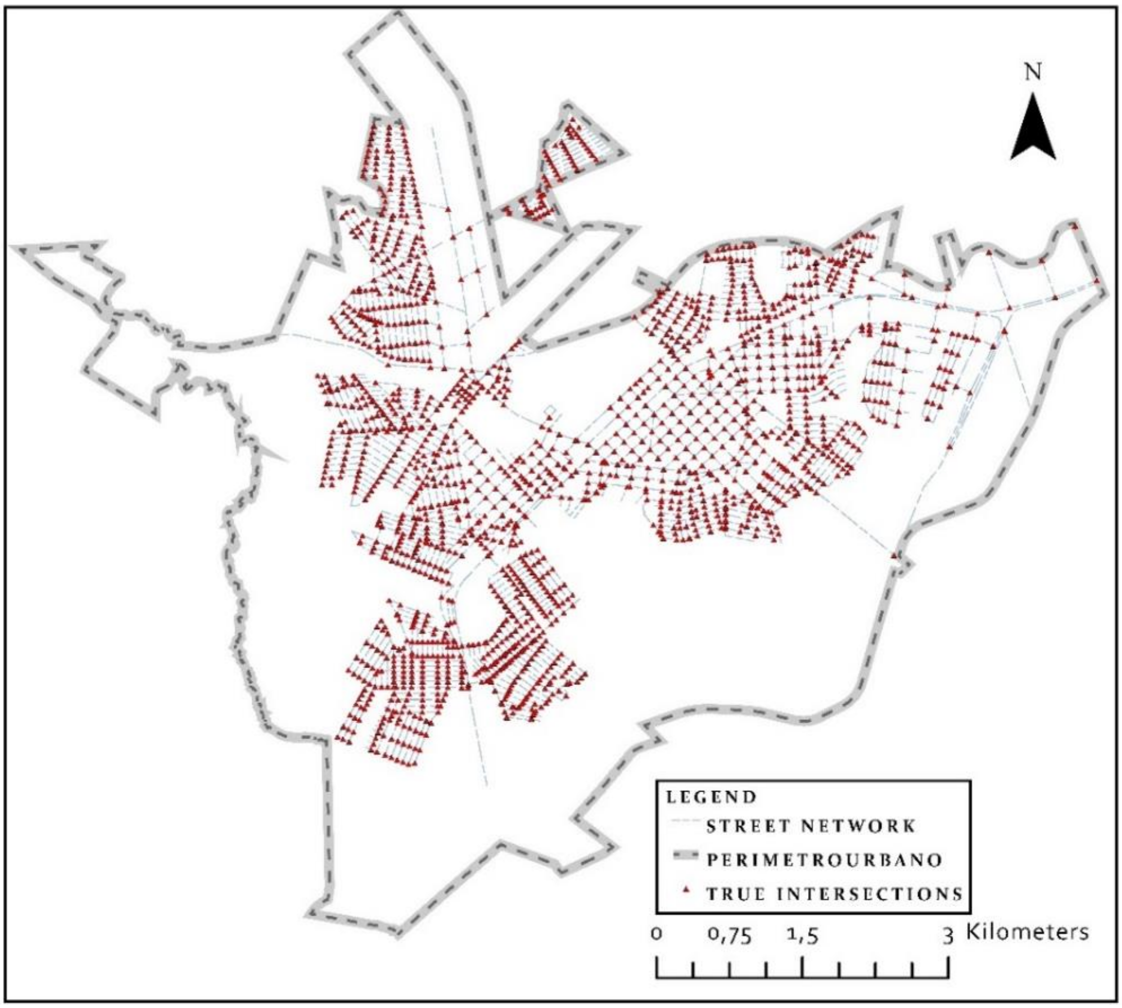
Figure 24 – The kNN rule: with k = 3: the intersection is assigned to the class 1.



Source: Organized by the author, 2017

After such procedure, intersection density was calculated dividing the number of intersections (Figure 25) in each census tract and buffers scales (200m,400m,600m, 800m and 1000m) by its area using the software Excel 2013 Version.

Figure 25 – True intersections on Rolândia's street network.



Source: Elaborated by the author, 2018.

3.4.1.2 Methodological approach for Land Use Mix

Entropy, or land use mix, is a measure of diversity of uses present in an area unit. In this research, taking as a starting point the work proposed by Frank et al., (2010), the mixture between 5 uses was considered: residential, commercial, entertainment services (including restaurants, for example), and institutional (including schools, government buildings, etc.) (Table 7).

Table 7 – Examples of establishments for each land use category.

Land use	**What attends to each use?**
RESIDENTIAL	Ground floor dwellings and tall residential buildings, considering the total number of dwellings
RETAIL	A place where the sale of goods to the public is for consumption and not for resale. E.g.: pharmacy, supermarket, bakery, clothes shop, etc.
SERVICE	A place supplying a payable public need. E.g.: medical care center, pet shop, office, small factory or industry, etc.
INSTITUTIONAL	Every place that belongs to the government administration or every place where people gather usually for the same purpose. E.g.: townhall, court of law, public health care center, public and private school, church, neighborhood association, etc.
ENTERTAINMENT	Every place for leisure activities. E.g.: bar, restaurant, cafeteria, gym, club, country house, etc.

Source: Motomura (2018). Adapted by the author (2018).

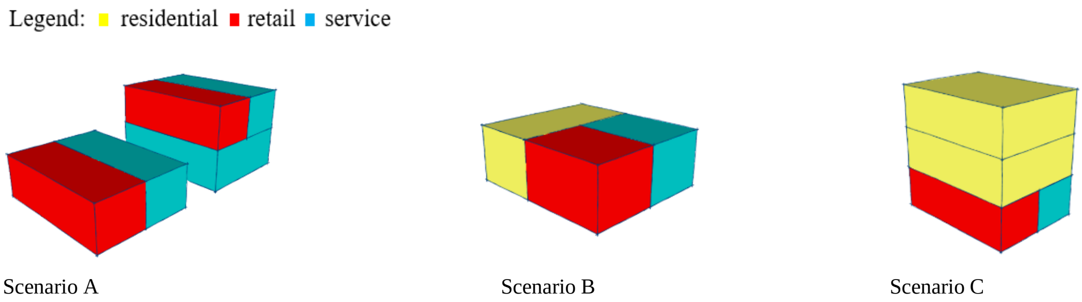
The resulting values are normalized between 0 and 1, where 0 would indicate the existence of only one use in a given area and 1 would indicate a complete and equal distribution of the five uses. The entropy was calculated through the following formula based on (SHANNON, 1948), where k = categories of land use; p = proportion between the area of land use and the area of the census tract; and ln = logarithm (FRANK et al., 2010):

$$-\sum k = \left(\frac{pk \times \ln pk}{\ln N}\right)$$

The entropy calculation originally considered in the walkability index proposed by Frank et al. (2010) does not consider the existence of different uses in the same urban parcel. The concomitance of different uses in the same land lot is common in Brazil. In order to best represent local reality, the total area of mixed-use plots was divided taking into consideration the type of land use and the number of floors.

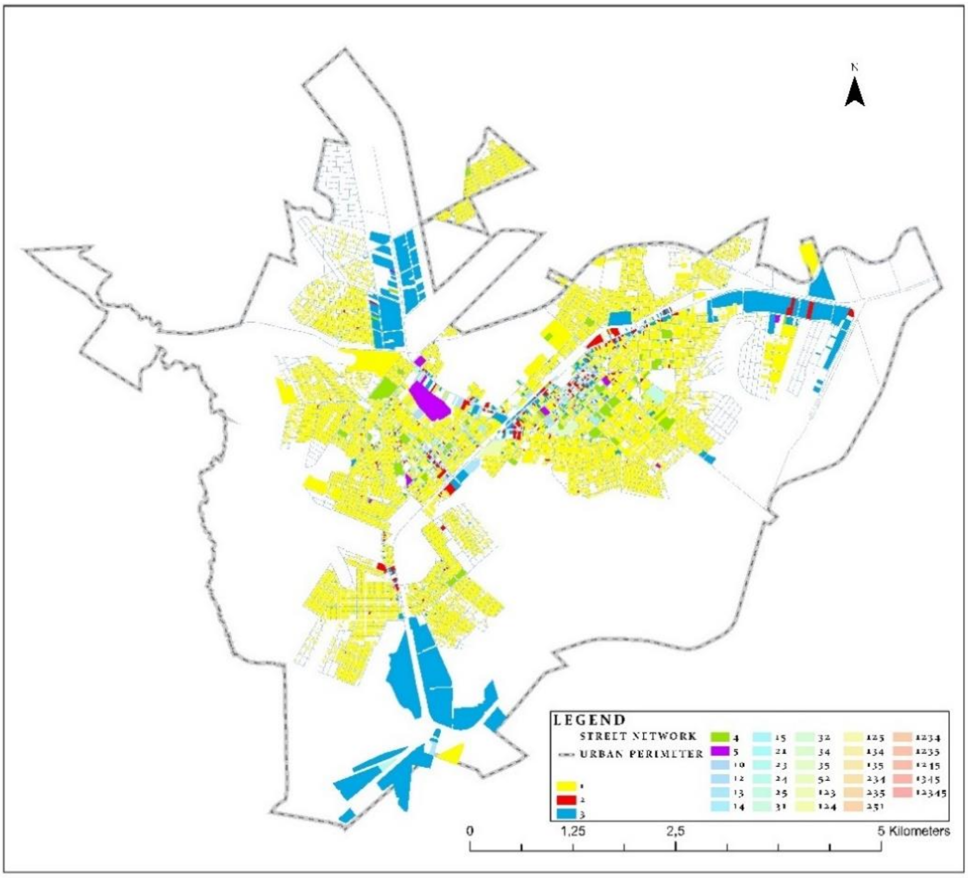
When residential use was not present the total area was divided by the number of uses, regardless of the number of floors (Figure 26a). When residential use was present, but the building had only 1 floor the plot area was equally divided among the number of uses weighting the result in relation to the number of existing uses (Figure 26b). When residential use was present and the building had more than 1 floor, the ground floor had its area weighted between non-residential activities and, residential use was considered as the entire floor area of the second level up (Figure 26c). This division was carried out according to the typologies existing in Brazilian average-sized towns. It is understood that in this way it was possible to identify a more accurate estimate of how many m² of each type of land use exists in the city of Rolândia. The complete land use map is available in Figure 27.

Figure 26 – Weighting of land use category and number of pavements.



Source: LEÃO; OLAK; KANASHIRO (2018). Modified by the author, 2017

Figure 27 – Land use map of Rolândia-PR.

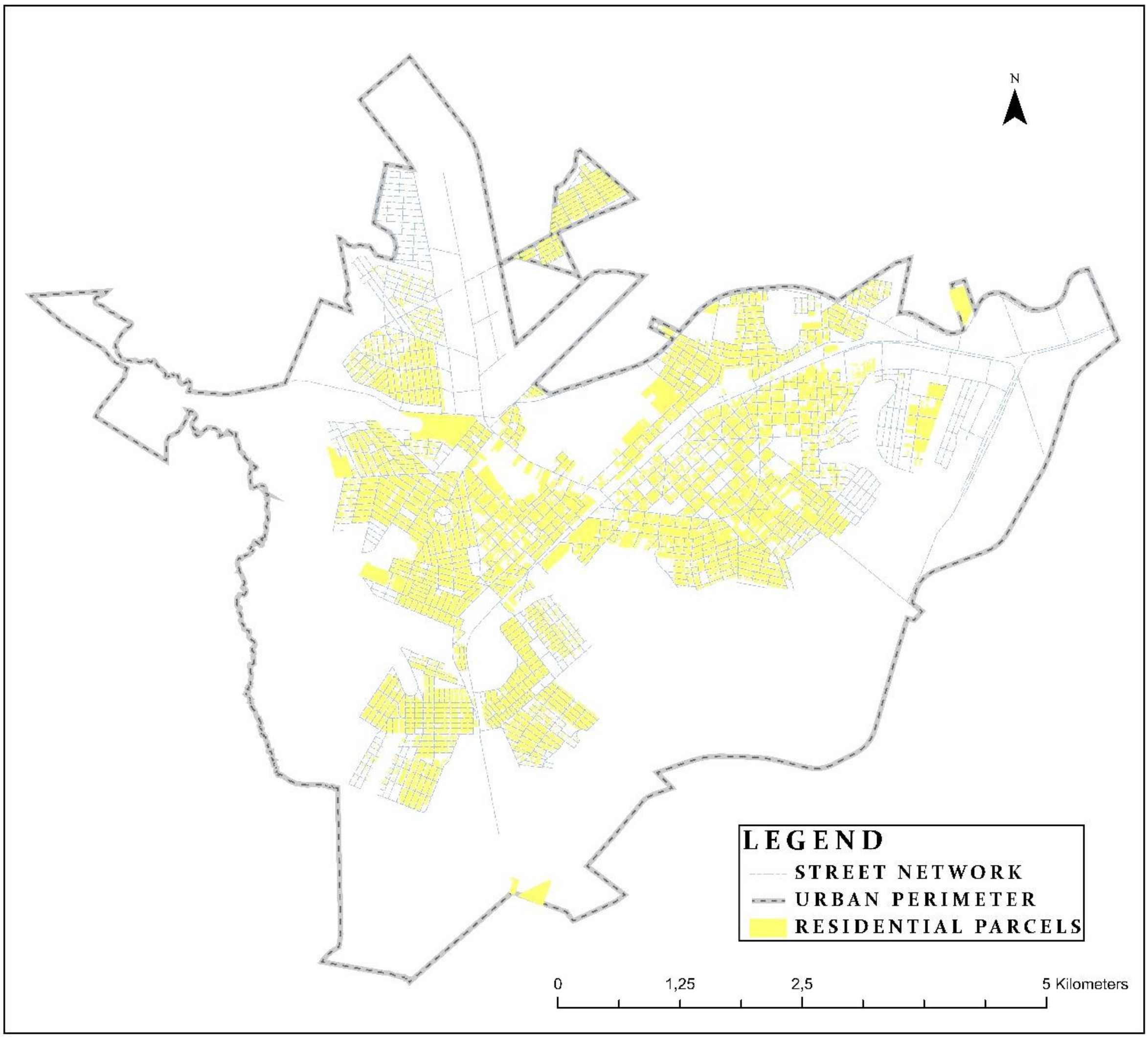


Source: Environmental design research group, 2018. Organized by the author, 2018.

3.4.1.3 Methodological approach for Net Residential Density

Residential density is a measure of the number of residential units (Figure 28) per unit of area (SAELENS; SALLIS; FRANK, 2003). After counting all the households in the municipality of Rolândia, the residential density ratio was calculated for each unit of analysis considered.

Figure 28 – Residential parcels in Rolândia-PR.

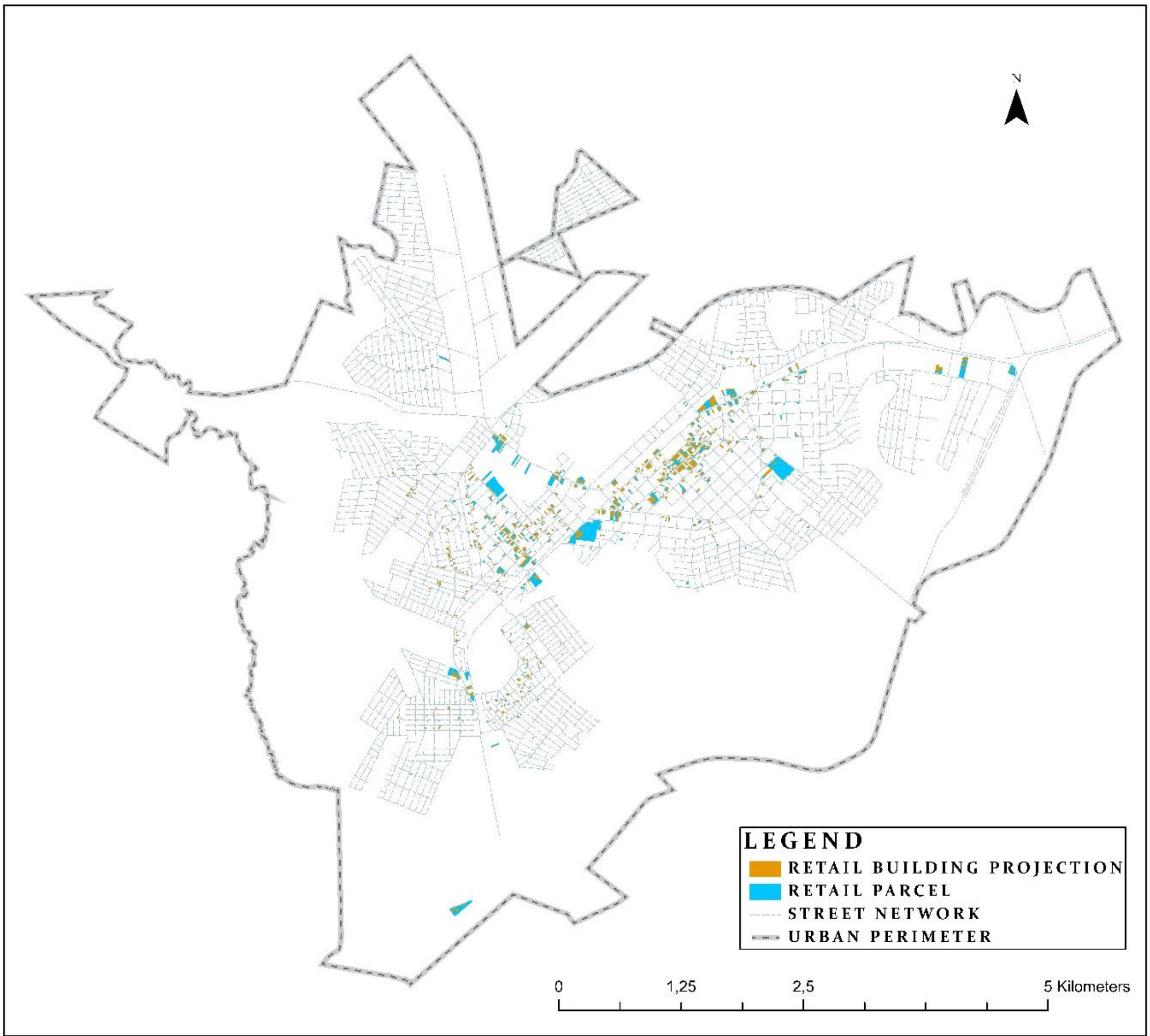


Source: Environmental design research group, 2018. Organized by the author, 2018.

3.4.1.4 Methodological approach for Retail Floor Area Ratio

Retail floor area ratio measures the area of the retail parcels divided by the footprint of the building destined for retail use. A low ratio would indicate that the plot is likely to direct more parking area while a larger value would indicate less surface area to be intended for this purpose. Dedicating less urban surface to parking lots is understood as facilitating pedestrian access (FRANK et al., 2010). The full retail parcels and retail building footprint map is available in Figure 29.

Figure 29 – Retail parcels and building projections in Rolândia-PR.



Source: Environmental design research group, 2018. Organized by the author, 2018.

3.4.2 Space Syntax Walkability indices construction

Simulations number five and six of index options are related to the space syntax measures. Space syntax considers the proximity of one line to all others in the system or to those contained in a predetermined radius, representing street segments with a tendency to concentrate pedestrian flow and, therefore, commercial activities (HILLIER et al., 1993).

Firstly, residential density is analyzed with syntactic measures weighted by two following what is proposed by Koohsari et al. (2016), and lastly a measure of the same index is proposed with residential density and space syntax measures being weighted the same. These indices considering space syntax can be represented by the following equations, respectively:

$$Walkability\ index\ \#5 = [(2 \times z - sintatic\ measure) + (z - \ residential\ density)]$$

$$Walkability\ index\ \#6 = [(1 \times z - sintatic\ measure) + (z - \ residential\ density)]$$

From the systematization of each variable by census tract and buffer, the method proposes normalization by z score (Table 8). For all calculations, the software used was Excel 2013 (APPENDIX B). The construction of the indices was carried out in a georeferenced environment through the software ArcGIS 10.4. The residential density calculations remain the same as previously described. Calculations of space syntax measures are further detailed in the next subchapters.

Table 8 – Walkability index considering space syntax example.

Tract or buffer	Residential density		Integration or choice		Final Walkability score
	Normalized Value (z-score)	Normalized value	Crude value	Normalized Value (z-score)	
1	6,569	0,257	64,313	0,196	0,223
2	5,301	-0,098	75,213	0,771	0,515
3	5,214	-0,122	61,939	0,071	-0,009
4	6,856	0,337	58,383	-0,116	0,022
5	4,508	-0,320	60,074	-0,027	-0,154
6	0,060	-1,563	22,393	-2,013	-2,076

Source: Organized by the author, 2017

3.4.2.1 Methodological approach for Space Syntax measures

Space Syntax seeks to describe, through quantitative measures, the configuration of the urban grid, relationships between public and private space, the urban system as the distribution of land use, cohesion and social exclusion, accessibility and security (CARVALHO; SABOYA, 2017). In space syntax, the urban space is divided into spatial units known as axial lines. These are the largest straight lines capable of covering a whole system of public spaces (HILLIER; HANSON, 1984) The relations between the axial lines of a system can be analyzed through the Integration (1) and Choice (2) measures.

Integration Formula (1)

$$MD_i = \frac{\sum_{j=1}^{k} d_{ij}}{(k-1)}$$

Where:
MDi= Average depth;
dij= depth of the j line in relation to the I line;
k = total number of system components

Choice Formula (2)

$$Choice\ i = \frac{n\ \ shortest\ paths\ trough\ i}{n\ all\ shortest\ paths}$$

Source: Hillier and Hanson, 1984.

The integration of an axial line in a system describes how close it is to all other axial lines. This proximity can be measured by the number of axial lines, through three types of metrics: angular, topological or metric. However, in axial maps angular and metric measures are more efficient. Angular metrics better capture the ease of transportation through the complexity of the urban grid, whereas metric analyses, from a determined metric radius, is more useful for pedestrian and neighborhood analysis.

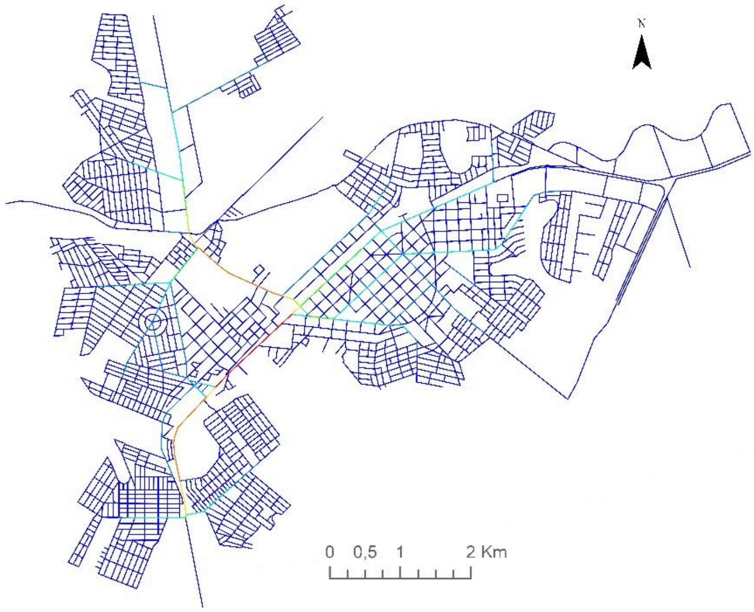
Lines that are more connected and closer to all others in a system are called integrated lines, while those farther are called segregated lines. The Choice measure, however, translates how much an axial line is located among other possible paths of the system. Thus, a line with a high value of choice is not necessarily the one closest to the others, but the one that most connects other paths.

In addition to being able to be calculated from topological (by axial lines) or metric (by line segments), the Integration and Choice measure can describe the relation of one axial line to all others of a system or only to those contained in a predetermined radius. According to Carvalho and Saboya (2017), many researches use a predetermined radius to find the influence of certain factors on smaller scales.

Integration and choice were calculated using street centerline data obtained from the base map of the municipality provided by the city hall of Rolândia and adapted for the representation of axial lines. Then, axial lines were imported into the QGIS software, a free and open source GIS. Through the Space Syntax toolkit, the syntactic integration and choice measures were calculated for each street segment in radii ranging from 100 to 2000 with 100-meter intervals. All space syntax maps produced, for both choice and integrations are available in the APPENDIX A, examples of the maps utilized are Figure 30 and Figure 31.

Figure 30 – Space Syntax global Integration.

Figure 31 – Space Syntax global Choice.



Source: Rolândia City Hall, 2017. Elaborated by Vitoria Sanches, (2018).

Firstly, axial lines were converted into centroid points and later accounted for each buffer. An average integration and choice score were calculated for each radius and for each spatial unit representation scale. Space syntax is based on the street network and in the case of the census tracts, similar to intersection density, many axial lines' centroids were allocated over boundaries of adjacent census tracts. In such cases the proposed methodology follows the k-Nearest Neighbor (kNN) classification approach introduced in the last chapter.

3.5 Analytical Strategy

This analysis has three objectives: (1) to verify the relationship between BE factors and self-reported walking data, aiming to uncover which BE variables, measures and constructs most influence walking levels (2), to analyze the relationship between BE factors and self-reported perceptions of satisfaction aiming to verify their concordance and (3) to explore the sensitivity of all results to spatial scale by estimating separate models using BE factors aggregated at three buffer-based scales (200 m, 400 m, 600 m, 800 m, 1000 m) and census tract level.

Regression analysis models, especially logistic regression, have been used in a variety of researches concerning BE and health (TROPED et al., 2003; VAN CAUWENBERG et al., 2014; SUGIYAMA et al., 2015b) and can be considered a standard analysis approach. However, these models may not give a faithful data description if their obligatory requirements and assumptions are not met, or whenever higher-order interactions among explanatory/independent variables exist (EVERITT, 2005). When data is linearly separable, such regression approaches, especially logistic, are in fact ideal, however, real life-contextual data rarely is. Therefore, taking into account some eventual problems with usual regression models, alternative approaches, such as computational methods used to extract patterns from data, have been developed (GULLO, 2015).

These methods encompass artificial intelligence and machine learning. These fields of study aim to give computers the ability to learn without being explicitly programmed, therefore being able to recognize hidden patterns in datasets (SAMUEL, 1959). Since artificial intelligence first achieved recognition as a discipline in the mid-1950's, machine learning (ML) has been a central research area (QUINLAN, 1986). ML has been described as a technical field that lies at the intersection of computer science and statistics (JORDAN; MITCHELL, 2015).

ML can be conceptualized as the research area that looks for algorithms that allow the recognition of patterns such as the distinction of numbers or faces and advances on how computers can infer information from data (CARBONEL; MICHALSKI; MITCHELL, 1997). Such methods have had intensive effects across a range of industries concerned with data-intensive issues (JORDAN; MITCHELL, 2015). Notwithstanding, they are rarely used in urban planning having the work conducted by Zampieri (2012) being mention-worthy. Considering these regards, a ML approach was used to model this researches' relationships of interest. All data in this research was, by nature, labeled, therefore the ML algorithms were applied to learn patterns from actual examples from each class, which categorizes the employed methodology as supervised learning. Supervised learning is conceptualized as ML processes that contain a guided training phase. Unsupervised learning is characterized by processes executed when the algorithm itself looks for structure in data and groups it in clusters (KOTSIANTIS, 2007).

From a practical perspective, the purpose of supervised ML is to learn from training data to make as good as possible predictions on new, unseen, data. Thus, ML algorithms have a training process and its output is used to predict unforeseen data (GHAHRAMANI, 2015). The quality of such predictions indicates the quality of the model. The general idea is that unforeseen data is similar to known data, so a good model is the one that leads to good predictions. This means that ML can solve two main types of tasks: regression and classification. Regression tasks stem from a supervised learning problem where the answer is a continuous value. Classification tasks stem from a supervised learning problem where the answer to be learned is one of the finitely possible values (classes) (GULLO, 2015).

A diverse array of ML algorithms has been developed to cover the wide variety of data and problem types (JORDAN; MITCHELL, 2015). A more recent approach from machine learning, that has been proposed for prediction and variable selection in various fields, is the nonlinear and nonparametric Random Forest (RF) method. It is a supervised ML technique that builds an ensemble of decision trees, for classification or regression. Linear regression is a classical parametric method which requires explicit modeling of nonlinearities and interactions, if necessary. It is known to be reasonably robust, however Random forests, on the other hand, are nonparametric and allow nonlinearities and interactions to be learned from the data without any need to explicitly model them (GRÖMPING, 2009).

RF has its foundation set on decision tree algorithms, sequential models that logically combine a sequence of simple tests; each test compares a numeric attribute against a threshold value or a nominal attribute against a set of possible values (classification or regression). When a data point falls in a partitioned region, a decision tree classifies it as belonging to the most frequent class in that region. This type of data structure is formed by connected nodes that starts with a root node, and follows through internal nodes until a terminal one, also called leave. For decision and regression trees, each internal node has a test for a variable which indicates the flow to reach the appropriate leaf. This procedure is repeated until reaching a terminal node, that will contain a predicted class for classification tasks, or a predicted value for regressions (LOH, 2011). The error rate is the total number of misclassified points divided by the total number of data points, and the accuracy rate is one minus the error rate (KOTSIANTIS, 2013). The algorithm attempts to generalize, or find patterns in, the data. It does so by determining which tests (questions) best divide the instances into separate classes, forming a tree.

Tree based regressions are used to model problems when the predicted variable is continuous by fitting a step function to the data points. The tree is constructed by recursively sub-dividing the space into smaller partitions finding regions with more homogeneous group to make a prediction. Each split of the space is based on a single variable selected based on a splitting criterion where a threshold is selected to make split the space. These splits happen on the nodes of a tree, and the terminal nodes - also called leaves - carries the response values. After the tree is built, a prediction is achieved by following the path from root node down to its appropriate leaf (GRÖMPING, 2009). Different from classification, which has a class on the leaf, in regression the leaf carries a continuous value obtained from the dependent variable values on the samples inside the partition made by the previous splits.

RF are an ensemble method that combines several individual trees, forming a ‘forest’. From the original dataset several bootstrap samples are drawn, and a classification/regression tree is fit to each bootstrap sample. This type of sampling is used to study the variability of estimated characteristics of the probability distribution of a set of observations. It involves sampling with replacement, to produce random samples of size *n* from the original data, each of these is known as a bootstrap sample and each provides an estimate of the parameter of interest (EVERITT; SKRONDAL, 2010). From the complete forest the status of the response variable is predicted as an average majority vote of predictions of all trees (STROBL et al., 2007).

Linear Regression is a classic global method that uses a single formula to fit the whole space. It uses the whole dataset to train a linear predictor, but assembling a single global model becomes difficult when there is lots of features that interact in nonlinear ways. Therefore, it's easier for regression tress to fit a simpler model on its partitions and generate a more accurate model compared to linear regression (DE’ATH; FABRICIUS, 2008). In the case of Random Forest regression, also called Regression Forest, the idea is to use an ensemble of trees in order to get a more powerful predictor. The RF algorithm is based on the bagging approach, which is a technique where it creates a set of sub-trees that are trained with its own random subset of features and samples. This approach makes it robust against overfitting and creates accurate classifiers and regressors (BREIMAN, 2001). Also, the nature of RF makes it very user-friendly, in the sense it has few parameters to tune (in this work only the number of sub-trees as set and the rest was left as the default values) and is usually not very sensitive to their values, which makes it a great fit for the problem assessed in this study.

RF can highly increase prediction accuracy when compared to individual classification trees, because the ensemble adjusts for the instability of the individual trees induced by small changes in the learning sample. On the other hand, the interpretability of a random forest is not as straightforward as that of an individual tree, as it is by nature much more complex (STROBL et al., 2007). Another advantage of using RF models is the feature section properties. This process of identifying only the most relevant features makes models simpler to interpret, can reduce the variance of the model and the computational cost (and time) of training a model. Tree-based strategies such as Random Forests are often used for feature selection as they naturally rank features by how well they improve model (KURT; TURE; KURUM, 2008).

The most relevant output from RF, is a measure of the importance of the predictor variables. Variable importance is a difficult concept to define in general, because the importance of a variable may be due to its (possibly complex) interaction with other variables (LIAW; WIENER, 2002). Ranking predictive importance of features for a given problem can serve two different purposes: to identify the variables that are more related to the response variable, or to selected a small subset of features to achieve a sufficiently good prediction performance (GRÖMPING, 2009). In this work, feature importance was extracted with the intention of analyzing the variables that are more related to the response variable, walking levels, in order to interpret its causal effect on the problem.

RF address the importance of the features using permutating the features of the out-of-bag (OOB) samples and calculating the OOB error. The original proposal of RF defines OOB samples as the set of samples which are not used for building the current tree, and evaluating the model on those samples gives the out-of-bag error that is used to evaluate variable importance. In case a feature when replaced by another randomly selected feature results in an error increase, this feature is related negatively to the problem. On the other hand, if the error decreases when the feature is replaced, this feature is positively related to the response variable (GENUER; POGGI; TULEAU-MALOT, 2012). In summary, the random forest algorithm estimates the importance of a variable by looking at how much prediction error increases when data for that variable is permuted while all others are left unchanged. The necessary calculations are carried out tree by tree as the RF is constructed.

Within a very short period of time, RFs have become a major data analysis tool, that performs well in comparison with many standard methods (DÍAZ-URIARTE; ALVAREZ DE ANDRÉS, 2006). What has greatly contributed to the popularity of random forests is the fact that they can be applied to a wide range of problems, even if they are nonlinear and involve complex high-order interaction effects. If the aimed result is a categorical variable, classification can be performed. If the response is continuous, regression can be performed (LIAW; WIENER, 2002). With this technique, no precise information is required about the form of the relationship between response and input variables (BREIMAN et al., 1984). Thus, RF are considered robust to errors and outliers, efficient in big data sets (BREIMAN, 2001) and widely used in real life applications for various study domains (OSHIRO, 2013).

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RF has excellent performance and although it is not widely used in the urban planning field of study it has several characteristics that make it ideal for its data sets. Some advantages of RF are: can be used when there are more variables than observations; for two-class and multi-class problems; performs both classification and regression; has good predictive performance even when most predictive variables are noisy; does not require a pre-selection of features; is not prone to overfitting; can handle a mixture of categorical and continuous predictors; incorporates interactions among predictor variables; there are high quality-free implementations and returns measures of variable importance (DÍAZ-URIARTE; ALVAREZ DE ANDRÉS, 2006).

Given these promising features, in this research all possible individual constructs and indices proposed were tested for each of the six neighborhood scales using RF. A summary of the considered variables for each scale can be observed in Table 9. In the RF models all variables presented in this table are input variables and response variables are meter walked per area unit and perceptions of satisfaction with the built environment.

Table 9 – Objective walkability measures and constructs considered.

	Walkability variables	Walkability indices	
Traditional walkability	Z-score Residential Density	Walkabily Index	
	Z-score Intersection density	Walkabily Index 1X	
	Z-score Retail FAR	Walkabily Index 1X R	
	Z-score Land use mix	Walkabily Index R	
Value	Z-score Mean land value		
	Z-score Mean estate value		
Space Syntax	Z-score Choice 100	1x Space Syntax Walkability Choice 100	2x Space Syntax Walkability Choice 100m
	Z-score Choice 200m	1x Space Syntax Walkability Choice 200m	2x Space Syntax Walkability Choice 200m
	Z-score Choice 300m	1x Space Syntax Walkability Choice 300m	2x Space Syntax Walkability Choice 300m
	Z-score Choice 400m	1x Space Syntax Walkability Choice 400m	2x Space Syntax Walkability Choice 400m
	Z-score Choice 500m	1x Space Syntax Walkability Choice 500m	2x Space Syntax Walkability Choice 500m
	Z-score Choice 600m	1x Space Syntax Walkability Choice 600m	2x Space Syntax Walkability Choice 600m
	Z-score Choice 700m	1x Space Syntax Walkability Choice 700m	2x Space Syntax Walkability Choice 700m
	Z-score Choice 800m	1x Space Syntax Walkability Choice 800m	2x Space Syntax Walkability Choice 800m
	Z-score Choice 900m	1x Space Syntax Walkability Choice 900m	2x Space Syntax Walkability Choice 900m
	Z-score Choice 1000m	1x Space Syntax Walkability Choice 1000m	2x Space Syntax Walkability Choice 1000m
	Z-score Choice 1100m	1x Space Syntax Walkability Choice 1100m	2x Space Syntax Walkability Choice 1100m
	Z-score Choice 1200m	1x Space Syntax Walkability Choice 1200m	2x Space Syntax Walkability Choice 1200m
	Z-score Choice 1300m	1x Space Syntax Walkability Choice 1300m	2x Space Syntax Walkability Choice 1300m
	Z-score Choice 1400m	1x Space Syntax Walkability Choice 1400m	2x Space Syntax Walkability Choice 1400m
	Z-score Choice 1500m	1x Space Syntax Walkability Choice 1500m	2x Space Syntax Walkability Choice 1500m
	Z-score Choice 1600m	1x Space Syntax Walkability Choice 1600m	2x Space Syntax Walkability Choice 1600m
	Z-score Choice 1700m	1x Space Syntax Walkability Choice 1700m	2x Space Syntax Walkability Choice 1700m
	Z-score Choice 1800m	1x Space Syntax Walkability Choice 1800m	2x Space Syntax Walkability Choice 1800m
	Z-score Choice 1900m	1x Space Syntax Walkability Choice 1900m	2x Space Syntax Walkability Choice 1900m
	Z-score Choice 2000m	1x Space Syntax Walkability Choice 2000m	2x Space Syntax Walkability Choice 2000m
	Z-score Integration 100m	1x Space Syntax Walkability Integration 100m	2x Space Syntax Walkability Integration 100m
	Z-score Integration 200m	1x Space Syntax Walkability Integration 200m	2x Space Syntax Walkability Integration 200m
	Z-score Integration 300m	1x Space Syntax Walkability Integration 300m	2x Space Syntax Walkability Integration 300m
	Z-score Integration 400m	1x Space Syntax Walkability Integration 400m	2x Space Syntax Walkability Integration 400m
	Z-score Integration 500m	1x Space Syntax Walkability Integration 500m	2x Space Syntax Walkability Integration 500m
	Z-score Integration 600m	1x Space Syntax Walkability Integration 600m	2x Space Syntax Walkability Integration 600m
	Z-score Integration 700m	1x Space Syntax Walkability Integration 700m	2x Space Syntax Walkability Integration 700m
	Z-score Integration 800m	1x Space Syntax Walkability Integration 800m	2x Space Syntax Walkability Integration 800m
	Z-score Integration 900m	1x Space Syntax Walkability Integration 900m	2x Space Syntax Walkability Integration 900m
	Z-score Integration 1000m	1x Space Syntax Walkability Integration 1000m	2x Space Syntax Walkability Integration 1000m
	Z-score Integration 1100m	1x Space Syntax Walkability Integration 1100m	2x Space Syntax Walkability Integration 1100m
	Z-score Integration 1200m	1x Space Syntax Walkability Integration 1200m	2x Space Syntax Walkability Integration 1200m
	Z-score Integration 1300m	1x Space Syntax Walkability Integration 1300m	2x Space Syntax Walkability Integration 1300m
	Z-score Integration 1400m	1x Space Syntax Walkability Integration 1400m	2x Space Syntax Walkability Integration 1400m
	Z-score Integration 1500m	1x Space Syntax Walkability Integration 1500m	2x Space Syntax Walkability Integration 1500m
	Z-score Integration 1600m	1x Space Syntax Walkability Integration 1600m	2x Space Syntax Walkability Integration 1600m
	Z-score Integration 1700m	1x Space Syntax Walkability Integration 1700m	2x Space Syntax Walkability Integration 1700m
	Z-score Integration 1800m	1x Space Syntax Walkability Integration 1800m	2x Space Syntax Walkability Integration 1800m
	Z-score Integration 1900m	1x Space Syntax Walkability Integration 1900m	2x Space Syntax Walkability Integration 1900m
	Z-score Integration 2000m	1x Space Syntax Walkability Integration 2000m	2x Space Syntax Walkability Integration 2000m
	Z-score Integration rn	1x Space Syntax Walkability Choice rn	2x Space Syntax Walkability Integration rn
	Z-score Choice rn	1x Space Syntax Walkability Integration rn	2x Space Syntax Walkability Choice rn

Source: Organized by the author, 2017

3.5.1 Analytical approach: Walking levels and the built environment.

This analysis aims to verify the relationship between BE factors and self-reported walking levels, uncovering which built environment variables, measures and constructs most influence walking levels. As walking levels are a continuous variable Random Forest Regressor was used (LIAW; WIENER, 2002). This process was conducted in two steps, firstly walking levels were analyzed with each individual walkability variables (Subchapter 3.5.1.1) and secondly with walkability indices (Subchapter 3.5.1.2).

The quality measure of the models is the output value of the coefficient of determination (R^2) of the prediction. Such a measure is well established in classical regression analysis (RAO, 1965). This coefficient is defined as “the proportion of variance explained by the regression model” (NAGELKERKE, 1991). Thus, it can be seen as a measure of the model’s success in predicting the dependent variable through the independent ones. The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse) (PEDREGOSA et al., 2012).

The RF Regressor was implemented using the *Scikit-learn* machine learning library for the Python programming language (PEDREGOSA et al., 2012). Graphs were generated through the Seaborn Python data visualization library. The choice for this language was due to its ample use in geoprocessing (DOBESOVA, 2011; GRASER; OLAYA, 2015). It also offers a broad range of packages for ML.

3.5.1.1 Analytical approach: Walking levels and walkability variables

This first regression analysis began with a screening of all the individual walkability variables’ correlation to walking levels in all six units of analysis. This was done through a simple Spearman’s rank correlation analysis. It is one of the most common methods in applied social research (FORSYTH; OAKES; SCHMITZ, 2009; FLORINDO et al., 2013; MAYNE et al., 2013; WELIANGE; FERNANDO; GUNATILAKE, 2014), particularly in the field of exploratory analysis of a large, real-world dataset. It is a technique of data exploration to identify and reveal the degree of association between a dependent variable and another (ADHIANTO et al., 2010). Spearman's correlation coefficient is a non-parametric (free distribution) statistical procedure, proposed as a measure of the strength of the association between two variables. However, it is not a measure of linear relationships between two variables and can be described without making assumptions about their frequency and distribution (HAUKE; KOSSOWSKI, 2011). For each scale, the individual walkability variables showed significantly correlated to walking levels at the p-value ≤ 0.05 and a p-value ≤ 0.01 levels. This step is conducted as a part of exploratory analysis in order to better understand the variables relationship before introducing them to the model.

In sequence six RF regression models, one for each unit of analysis, were created. Even though there is little need to fine-tune parameters to achieve excellent performance, the parameters used were: (1) “n_estimators” ou “ntree” which was set to 500 to obtain stable results, the values were tested from 10 to 500 with 10 unit intervals (2) “criterion” set to “mse” for the mean squared error, which is equal to variance reduction as feature selection criterion (3) max_depth set to 10 which limits the extent of trees and stabilized the model. The mtry (default = 5) parameter was set to its defaut value, as it has been reported that the default value is often a good choice (LIAW; WIENER, 2002). All other parameters were set to their default tuning/values.

RF are a truly ‘random’ statistical method in that the model results can vary from run to run. Therefore, it is of utmost importance that the stability of the model is verified (SHIH, 2011). To compare the performance of all generated models the quality output measure of the *coefficient of determination (R^2)* was cross-validated to obtain a distribution of the R^2 metric of quality. Cross-validation is an essential common practice to avoid overfitting, the production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably (EVERITT; SKRONDAL, 2010). In summary, it verified how well the models will generalize to new data. A random permutations cross-validation or *Shuffle & Split* was conducted for the results reported.

The *Shuffle & Split cross-validation method* will generate a user defined number of independent train / test dataset splits, running the models over and over and comparing the results. Samples are first shuffled and then split into a pair of train and test sets. *Shuffle & Split* allows for a finer control on the number of iterations and the proportion of samples on each side of the train / test split, randomly sampling the entire dataset during each iteration (PEDREGOSA et al., 2012). The number of iterations was set to 50 train/test dataset splits and the proportion of the split to 80% train / 20% test. After this process the output is and average of R^2 for all models. From this procedure the measure of the importance of the predictor variables was obtained.

In the same way, to get a stable and reliable measure of feature importance, a lot of trees have to be generated and even though this result may vary from run to run (LIAW; WIENER, 2002). Therefore, during the cross-validation step in this work, the importances are stored through all iterations and the final result is an average of normalized importance values.

3.5.1.2 Analytical approach: Walking levels and walkability indices

The second regression analysis began with a screening of all the walkability indices' correlation to walking levels in all six units of analysis. This was done, alike in the first regression analysis, through a simple Spearman's rank correlation analysis. In the same way various walkability indices showed significantly correlated to walking levels at the p-value $\leq$ 0.05 and a p-value $\leq$ 0.01 levels.

In sequence, six RF regression models, one for each unit of analysis, were created using the walkability indices presented in Table 9 as predictor variables and walking levels the predicted variable. The parameters used to run the models were the same as those presented in the last subchapter.

To compare the performance of all generated models the quality output measure of the *coefficient of determination (R^2)* was also cross-validated through the *Shuffle & Split method.* In the same manner, the number of iterations was set to 50 train/test dataset splits and the proportion of the split to 80% train / 20% test. After this process the output is and average of R^2 for all models. From this procedure the measure of the importance of the predictor variables was obtained. As 50 iterations were conducted for cross-validation, the importance value results are an average of all 50 models.

3.5.2 Analytical approach Perceptions of satisfaction of the built environment

The last analysis aims to analyze the relationship between BE factors and self-reported perceptions of satisfaction. The subjective data stems from a survey that obtained answers in a 5-point Likert scale. As this analysis concerns categorical variables, a classification task was performed (LIAW; WIENER, 2002).

Concerning this research, the most relevant output from RF Classification is a measure of the importance of the predictor variables. In this case BE measures and constructs are our predictor variables. Perceptions of satisfaction with the built environment are our predicted variables. The output ranks the variables in terms of the strength of their relationship to perceptions of satisfaction with the BE. Given in five possibilities of answers (5-point Likert scale) that were dichotomized in two classes, perceptions were analyzed in six different unit analysis levels (200m, 400m, 600, 800m, 1000m buffers or census tracts).

A first exploration of perception of satisfaction data was conducted through the execution of a Spearman's correlation test of perception data among itself. As all perception data lies within the same domains, some strong correlations were uncovered. Secondly, a screening of all walkability measures and constructs' correlation to perceptions of satisfaction with the environment was carried out. This was done, alike the previous analysis, through a simple Spearman's rank correlation test. However, this analysis yielded poor results, indicating the inexistence of correlations between the great majority of variables. This suggests that a more complex pattern of analysis can be underpinning the relationship between variables. As RF doesn't need feature selection or feature preprocessing to create satisfactory models, all variables were included in order to analyze more carefully their patterns that remained hidden in the exploratory correlation test.

The first step was to construct six RF classification models. For each of the questions considered six different models were constructed, one for each unit of analysis. To run the models, it was necessary to optimize two parameters: (1) "n_estimators" which is the number of trees in the forest, it was set to 500 to obtain stable results, the values were tested from 10 to 500 with 10-unit intervals, this many estimators ensures the asymptotic values convergence, that is less variance in the results; (2) "criterion" set to "gini" which is the measure of the quality of a split. All other parameters were set to their default tuning.

Several quality evaluation measures for the model can be drawn from the outputs of a random forest classification task. The first one is accuracy, a widely used performance metric, which represents the proportion of instances predicted correctly in relation to the total of predicted instances. The second are precision and recall. Precision shows how correct and relevant the results are while recall is the fraction of relevant documents that were retrieved. And lastly, the F1 score which is the weighted average of precision and recall, representing the final metric for model quality (TAVARES; MASTELINI; BARBON JR., 2017).

To compare the performance of all generated models the quality outputs measures of accuracy and F1 were cross-validated through the *Shuffle & Split method.* In the same manner as in the regression analysis, the number of iterations was set to 50 train/test dataset splits and the proportion of the split to 80% train / 20% test. After this process the output were averages of both accuracy and F1 value.

To illustrate de behavior of the classification performance a *Dummy Classifier* was used. This type of classifier makes a prediction using simple rules and gives a you a measure of "baseline" performance to compare with other (real) classifiers, i.e. the success rate one should expect to achieve even if simply guessing (PEDREGOSA et al., 2012). Because many machine learning tasks attempt to increase the success rate of (e.g.) classification tasks, evaluating the baseline success rate can afford a floor value for the minimal value one's classifier should out-perform. The strategy used to generate the *Dummy Classifier* predictions was the "stratified" one, that generates predictions by respecting the training set's class distribution (PEDREGOSA et al., 2012).

As RF Classification results were meager and the analysis was compromised due an overall lack of pattern between the predictor and predicted variables, a distribution analysis was conducted. The dataset under study has severe limitations when it comes to such individual data, therefore the distribution analysis was conducted with information on average time living in the neighborhood and walking levels. Further, the best performing variables from the regression analysis previously conducted were also analyzed regarding their relationship with perceptions. For such a comparison to be possible, variables were categorized into quartiles. For each quartile the percentage of positive and negative dichotomized perceptions were calculated. Perception were dichotomized where 1 indicates negative perceptions and 2 positive ones.

4 RESULTS AND ANALYSIS

4.1 Results: Walking levels and individual walkability variables

Six RF regression models were constructed, one for each unit of analysis. The dependent variable was walking levels (meters walked per unit area) and predictor variables were walkability variables present in Table 9. After cross-validation through the *Shuffle & Split method* final R^2 values were obtained. Model 5, correspondent to the 1000m network buffer scale, yielded the best results with an R^2 0.859 (Table 10). The standard deviation, which indicates the size of the measurement error (BLAND; ALTMAN, 1996), for this model seems to be minimal (SD = 0,086). Lower standard deviation values indicate that data points have a tendency to be closer to the mean (or the expected value) of the dataset.

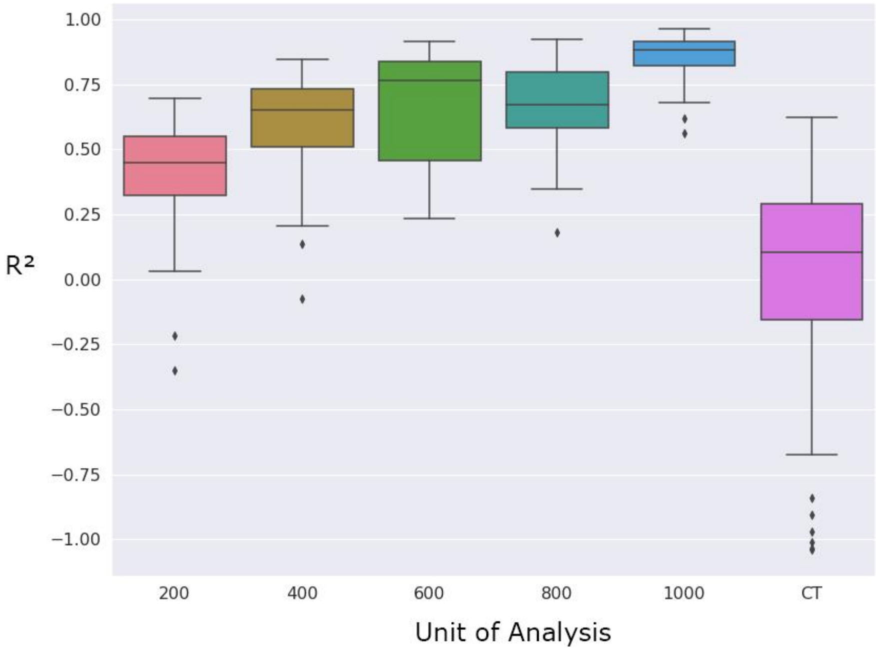
Table 10 – Mean R^2 and standard deviation of Random Forest regressions for individual walkability variables.

	Model 1 Buffer 200	*Model 2 Buffer 400*	*Model 3 Buffer 600*	*Model 4 Buffer 800*	*Model 5 Buffer 1000*	*Model 6 Census tract*
Mean R^2	0.398	0.583	0.691	0.677	0.859	-0.020
Standard Deviation	(0.222)	(0.203)	(0.193)	(0.164)	(0.086)	(0.436)

Source: Elaborated by the author, 2018.

The box-and-whiskers plot available on Figure 32 graphically depicts the variation of the coefficient of determination (R^2) of the predictions throughout the 50 iterations of the cross-validation process. As in Table 10 the inferior results the Census tracts scale yielded are distinct. The mean R^2 resulted in a negative value indicates that the census tract model is arbitrarily worse than randomness. When visually compared to other groups in the plot, the inefficacy of the results is emphasized by the larger number of outliers and greater data variation. The presence of R^2 outliers, data points that are far away from other values, is accentuated on all models except the 600m buffer model. It is clear that the 1000-meter network buffer excels in every aspect, the median is central, the thickness of the box is minimal, and the quartiles seem to be the most balanced. This result suggests, that the 1000m network buffer scale was the most adequate for modeling the relationship between individual walkability variables and walking in the case study. Therefore, further analysis was conducted considering this scale. This also indicates that larger radii might be even more suited for modeling such relationship. The possibility of increasing radius sizes until the optimal scale of buffer is found is a research possibility for future work.

Figure 32 – Boxplot of the mean R^2 values of Random Forest regressions for individual walkability variables.



Source: Elaborated by the author, 2018. Organized by Hugo Abonizio, 2018.

The measure of the importance of predictor variables indicates the features that are more closely related with the dependent variable and contribute more for its variation. The 10 most relevant variables for each of the models constructed can be observed in Table 11. The most relevant individual variables in the highest quality model, the 1000m buffer model, were *Entropy Z-Score, (0.609), Integration Z-score r2000 (0.136) and Residential density Z-score (0.060)*, however the land use mix variable presented itself as substantially better than the others, with an importance value over 4 times larger than the second most important feature. The second position on the importance ranking is always occupied by Integration measures, either in a global radius or the largest radius considered (2000m). In the same way, as the radii increases Residential density Z-score becomes more important, and in the 1000m network buffer model, it is the third most important variable.

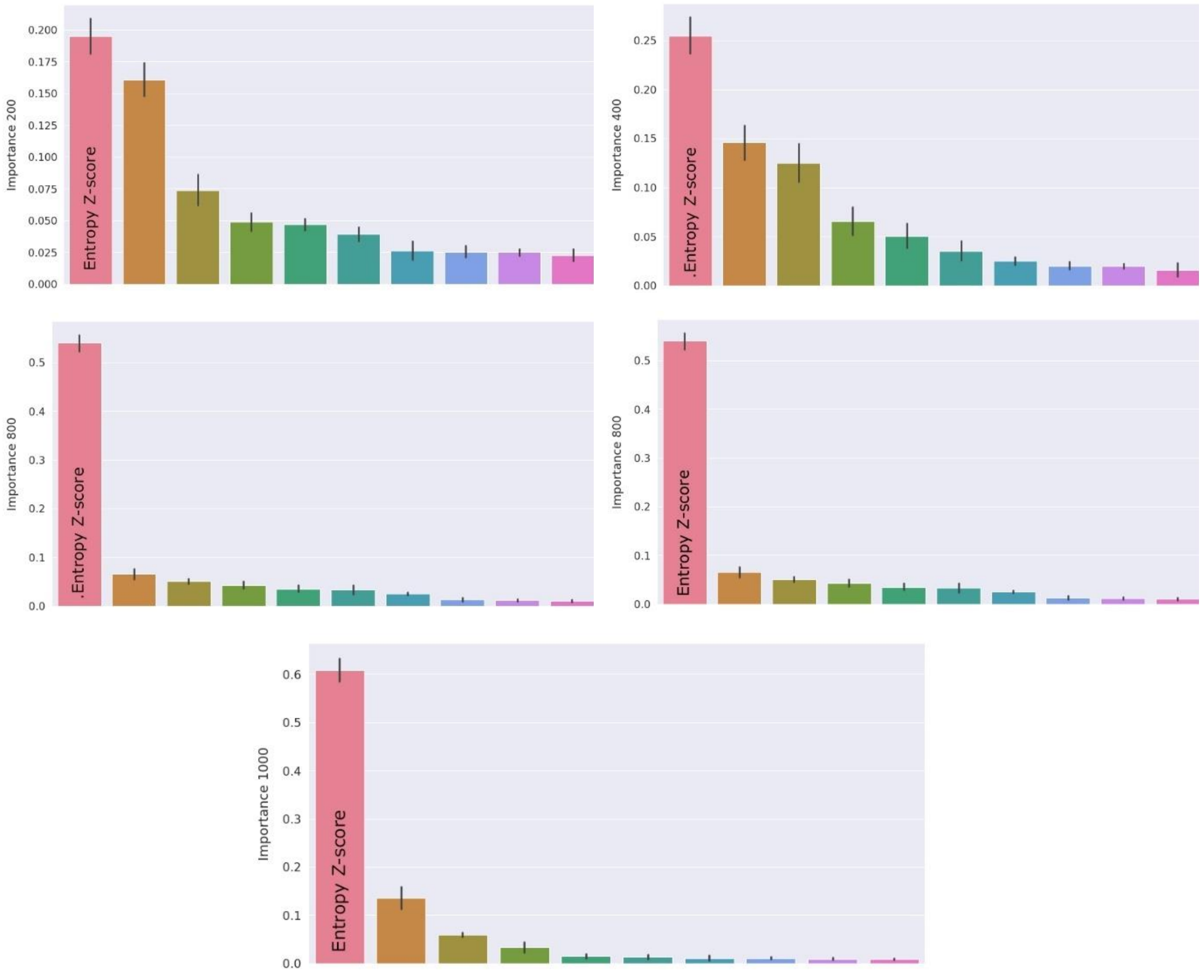
Table 11 – Feature importance for Rf urban form variables regression models.

	Model 1 ***Buffer 200***	***Model 2*** ***Buffer 400***	***Model 3*** ***Buffer 600***	***Model 4*** ***Buffer 800***	***Model 5*** ***Buffer1000***	***Model 6*** ***Census tract***
Feature Importance	*Entropy Z-Score (0.195)*	*Entropy Z-Score (0.254)*	*Entropy Z-Score (0.389)*	*Entropy Z-Score (0.540)*	*Entropy Z-Score (0.609)*	*Integ. rn Z-score (0.306)*
	Integ.rn Z-score (0.160)	*Integ.rn Z-score (0.146)*	*Integ.Z-score r2000 (0.124)*	*Integ.rn Z-score (0.065)*	*Integ.Z-score r2000 (0.136)*	*Mean Parcel Price (0.151)*
	Integ. Z-score r2000 (0.074)	*Integ. Z-score r2000 (0.125)*	*Choice Z-score r2000 (0.116)*	*Resid. density Z-score (0.051)*	*Resid. density Z-score (0.060)*	*Retail FAR Z-score (0.087)*
	Integ. Z-score r200 (0.049)	*Integ. Z-score r1800 (0.065)*	*Integ. Z-score r1900 (0.068)*	*Mean Estate Price (0.043)*	*Integ. rn Z-score (0.033)*	*Choice Z-score r1100 (0.062)*
	Retail FAR Z-score (0.047)	*Integ. Z-score r1600 (0.050)*	*Resid. density Z-score (0.037)*	*Inter. density Z-score (0.035)*	*Integ. Z-score r1900 (0.014)*	*Integ. Z-score r2000 (0.043)*
	Integ. Z-score r100 (0.039)	*Integ. Z-score r1900 (0.035)*	*Integ. rn Z-score (0.026)*	*Integ. Z-score r2000 (0.033)*	*Mean Parcel Price (0.013)*	*Mean Estate Price (0.024)*
	Integ. Z-score r1900 (0.026)	*Choice Z-score r700 (0.025)*	*Choice Z-score r900 (0.025)*	*Retail FAR Z-score (0.025)*	*Mean Estate Price (0.010)*	*Resid. density Z-score (0.021)*
	Mean Parcel Price (0.025)	*Choice Z-score r800 (0.020)*	*Integ. Z-score r1000 (0.021)*	*Mean Parcel Price (0.013)*	*Inter. density Z-score (0.010)*	*Entropy Z-Score (0.020)*
	Inter. density Z-score (0.025)	*Inter. density Z-score (0.020)*	*Choice Z-score r700 (0.019)*	*Choice Z-score r800 (0.011)*	*Choice Z-score r1500 (0.009)*	*Integ. Z-score r1900 (0.018)*
	Integ. Z-score r1300 (0.023)	*Integ. Z-score r1700 (0.016)*	*Choice Z-score r800 (0.016)*	*Choice Z-score r900 (0.010)*	*Integ. Z-score r100 (0.009)*	*Integ. Z-score r1800 (0.016)*

Source: Elaborated by the author, 2018. Organized by Hugo Abonizio, 2018.

Graphs were generated to visually verify the distribution of feature importance values. The census tract model had a minor performance when compared to other models, therefore a graph referring to its variable importance values was not presented. It can be observed on Figure 33 that there is a crescent disproportion: the larger the buffer radius, the more the Entropy Z-Score variable is found in a position of advantage over other variables.

Figure 33 – Feature importance histogram of Random Forest regressions for individual walkability variables.

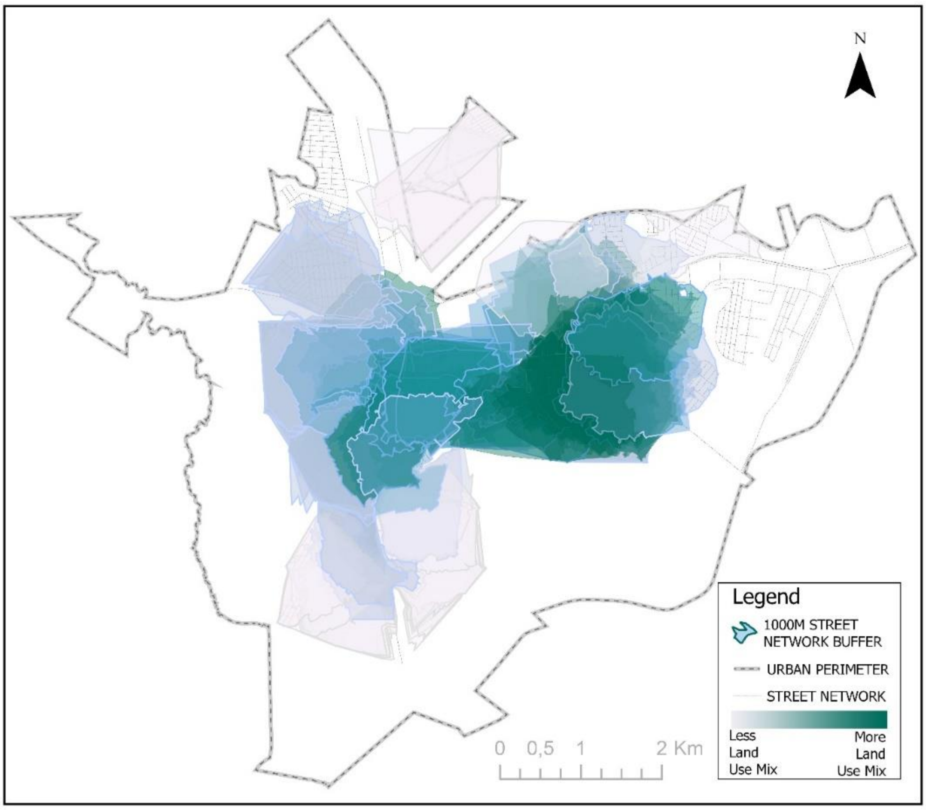


Source: Elaborated by the author, 2018. Organized by Hugo Abonizio, 2018.

Results of the Entropy Z-Score (Figure 34) seem to be strongly associated with walking, consistent with previous studies on land use patterns. Land use mix is at the base of many urban planning and transport studies, in that people move between activities located in different places. If activities are close enough to make walking easier, in areas of mixed land uses, then more people will probably walk (FORSYTH et al., 2008). Mixed use is also thought to provide more visual variety and the generated pedestrian traffic to promote informal policing.

To date, many studies have found a number of destinations to be associated with active travel, specially walking (GILES-CORTI et al., 2005; LEE; MOUDON, 2006a). Considering such outcome, the systematic approach to specific land uses and building typologies in the application of the entropy formula demonstrated a close relationship with walking levels. We are led to believe that measuring entropy using the Shannon index equation can minimize possible bias. One aspect to highlight is that even though the literature indicates that degree to which property values are driven by land values support the influence of walkability (MATTHEWS; TURNBULL, 2007; RAUTERKUS; MILLER, 2011; GUO; PEETA; SOMENAHALLI, 2017) no relationship was found in this study.

Figure 34 – Entropy Z-score map at the 1000m street network scale.

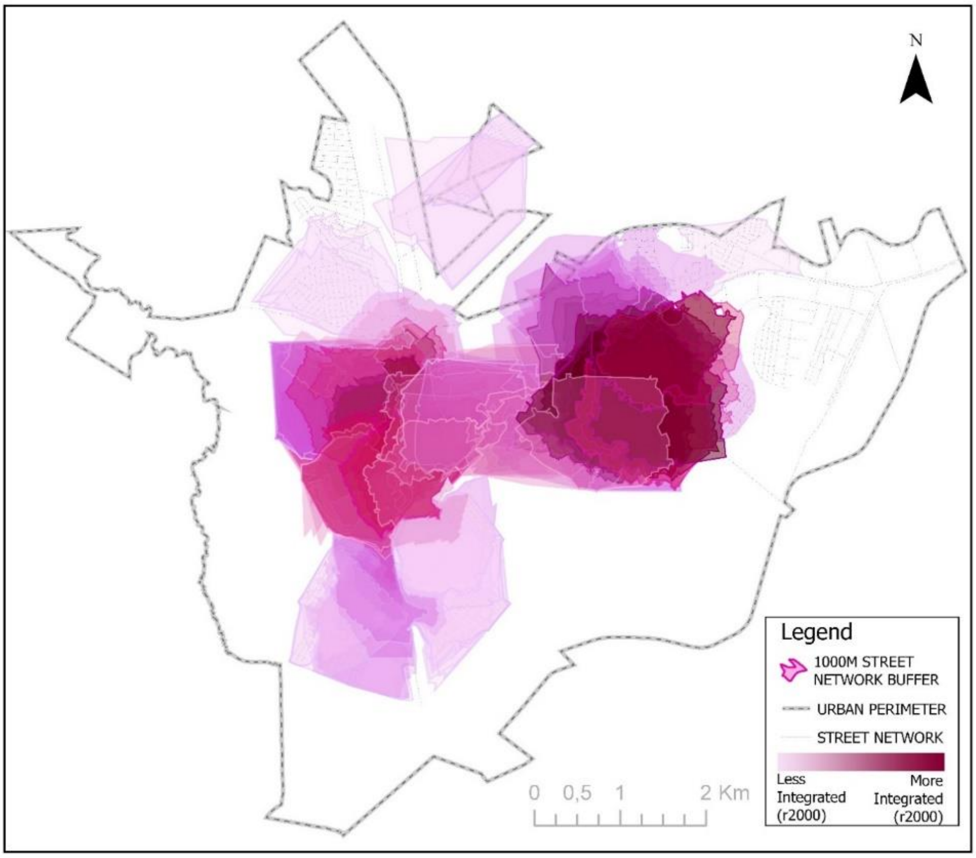


Source: Environmental design research group, 2018. Organized by the author, 2018.

The second RF finding indicated the relevance of the *Integration Z-score r2000 variable (*Figure 35*)*, supporting Hillier's theory and indicating that syntactic measures produce better outcomes when analyzing pedestrian movement than more traditional walkability measures (KOOHSARI et al., 2016a). Hillier and colleagues have argued that street network, which is essentially a formal aspect of urban form, could influence pedestrian movement through different distribution of commercial land uses according to the level of integration (HILLIER; HANSON, 1984). Considering the scale of the study case under investigation, the broader ranges of integration, that reach as much of the system as possible, were better related to walking. Therefore, the calculations that included the global Integration measure and the larger 2000 m local radius, which reaches whole sections of the system, had more relevant results.

According to Jiang; Claramunt and Klarqvist (2000), many studies have been carried out over the past two decades on the correlations that can be found between pedestrian flow and syntactic measures of local integration. The basic conclusion is that local integration can be used to study people's movements within urban systems. Such conclusions are of great impact as a tool for urban planners and designers can foresee pedestrian movement by analyzing the morphological structure of the design plan using space syntax techniques (JIANG; CLARAMUNT; KLARQVIST, 2000).

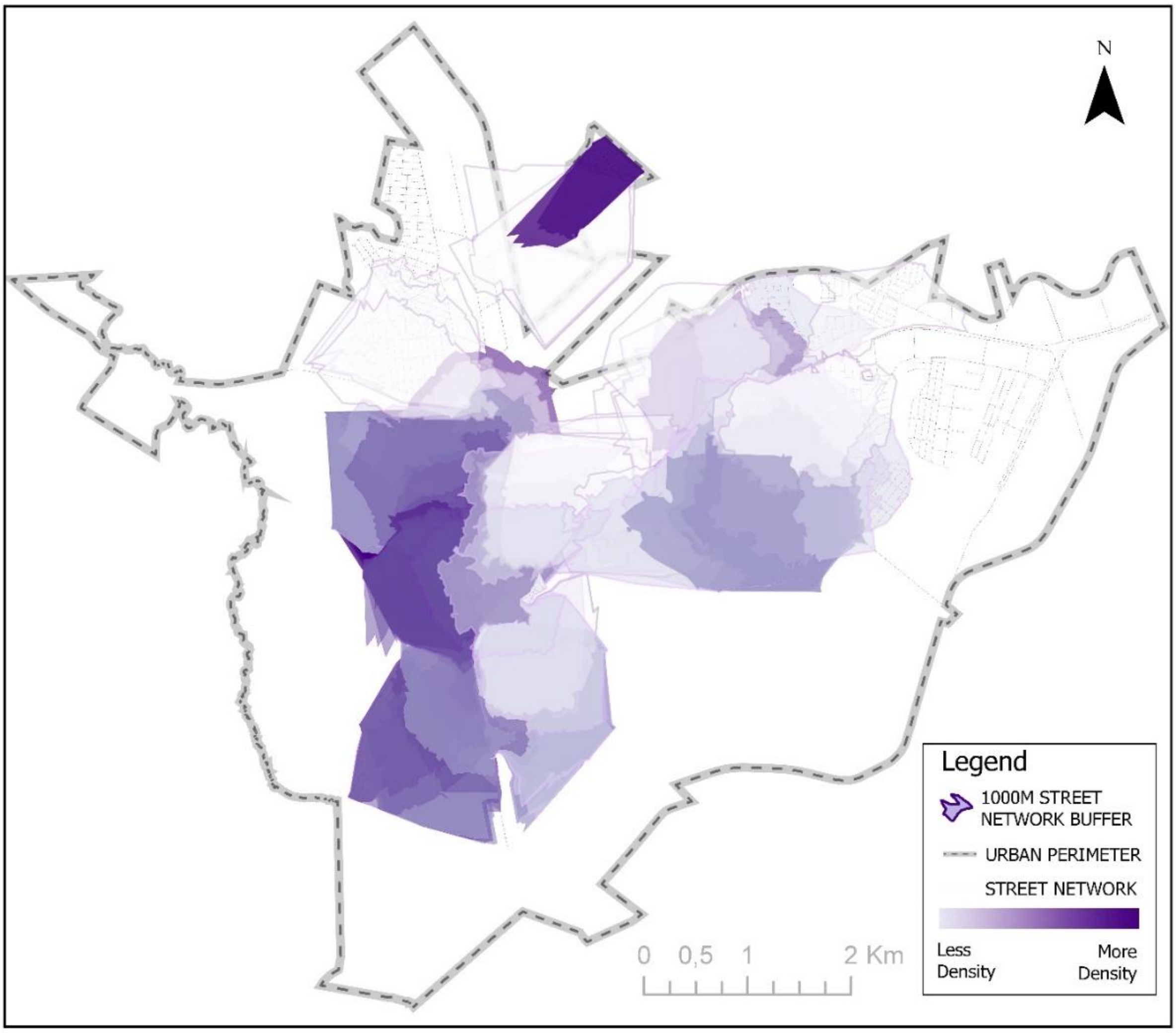
Figure 35 – Integration r2000m Z-score map at the 1000m street network scale.



Source: Environmental design research group, 2018. Organized by the author, 2018.

Residential density Z-score (Figure 36) also showed significant and consistent importance throughout unit analysis scales. This result is supported by the literature, such as in the study conducted by Frank and Colleagues (FRANK et al., 2008) where individuals were more likely to walk if they lived in neighborhoods with greater residential density. Alike in the study conducted by Lee and Moudon (2006b), residential density measures were found to be significantly associated with walking both at the parcel level and at the 1 km buffer area level. Overall, higher densities have many benefits in terms of efficient use of infrastructure, housing affordability and street life (FORSYTH et al., 2007).

Figure 36 – Residential density Z-score map at the 1000m street network scale.



Source: Environmental design research group, 2018. Organized by the author, 2018.

4.2 Results: Walking levels and walkability indices

In the second regression analysis Six RF regression models were constructed, one for each unit of analysis. The dependent variable was walking levels (meters walked per unit area) and predictor variables were the walkability indices present in Table 9. After cross-validation through the Shuffle & Split method, final R^2 values as a model quality metric were obtained. Model 5, correspondent to the 1000m network buffer scale, yielded the best results with an R^2 0.832 (Table 12 – Mean R^2 and standard deviation of Random Forest regressions of Walkability indices.). The standard deviation, which indicates the size of the measurement error (BLAND; ALTMAN, 1996), for this model seems to be minimal (SD = 0.094). Lower standard deviation values indicate that data points have a tendency to be closer to the mean (or the expected value) of the dataset.

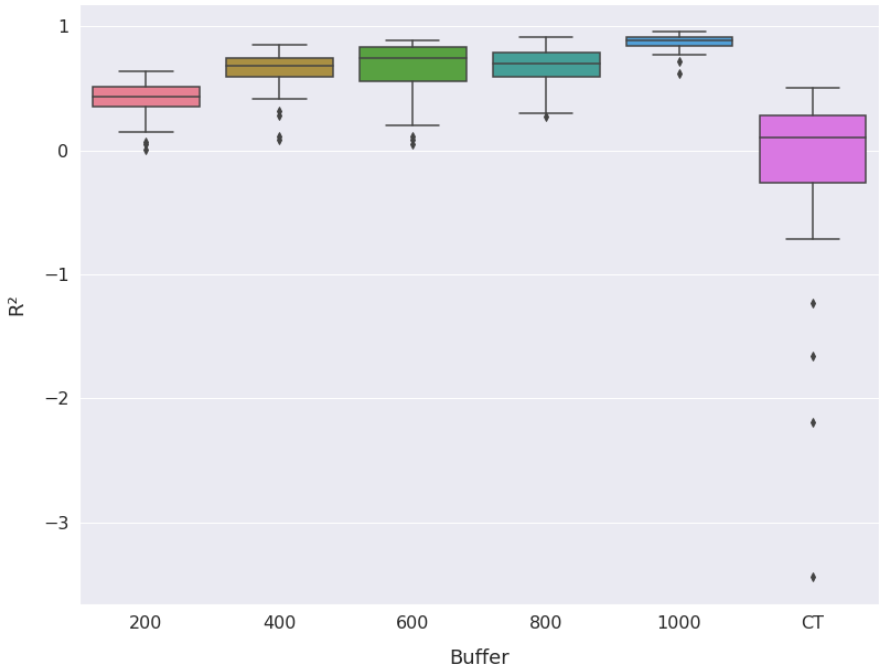
Table 12 – Mean R^2 and standard deviation of Random Forest regressions of Walkability indices.

	Model 1 Buffer 200	*Model 2 Buffer 400*	*Model 3 Buffer 600*	*Model 4 Buffer 800*	*Model 5 Buffer 1000*	*Model 6 Census tract*
Mean R^2	0.288	0.467	0.626	0.542	0.832	-0.226
Standard Deviation	(0.237)	(0.204)	(0.131)	(0.185)	(0.094)	(0.767)

Source: Environmental design research group, 2018. Organized by the author, 2018.

The box-and-whiskers plot available on Figure 37 graphically depicts the variation of the coefficient of determination (R^2) of the predictions throughout the 50 iterations of the cross-validation process for this regression. Much like the previous analysis the inferior results the Census tracts unit of analysis scale yielded are distinct. The mean R^2 resulted in an even lower negative value, indicating that the model is arbitrarily much worse than randomness. When visually compared to other groups in the plot, the inefficacy of the results is mostly emphasized by the large number of outliers that deformed the other group boxed and greater data variation. It is clear that in the walkability indices verification the 1000-meter network buffer excels in every aspect, the median is central, the thickness of the box is minimal, and the quartiles seem to be the most balanced. This result suggests, firstly, that the 1000m network buffer scale was the most adequate for modeling the relationship between walkability indices and walking. Therefore, further analysis was conducted considering this scale.

Figure 37 – Boxplot of the mean R^2 values of Random Forest regressions for walkability indices.



Source: Environmental design research group, 2018. Organized by the author, 2018.

The measure of the importance of predictor variables, in this case walkability indices, is indicated in Table 13, that contains the 10 most relevant variables for each of the models constructed. The most relevant walkability indices in the highest quality model, the 1000m buffer model, were *Walkability Index #5 Integration rn (0.408); Walkability Index #4 (0.246) and Walkability Index #6 Integration rn (0.162)*. In this case, the *Walkability Index #5 Integration rn* presented an importance twice as relevant as the second runner up index.

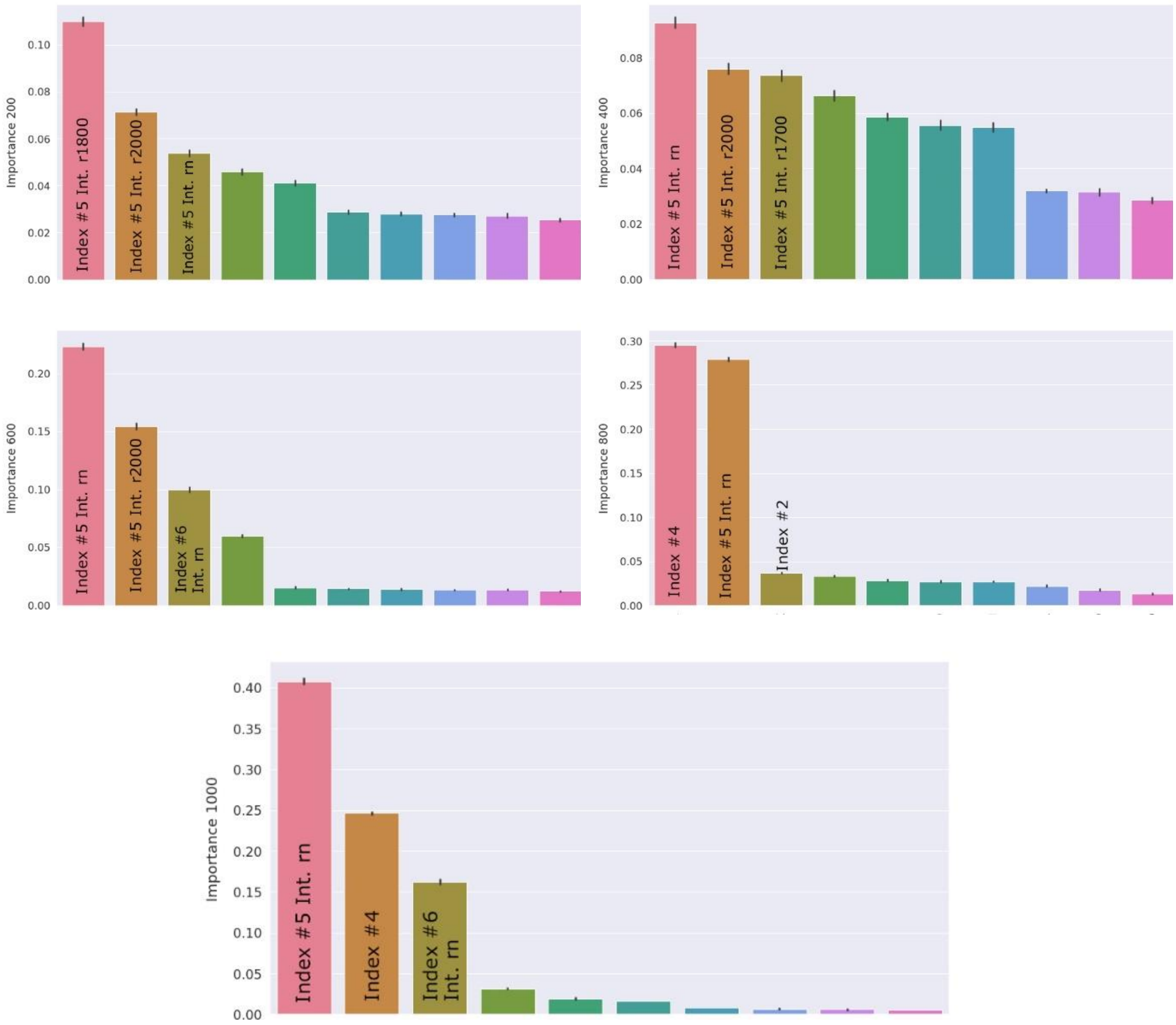
Table 13 – Feature importance for RF urban form walkability indices regression models.

	Model 1 Buffer 200	Model 2 Buffer 400	Model 3 Buffer 600	Model 4 Buffer 800	Model 5 Buffer1000	Model 6 Census tract
Feature Importance	*Walkability Index #5 Integration r1800 0.110*	*Walkability Index #5 Integration rn 0.093*	*Walkability Index #5 Integration rn 0.223*	*Walkability Index #4 0.295*	*Walkability Index #5 Integration rn 0.408*	*Walkability Index #5 Integration rn 0.222*
	Walkability Index #5 Integration r2000 0.071	*Walkability Index #5 Integration r2000 0.076*	*Walkability Index #5 Integration r2000 0.155*	*Walkability Index #5 Integration rn 0.279*	*Walkability Index #4 0.246*	*Walkability Index #5 Choice rn 0.095*
	Walkability Index #5 Integration rn 0.054	*Walkability Index #5 Integration r1700 0.074*	*Walkability Index #6 Integration rn 0.100*	*Walkability Index #2 0.037*	*Walkability Index #6 Integration rn 0.162*	*Walkability Index #2 0.043*
	Walkability Index #5 Integration r1700 0.046	*Walkability Index #5 Integration r1600 0.066*	*Walkability Index #4 0.060*	*Walkability Index #5 Choice rn 0.033*	*Walkability Index #5 Choice rn 0.032*	*Walkability Index #6 Choice 1100 0.035*
	Walkability Index #5 Integration r1900 0.041	*Walkability Index #4 0.059*	*Walkability Index #5 Integration r1500 0.015*	*Walkability Index #6Integration rn 0.029*	*Walkability Index #5 Integration r2000 0.019*	*Walkability Index #5 Choice 1100 0.029*
	Walkability Index #6 Integration rn 0.029	*Walkability Index #5 Integration r1500 0.056*	*Walkability Index #6 Choice 100 0.015*	*Walkability Index #5 Integration r2000 0.027*	*Walkability Index #6 Choice rn 0.016*	*Walkability Index #6 Choice 500 0.028*
	Walkability Index #5 Choice rn 0.028	*Walkability Index #5 Integration r1900 0.055*	*Walkability Index #5 Integration r1700 0.014*	*Walkability Index #6Choice rn 0.027*	*Walkability Index #5 Integration r100 0.008*	*Walkability Index #5 Choice 100 0.026*
	Walkability Index #4 0.028	*Walkability Index #6Choice rn 0.032*	*Walkability Index #5 Integration 100 0.014*	*Walkability Index #3 0.022*	*Walkability Index #6 Integration r100 0.007*	*Walkability Index #5 Choice 400 0.023*
	Walkability Index #6 Integration r2000 0.027	*Walkability Index #5 Integration r1800 0.031*	*Walkability Index #3 0.013*	*Walkability Index #5 Integration 1900 0.018*	*Walkability Index #2 0.006*	*Walkability Index #6 Choice rn 0.022*
	Walkability Index #5 Integration r100 0.025	*Walkability Index #6 Integration rn 0.029*	*Walkability Index #5 Choice rn 0.012*	*Walkability Index #5 Integration 1800 0.013*	*Walkability Index #5 Choice 2000 0.006*	*Walkability Index #6 Choice 200 0.021*

Source: Environmental design research group, 2018. Organized by the author, 2018.

Walkability index #5 had the best performance overall, except on the 800m buffer model where it was secondary with a very close importance value to the most important feature. It can also be observed, on Figure 38, that as the units of analysis grew in size the *Walkability index #4,* proposed by Frank (2010) in its variation that excluded from the equation the Retail FAR measure and the double weight attributed to the intersection density variable, gained importance over other variables. The second position on the importance ranking of the best model, the 1000m buffer, was mostly occupied by Space Syntax Walkability indices in a local 2000m Integration measure or global radii. In the same way, the third importance position was mostly occupied by space syntax composed measures.

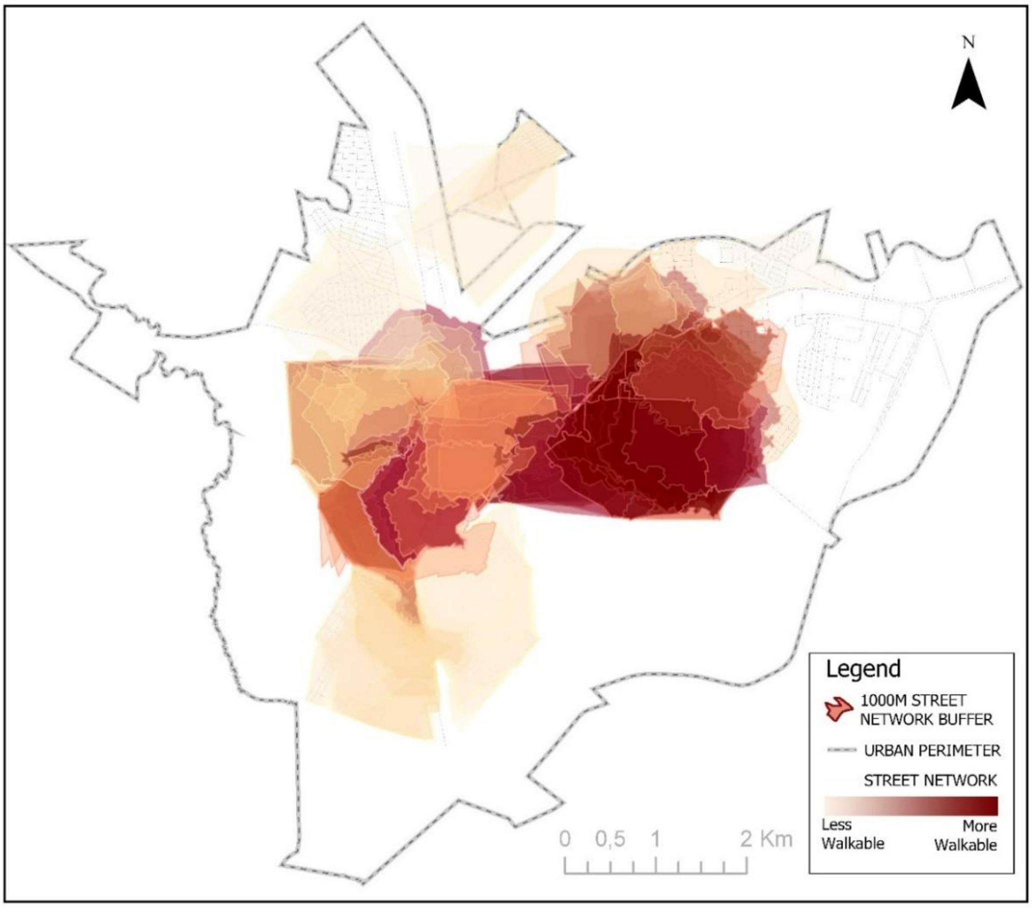
Figure 38 – Feature importance histogram of Random Forest regressions for walkability indices.



Source: Environmental design research group, 2018. Elaborated by Hugo Abonizio, 2018.

Walkability indices using global Integration radius weighted by two (index #5), as applied by Koohsari et al. (2016), was more closely related to walking (Figure 39). Whereas the same index with both variables weighted the same (index #6) didn't achieve the same performance. Although both indices show collinearity, the best results of the weighted version highlight the importance of the Integration measure, that by nature aggregates variables such as land use mix and intersection density. It is noteworthy that the most relevant space syntax measures were those where larger or global radii were considered (2000m, 1800m and 1700m Integration radii). This implies that even larger radii might compose better objective walkability measures, it would be ideal to test models until the optimal space syntax radius if found. Such an assumption is a possibility for future work.

Figure 39 – Walkability index #5 - 2 Space Syntax Walkability Global Integration radius map at the 1000m street network scale.



Source: Environmental design research group, 2018. Organized by the author, 2018.

On the other hand, more traditional versions of the walkability indices (indices #1, #2, #3) showed minimal contribution. For the case study, only the *Walkability index #4 (*Figure 40*),* that disregards retail FAR and weights intersection density only once, showed relevant importance scores. This finding represents an indication that among the measures considered on traditional indices, retail FAR relates weakly to pedestrian movement and double weighted intersection density may not be necessary for average sized Brazilian towns.

The implications of these results are considerable. Calculating space syntax measures requires only street centerline data which is easily obtained. Developing a walkability index that is less data-intensive and easier to produce is of great interest in Brazilian towns, where there are very few resources and information on parcel-level data is scarce.

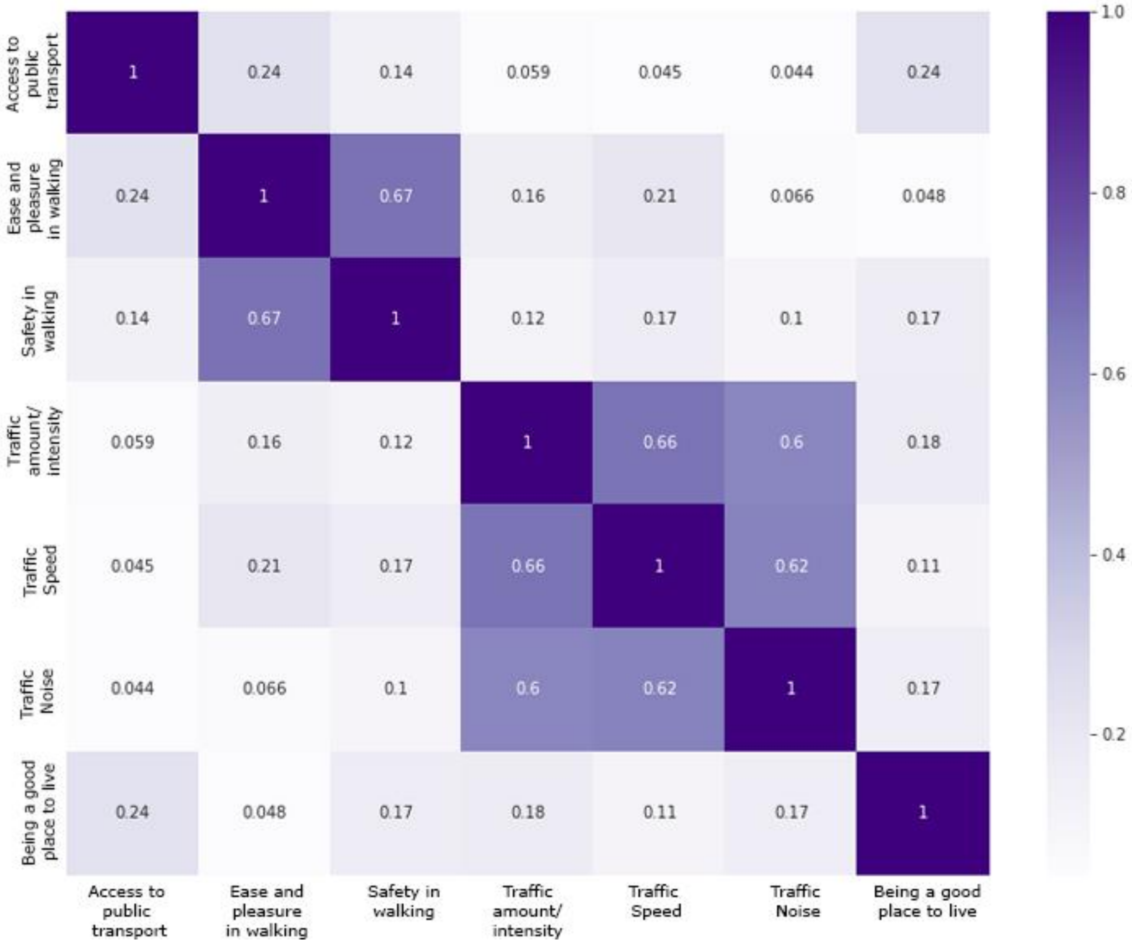
Figure 40 – Walkability index #4 at the 1000m street network scale.

Source: Environmental design research group, 2018. Organized by the author, 2018.

4.3 Results: Perceptions of satisfaction of the built environment

For the third and last analysis conducted, a Spearman's correlation test of perception data among itself was initially conducted. It can be observed in Figure 41, which represents a heat map of correlation results, that not all perceptions correlate with each other, even though they belong to the same domain - *Travel Network*, *Safety and Walkability* and *Traffic and Noise*. The *Travel Network* perceptions correlate little with other ones and the *Traffic and Noise* correlate highly within its own domain. The Safety and Walkability perceptions have a strong correlation within themselves, with an exception of the "being a good place to live". This question, alike the *Travel Network* question of "access to public transportation, relates poorly to all other perceptions. This result is an indication of possible side effects of the previously mentioned unbalanced responses.

Figure 41 – Correlation matrix heat map beteween perception of satisfacion answers.



Source: Environmental design research group, 2018. Organized by the author, 2018.

In sequence, fourty-two (42) RF classification models were constructed, six spatial unit representations for each of the seven-survey perception questions. The dependent variable for each of the models where the dichotomized answers for each question. Predictor variables were all items present in Table 9. Meters walked per unit area were also included as a predictor. The Dummy Classifier was also considered to provide a benchmark for results (Table 14). In order to compare the performance of all generated models the quality outputs of *accuracy* and *F1* were cross-validated through the *Shuffle & Split method.*

Table 14 – Quality metrics for Random Forest classification models.

		Access to public transport	*Ease and pleasure in walking*	*Safety in walking*	*Traffic amount/ intensity*	*Traffic Speed*	*Traffic Noise*	*Being a good place to live*
200m Buffer	*Accuracy*	*0.857*	*0.599*	*0.564*	*0.602*	*0.572*	*0.599*	*0.915*
	F1	*0.923*	*0.424*	*0.455*	*0.700*	*0.675*	*0.584*	*0.413*
400m Buffer	*Accuracy*	*0.852*	*0.646*	*0.522*	*0.590*	*0.599*	*0.633*	*0.887*
	F1	*0.920*	*0.505*	*0.398*	*0.692*	*0.694*	*0.645*	*0.213*
600 m Buffer	*Accuracy*	*0.830*	*0.611*	*0.519*	*0.591*	*0.648*	*0.564*	*0.923*
	F1	*0.906*	*0.436*	*0.382*	*0.694*	*0.729*	*0.570*	*0.480*
800m Buffer	*Accuracy*	*0.845*	*0.591*	*0.457*	*0.640*	*0.619*	*0.556*	*0.915*
	F1	*0.916*	*0.392*	*0.334*	*0.719*	*0.698*	*0.545*	*0.493*
1000m Buffer	*Accuracy*	*0.823*	*0.632*	*0.463*	*0.620*	*0.640*	*0.647*	*0.908*
	F1	*0.903*	*0.429*	*0.345*	*0.701*	*0.720*	*0.632*	*0.497*
Census Tract	*Accuracy*	*0.851*	*0.584*	*0.513*	*0.613*	*0.627*	*0.549*	*0.894*
	F1	*0.917*	*0.363*	*0.395*	*0.692*	*0.710*	*0.570*	*0.294*
Dummy	*Accuracy*	*0.740*	*0.540*	*0.465*	*0.617*	*0.521*	*0.557*	*0.838*
	F1	*0.840*	*0.320*	*0.420*	*0.620*	*0.553*	*0.566*	*0.066*

Source: Environmental design research group, 2018. Organized by the author, 2018.

When comparing the model results for the quality measures Accuracy and F1 a clear pattern of high values is presented. This data behavior when compared to the Dummy Classifier indicated an inferior success rate, most values were proximal to the dummy results which are the minimal benchmark the classifiers should out-perform. Therefore, it is assumed that such results are spurious. It must be noted that a model that just repeats the labels of the samples that it has just seen would have a perfect score, but would fail to predict anything useful on yet-unseen data. This situation is called overfitting. The data used in this study is prone to overfitting as the classes are heavily unbalanced, as pointed out earlier in this work. Even with RF being an algorithm that is robust against overfitting (Breiman, 2001) and with the conduction of cross validation, it wasn't possible to extract distinguishable patterns from this data set.

A distribution analysis was conducted in an attempt to further understand the relationship between perceptions and walkability (Figure 42). The first descriptive distribution analysis considered information on average time living in the neighborhood, a measure often understood to influence travel behavior (BOHTE; MAAT; VAN WEE, 2009; CAO; MOKHTARIAN; HANDY, 2009; JACK; MCCORMACK, 2014). Further based on these researches, three of the perceptions of satisfaction answers were selected from the *Safety and Walkability* Satisfaction Factor: "Ease and pleasure in walking", "Safety in walking" and "Being a good place to live". These are the only questions specifically related to walkability and would, in theory, have stronger relationships with the walkability urban form variables under analysis.

The first distribution analysis regarded perceptions according to time living in the neighborhood, quantified in years. Quartiles were divided as follows: first quartile from 0 to 2 years; second quartile from 2 to 7 years; third quartile from 7 to 20 years and fourth quartile more than 20 years (of from 20 to 53 years).

The second distribution analysis regarded perceptions according to the amount of walking from the individual that reported the perception. The selected data for this was the aggregation of 1000m network buffers, the best unit found in the regression models. Quartiles were divided as follows: first quartile from 0 to 0,36 kilometers; second quartile from 0,36 to 0,73 kilometers of walking reported; third quartile from 0,73 to 1,24 years; fourth quartile from 1,24 to 5,84 kilometers.

The third distribution analysis regarded perceptions distributions according walkability, specifically measured objectively trough the best performing index pointed out by the previous regression analysis, the Walkability Index #5 - Space Syntax Walkability Index at the Global Integration scale aggregated in 1000m street network buffer. Quartiles were divided as follows: a first quartile from -5.674 to -1.559 representing low walkability; a second quartile from -1.559 to 0.567 representing medium-low walkability; third quartile from 0.567 to 1.217 representing medium-high walkability; and the fourth quartile from 1.217 to 4.307 representing high walkability.

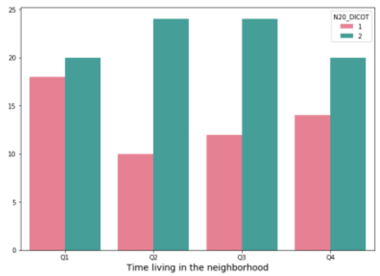
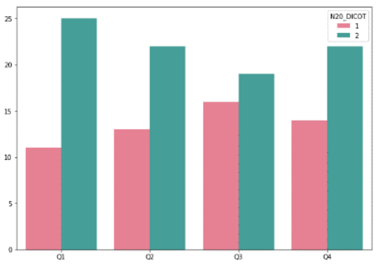
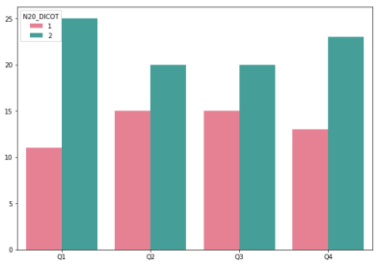
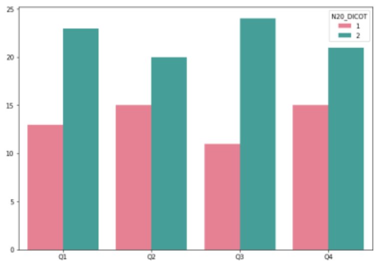
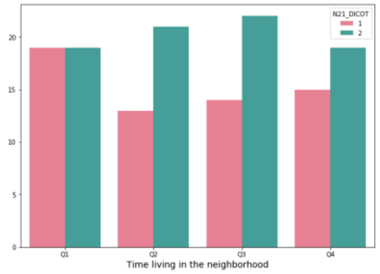
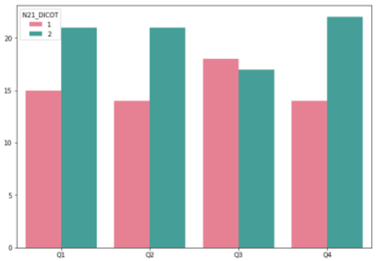
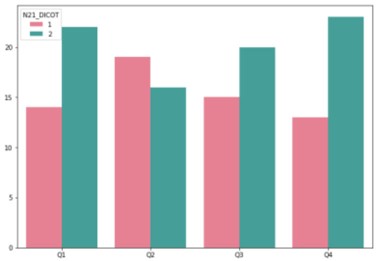
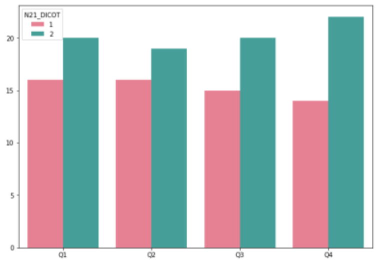
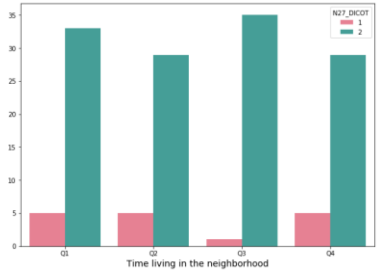
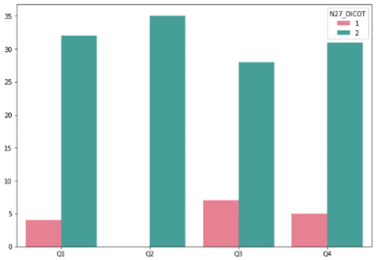
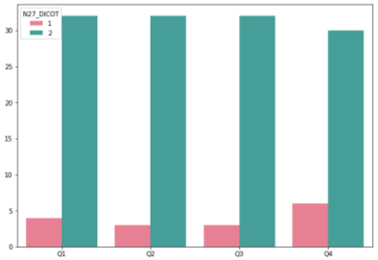
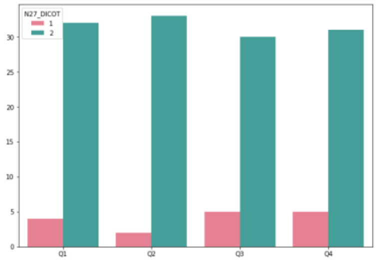
The fourth and final distribution analysis regarded perceptions distributions according the Entropy Z-score aggregated in1000m street network buffer scale. Quartiles were divided as follows: a first quartile from -2,26 to -0,87 representing low entropy scores; a second quartile from -0,87 to -0,02 representing medium-low entropy scores; third quartile from -0,02 to 0,67 representing medium-high entropy scores; and the fourth quartile from 0,67 to 2,40 representing high entropy scores.

It can be observed on Figure 42 that the distribution of perceptions of "Ease and pleasure in walking" was constant throughout the variables under analysis, it doesn't matter if the individual has been living in that neighborhood for longer or not, walks more or not, lives is a more walkable environment or in a neighborhood with more mix of uses. In this case, the difference between positive and negative perceptions were relatively balanced.

When it comes to "Safety in walking" there were slight variations between graphs. The *Entropy z-score* distributions of such perceptions seemed to be balanced and constantly positive regardless of the entropy z-score quartile, less or more land use mix. However, regarding perceptions of satisfactions with "*Being a good place to live"* the distributions was constant throughout variables but the classes, positive and negative, are heavily unbalanced. The majority of people have positive perceptions regardless of the variable under analysis.

Overall it can be assumed that the RF classification results mirrored, in a way, this distribution analysis: there doesn't seem to be a perception pattern in this dataset that can be recognized with the variables considered in this study. There is a possibility that the walkability urban form variables used here are not sufficient to understand perceptions of satisfaction, or further, that individual variables need to be controlled. These results refuted the proposition initially established by this research that there is a correlation between perceptions of satisfaction with the BE, walking levels and walkability.

Figure 42 – Distribution graphs of perception of satisfaction answers according to individual and urban form variables.

	Time living in the neighbourhood vs Perceptions.	Walking vs Perceptions.	Walkability Index #5 vs Perceptions.	Entropy Z-score vs Perceptions.
Ease and pleasure in walking				
Safety in walking				
Being a good place to live				

Source: Environmental design research group, 2018. Organized by the author, 2018.

5 DISCUSSIONS

This research's aim was to evaluate the efficacy of objective walkability measures of an average sized Brazilian. To that end, walkability indices proposed by the literature and some variations hypothesized to be relevant were tested through a comparison with self-reported walking. The urban form variables that compose such indices were, in the same way, tested for a deeper understanding of the phenomenon. The process of analysis and the results of this study indicated that the BE as a support for walking on average-sized Brazilian Towns is a particularly contextual phenomenon. The relationship between perceptions of satisfaction with the built environment was also analyzed as to investigate perception's contribution and relationship to walkability analysis. Through this investigation the hypothesis that there is a coherence between perceptions of satisfaction and walkability was tested.

When comparing objective walkability variables to self-reported walking on the averaged-sized Brazilian town of Rolândia-PR/BR, it was possible to uncover the specific spatial elements that influence walking. The urban form measures *of Entropy, Space Syntax integration at the 2000 m radius, and Residential Density* were identified as being more strongly related to walking. Entropy specifically was found to be the main correlate of walking. These findings are consistent with the literature as they represent, in a context specific way, the traditional 3D's concept of land-use **D**iversity, pedestrian-oriented **D**esign and **D**ensity (CERVERO; KOCKELMAN, 1997).

Land-use diversity (land-use mix) is represented here by the Entropy measure, which has consistently been found associated with walking (SAELENS; HANDY, 2008). Density is represented by the Residential density variable, regarded as important as it directly affects the compactness of an area, influencing walking (MOUDON et al., 2006). Design usually encompasses street connectivity—describing the degree to which destinations are connected by streets (LU; XIAO; YE, 2017). The most common method for assessing connectivity in walkability studies is intersection density (FRANK et al., 2005; OWEN et al., 2007) . However, this work's results indicate that the space syntax measure of local integration greatly surpassed the traditional metric for street connectivity in its importance to predict walking levels. When compared with intersection density, the space syntax measure of integration is less intuitive and thus may be more difficult to grasp for practitioners and decision makers. However, the necessary data for space syntax analysis is more easily obtained, it captures aspects of the street network that are relevant to pedestrians and identifies connectivity not only for an area but also for a single street segment (KOOHSARI et al., 2016a). It must be emphasized that land use mix, residential density and integration have a threshold of positive influence on walking. Here, we do not indicate such quantity baseline. We can only infer that such variables influence walking behaviors.

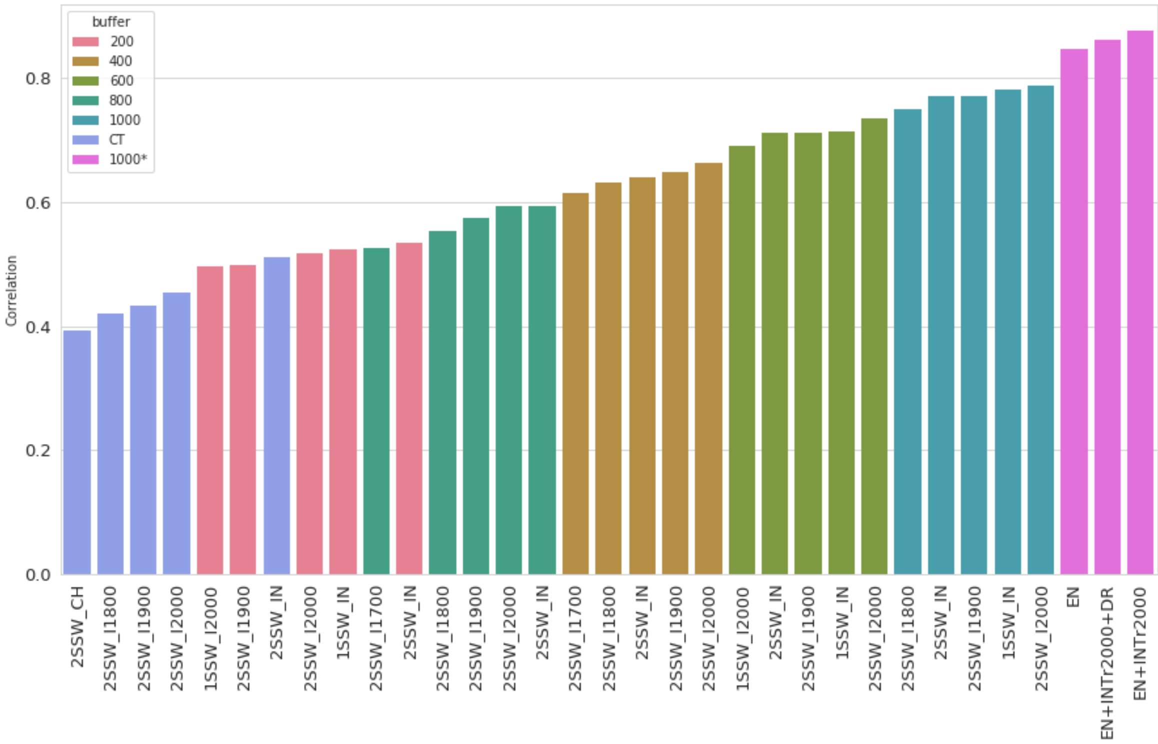
After such considerations, one important aspect of the performance of individual walkable urban form variables is the excelling influence of Entropy over other variables tested. This means that land use mix exerts a main role in impacting walking levels in the context of a medium sized Brazilian town. Measuring entropy using the Shannon index equation with a detailed-systematic approach to specific land uses and building typologies has effectively contributed to such outcome. Therefore, as hypothesized the environmental variables related to walking behavior are not necessarily the same in averaged-sized towns as the ones in larger Brazilian cities and high income developed countries. Consequently, there is a demand for specific approaches to measuring the objective walkability-built environment effectively, possibly considering land use mix as a central walkability measure.

Furthermore, this researches' results also indicate that traditional composite walkability indexes—combining density, land-use mix, street connectivity and retail floor area ratio—widely used to predict walking (FRANK et al., 2010; FRANK et al., 2005; GLAZIER et al., 2014; GRASSER et al., 2013; SUNDQUIST et al., 2011), are not completely effective in medium sized Brazilian towns. This initial finding is of great implication to the operationalization of walkability measurement, indicating that more traditional walkability indices might not be suited for our social, cultural and urban reality. However, the variations of Frank (2010)'s walkability index that disregards retail FAR and the weighting attributed to the intersection density, such as applied by Reis et al. (2013), had a good performance in the models (Walkability index #4). Based on this result it can be inferred that retail FAR is an ineffective measure for average-sized Brazilian towns. Further, it can be concluded that intersection density is a measure that doesn't influence walking as heavily as in high income countries, such as Australia and the United States.

The best performing walkability index was the Index #5 calculated for Integration at a global scale. This indicates the superiority of space syntax measures over intersection density, as well as the relevance of residential density in influencing walking. The performance of this index was outstanding, being twice as important as other indices in predicting walking. It can be discussed that in studying human action, such as walking, the "prime mover" is individual motivation or goal-directed behavior, however, our results indicate the possibility of effectively predicting pedestrian walking behavior without explicitly assuming anything about individuals or their cognitive capacity, as clues of such natural cognition may be implicit in space syntax theory and analysis (PENN, 2003).

Entropy was the outstanding walkability variable; however, the optimal walkability index didn't include this land use mix variable. Considering this disparity, further possibilities can be raised. It can be apprehended that there might be another composed objective walkability measure that hasn't been initially proposed here. By aggregating entropy with the variables of the best performing index it might be possible that an even stronger objective walkability measuring tool would be created. Through an initial testing of Spearman correlation of walking levels with one option of index that includes entropy, residential density and integration; and a second option considering only entropy and integration (Figure 43). It can be observed that further possibilities can be explored for medium sized Brazilian towns. This is a conjecturing based in this researches' results that can be explored in future studies.

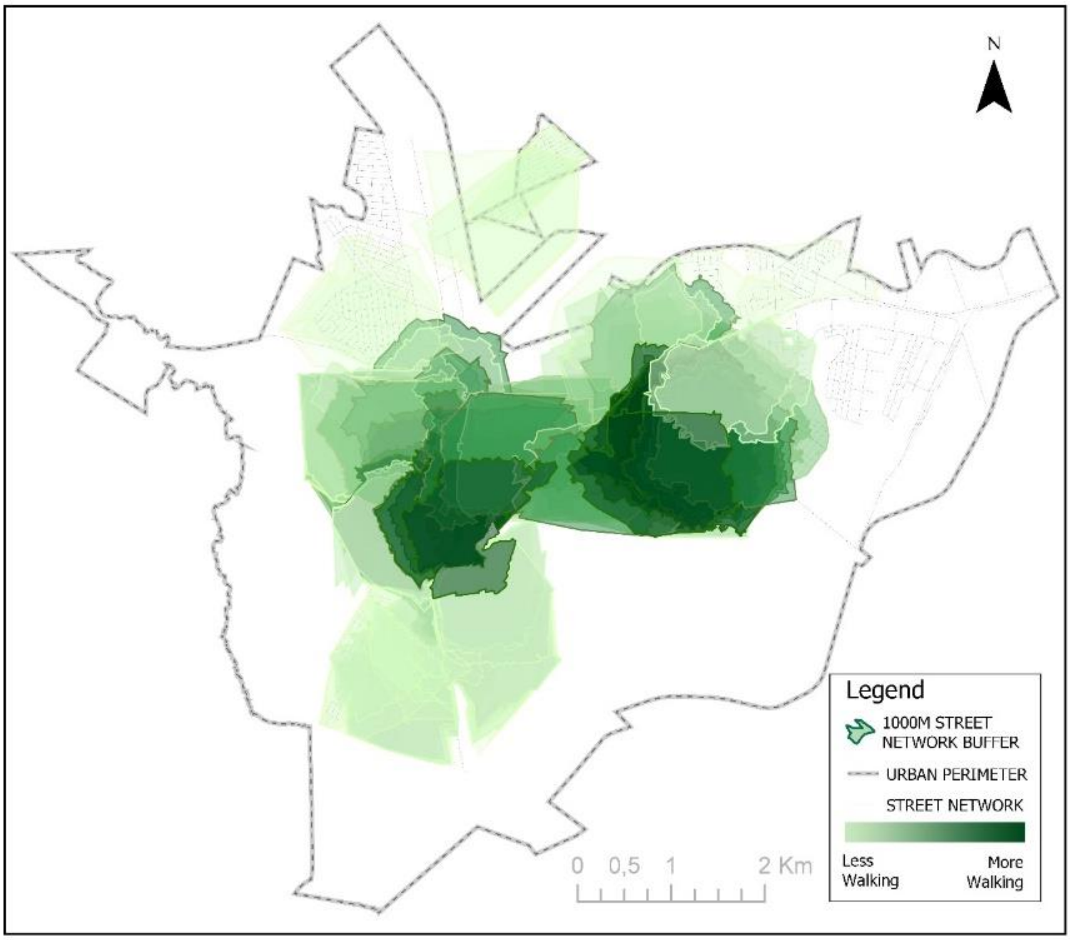
Figure 43 – Correlations between possible walkability indices and walking.



Source: Environmental design research group, 2018. Organized by the author, 2018.

When analyzing the urban form of Rolândia and how it relates to walkability, a first specific aim of this research, it was detected that higher indications of entropy z-score, residential density, and the space syntax integration measure in the 2000m radii are being consistently located in two clusters: 1. central and 2. northwest. While established central areas present higher values, lower values are situated in the outskirts of the urban perimeter (Figure 44). These spatial characteristics are closely related to urban growth and its historical process. According to (KRAFTA, 2014), urban growth adds fragments to existing cities that assume identities trough time.

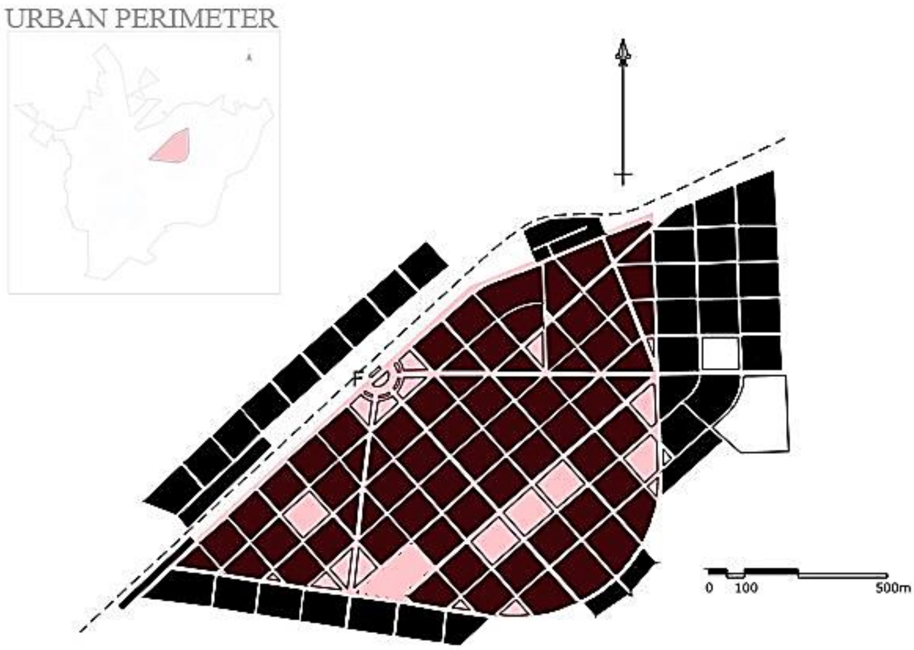
Figure 44 – Walking levels map at the 1000m street network scale.



Source: Environmental design research group, 2018. Organized by the author, 2018.

Rolândia can be considered a new town, planned by CTNP (*Companhia de Terras Norte do Paraná*) in the 1940´s, with its initial core characterized by a parabolic shape delimited by a railroad (Figure 45). The railway was a fundamental element for the colonization process and implementation of new towns in Northern Paraná (YAMAKI, 2003). This initial core, called "Gleba Roland", was characterized by three radial lines that have guided urban developing (REGO AND MENEGUETTI, 2006). This historical process explains the existence of such an intensity of phenomena observed in this area, from higher land use mix and price, to high walkability and increased walking in this area.

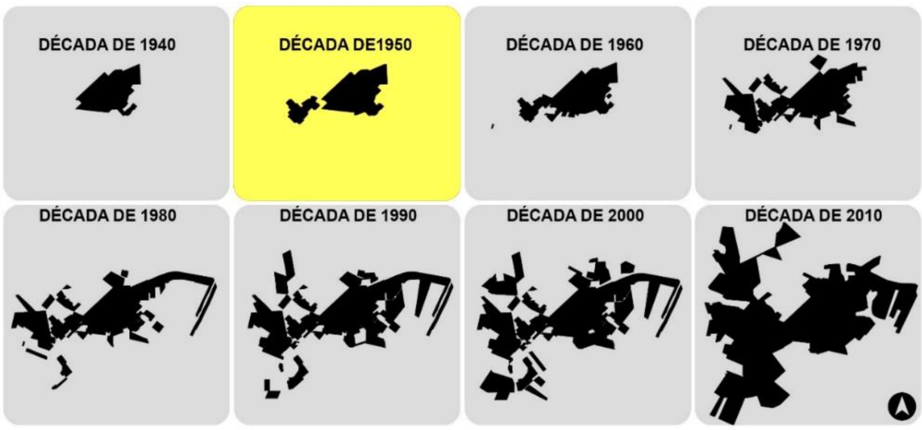
Figure 45 – Rolândia’s initial 1940’s core.



Source: Rego and Meneghetti (2006). Modified by the author, 2017

The second area, in the northwest, was the first expansion outside the original polygon, around the 1950’s (Figure 46). This secondary centrality, with the railway as a barrier to the city center, developed its own center with retail and services, with a higher residential density and integration characteristics. Currently, it represents another significant core for high values of walkability indicators.

Figure 46 – Rolândia’s urban expansion from 1940 to 2010.



Source: ITEDES, 2017. Modified by the author, 2017

Subsequent expansions kept advancing until limited by natural boundaries and municipality territory. In the 1990's an industrial sector and social housing developments arose on the outskirts, justifying the low indicators of walkability, connectivity, and walking levels.

When it comes to spatial units, a specific aim of this research was identifying the adequate spatial unit for capturing BE features on the walkability assessment of average-sized Brazilian towns. The 1000-meter street network buffer yielded the best models. This radius of 'sliding scale' unit of analysis relevance (GEHRKE; CLIFTON, 2014) follows literature evidence that considers BE exposure classifications to within 1000 meters as optimal (HOUSTON, 2014). This result is also consistent with the walking patterns present in the case study, where a majority of walking trips is restricted within the 1000-meter distance range.

The third and last specific aim of this research was analyzing if a relationship between relevant walkability variables and indices perceptions of satisfaction exists and contributes to walkability analysis. Therefore, the hypothesis that there is a coherence between perceptions of satisfaction and walkability indices was tested. However, the results presented here do not confirm this proposition. It could be observed by the RF classification results and the distribution analysis, that there is no clear pattern when it comes to the relationship between these variables and the urban context under examination. Neither residing in a determined neighborhood for longer, walking more, living in a neighborhood that is more walkable or with more mix of uses resulted in a change in perception of satisfaction with the neighborhood environment.

The literature on the concordance between perceptions and the walkable BE is mixed and this low level of agreement confirms that perceptions should not be considered as proxies for objective measures (JAUREGUI et al., 2016a). This research contributes to this inconclusive research paradigm with indications that perceptions of satisfaction don't seem to relate to the walkability variables or indices considered in this work. However, the potential mediating role of environmental cognitions on the relationships between environmental attributes and walking were not considered here and may be moderated by socio-demographic factors (GEBEL et al., 2011). Further, micro-level walkability features are thought to possibly have a more instantaneous influence on pedestrian perception (SAELENS et al., 2003) than the meso-level walkability employed by this study. Testing micro-level walkability, as one of the determinants influencing walking travel behavior, with perceptions of satisfaction could potentially yield better results.

The need for policy-relevant interdisciplinary research, that may lead to more contextually desirable outcomes, is emphasized in the recent literature (SALLIS et al., 2016a). This work goes towards this recommendation, presenting methods that includes a case study, with an emphasis on local evidence, that may lead interventions in specific urban environments. Considering the relevance of land use mix, residential density and space syntax to walking behaviors, guidance for designing urban developments to support walkable communities could be subsidized.

In Brazil, although federal regulations exist, the municipalities hold the prerogative of structuring the street network, assigning locations for open space and institutional buildings, among other guidelines. Therefore, it would be possible, in theory, to conceptualize a more walkable, healthy, sustainable city through municipal initiative. However, urban planning in our local context might eventually be biased, tending to favor individuality and not the collective or communal.

The *Plano Diretor,* a type of Master plan, is the main instrument for guiding the development of Brazilian cities. It comprehends seven legal instruments - *Plano Diretor Law; Urban Subdivision Law; Urban Perimeter and expansion Law; Land use and occupation Law (Zoning); Transportation systems law; Building codes and Posture Codes*– however, three of these regulations may be connected to meso-scaled walkability: transport, land use and urban subdivision codes.

Specific laws for transportation in Brazil define the street network hierarchy. Currently, they focus on individual motorized transport, barely considering public transport and disregarding active travel. Thus, a shifting of priorities would be paramount. Prioritizing pedestrians would positively impact the environment and better quality of life overall by assigning the spaces that would be destined to cars to public usage. This study's findings do have a practical relevance, as they could help to subsidize the transformation of such obsolete regulation elements trough pragmatic evidence.

Brazilian land use regulations, mainly zoning codes, are widely used as an instrument to divide the city into large areas for the application of guidelines of land use occupation and location of residential densities. However, many flaws can be pointed out in this instrument, mainly, that land price defines and segregates socio-economic groups within the territory. By unfairly assigning public investment, this excluding character tends to homogenize groups within areas of the city, especially extreme low or high social classes.

Considering Land use mix, there are no clear parameters for the delimitation of these areas. It would be ideal to conceptualize the permission of land uses for all plots in the city, restricting only what is effectively incompatible with residential land use. This work's results contribute to this discussion in the sense that they indicate the relevance of entropy for active travel and could subsidize *Planos diretores* in the determination of land use, understanding urban tendencies of accessibility and distribution. This type of situation could act as an effort for the creation of neighborhoods that are denser, more compact and have a greater mix of uses.

The subdivision regulation, that also composes the *Plano Diretor,* regulates the parceling of urban land into plots, guiding new streets, defining percentages of open spaces and public facilities, block size and plot design. These guidelines directly influence the density and diversity of building typologies, street connectivity and consequently land use distribution. This researches' results could be applied to subsidize such guidelines, that influence the provision of infrastructure and linkage of urban activities.

6 CONCLUSIONS

This study provided an exploration of the efficacy of several walkability constructs and indices at multiple geographic scales of a medium sized Brazilian town. This analysis was conducted through the understanding of these measures in relation to walking levels. Further, perceptions of satisfaction with the built environment were analyzed as to their relationship with walking and walkability.

When analyzing walkability measures of the built environment in relation to walking levels, the 1000m network buffer scale best modeled the relationship. The most relevant features were Entropy Z-score and a walkability index (Walkability index #5) considering Space Syntax Walkability at a Global Integration radius weighted by two and residential density. These findings are of great implication to the operationalization of walkability measurement in Brazilian towns, indicating that more traditional walkability indices might not be suited for our social, cultural and urban reality. Further, this outcome indicates the relevance of meso-scale walkability measures in predicting walking behaviors and representing walkability.

Perceptions' relationships with walkability and walking were more clouded for interpretation. The uneven distribution of answers heavily influenced the outcomes. In the context of the case study, a pattern between perceptions and walking levels could not be found. Such perception's relationship to time living in the neighborhood, entropy, individual walking level and Space syntax walkability was also inconclusive. Future studies can conduct analysis controlling for socio-demographic characteristics, as evidences indicate that neighborhood socioeconomic level status confounds the association between walkability and neighborhood satisfaction (GRASSER; TITZE; STRONEGGER, 2016).

Solid evidences to guide urban planning guidelines that consider active transportation, go through the need to faithfully systematize objective built environment representations. Therefore, this research contributes to this discussion with data aggregation alternatives for walkability and general urban planning analysis. Census tracts, the usual unit of analysis used for data aggregation in walkability analyses performed poorly in representing this researches walkability data, whereas a street network buffer of 1000 meters performed best.

A change in paradigm would be necessary to encompass deeper evidence-centered analysis in urban planning and develop more effective regulation instruments. This work through the use of geoprocessing and different statistics or computational tools can aggregate value for the creation of more effective holistic urban plans. Opening space for community participation, real evaluations of existing proposed policies and the development of evidence-centered, contextually-tailored urban planning would be the way for creating more sustainable cities: connected, denser, destination-full and walkable.

This study presents some limitations but also moves forward in the discussion of specific walkability measures for average sized Brazilian towns. The main limitation is that the OD survey has not been created in the specificity of analyzing walkability, even though the database was an important and coherent source of information. It is essential to emphasize that the authors acknowledge the limitation in the self-report information approach (RIBEIRO et al., 2014), recall bias and inaccuracy are always a possibility.

Furthermore, as the relationship between people and their environment changes over time, using longitudinal study designs is of utter importance. (RIVA; GAUVIN; BARNETT, 2007). To investigate how walking behaviors are influenced by the built environment it is necessary to outperform cross-sectional associations through prospective and intervention study that enlighten the relationships between environment and behavior, indicating causality (OWEN et al., 2004). The route geocoding procedure also presents itself as a limitation as it did not considered aspects such as street hierarchy, stop signs, pedestrian crossings, etc. Even considering such limitations, results contribute to the current limited understanding of the association between walkability and neighborhood satisfaction, especially in a Brazilian context. More comparable, longitudinal research would be necessary to determine what impact walkability has on neighborhood satisfaction and to identify influencing variables.

Future studies on walkability measures for averaged-sized Brazilian towns should firstly explore larger radii of buffers for data aggregation as well as other types of buffer conceptualization. Additional refinements may be needed to improve the reliability performance perception analyses, larger samples and the application complete NEWS questionnaires should be considered. Socio-demographic characteristics should be incorporated into future studies as moderators and mediators of perceptions. Lastly, neural networks might be used for providing more interpretability to the phenomenon, subsidizing a more specific approach to conceptualizing an optimal walkability index.

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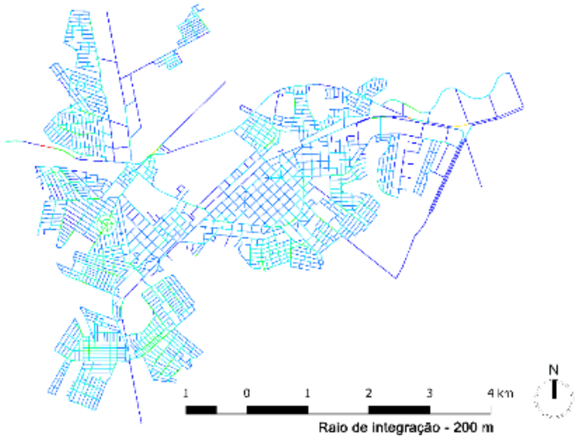
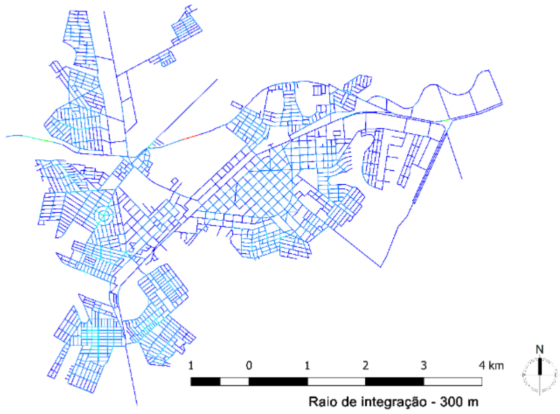
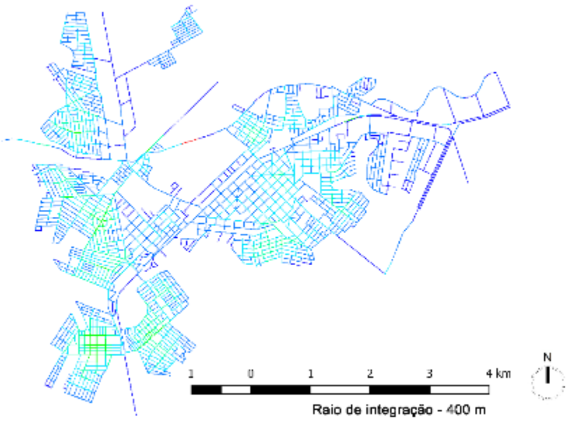
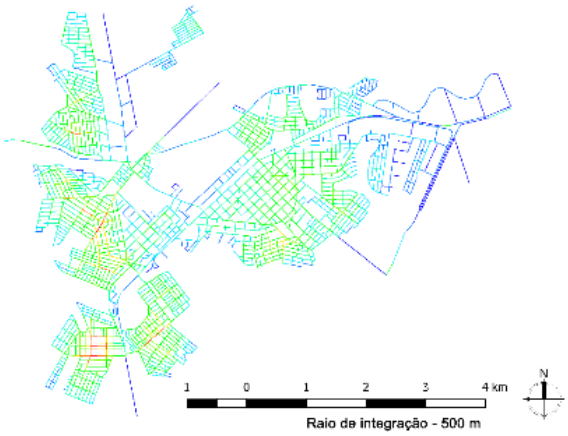
APPENDIX

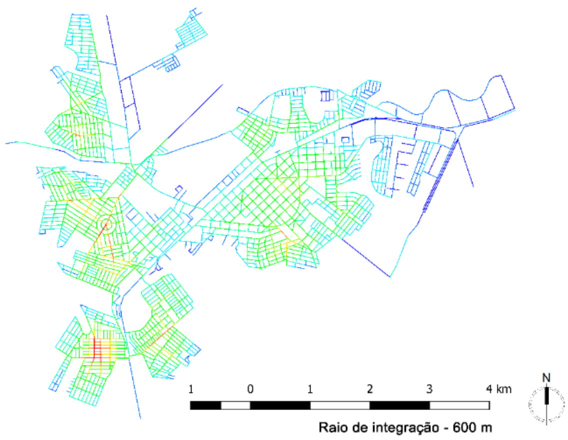
APPENDIX A – INTEGRATION AND CHOICE MAPS

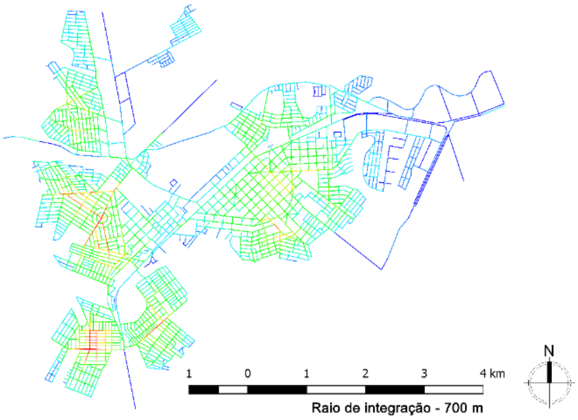


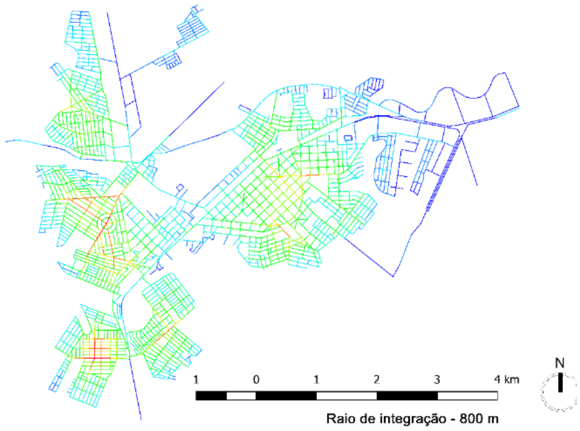









N
1 0 1 2 3 4 km
Raio de integração - 700 m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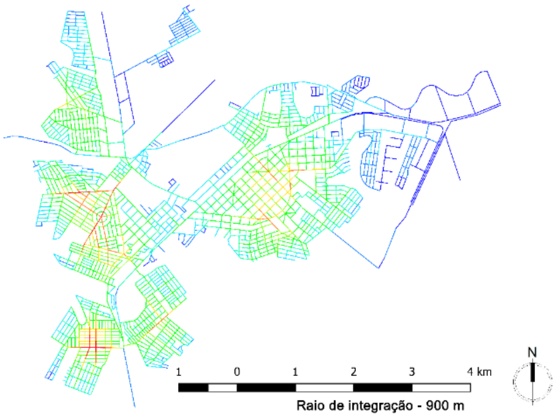
Raio de integração - 800 m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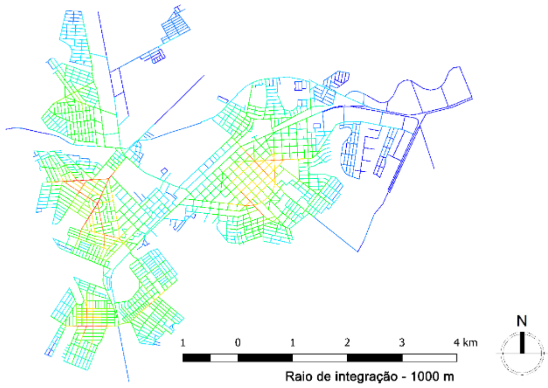
Raio de integração - 900 m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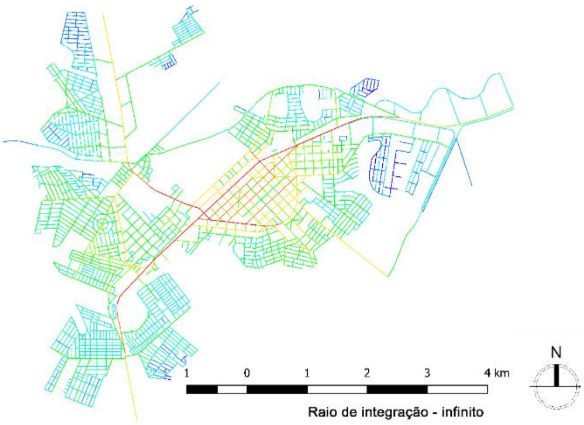
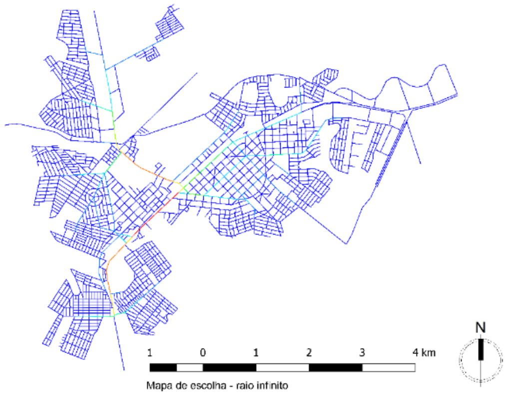
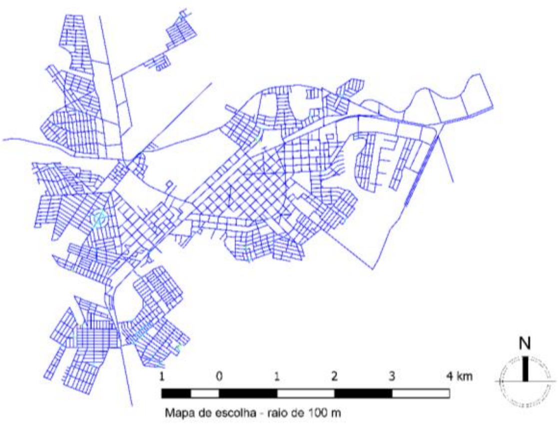
Raio de integração - 1000 m


N
1 0 1 2 3 4 km
Raio de integração - infinito


N
1 0 1 2 3 4 km
Mapa de escolha - raio infinito


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 100 m

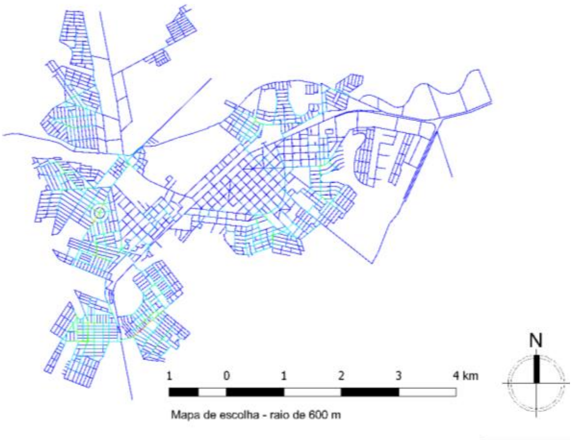

N
1 0 1 2 3 4 km
Mapa de escolha - raio de 200 m

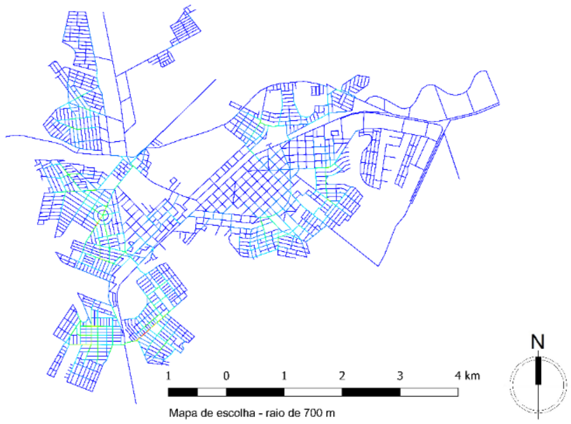

N
1 0 1 2 3 4 km
Mapa de escolha - raio de 300 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 400 m

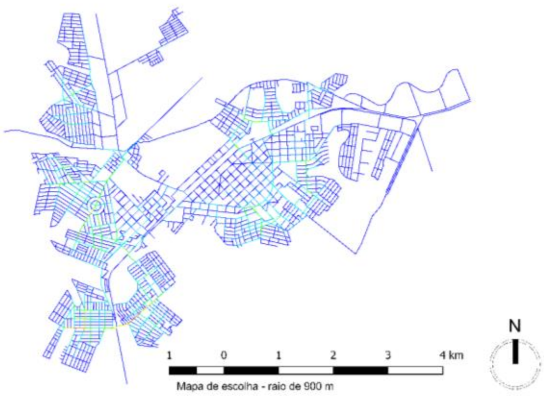

N
1 0 1 2 3 4 km
Mapa de escolha - raio de 400 m

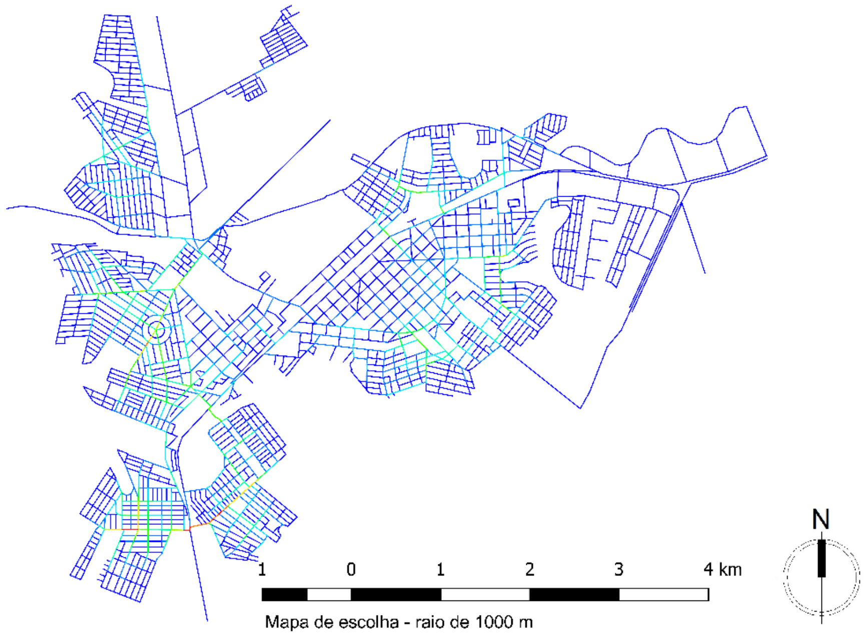

N
1 0 1 2 3 4 km
Mapa de escolha - raio de 500 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 600 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 700 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 800 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 900 m


N
1 0 1 2 3 4 km
Mapa de escolha - raio de 1000 m

APPENDIX B – EXAMPLE WALKABILITY INDEX CONSTRUCTION

ID	AREA_SETOR	RESIDENCIAS POR SETOR	DENSIDADE RESIDENCIAS	ZSCORE DENSIDADE RESIDENCIAS	INTERSECCOES POR SETOR	DENSIDADE DEINTERSECCOES	ZSCORE DENSIDADE DE INTERSECCOES	AREA LOTES COMERCIAIS	AREA EDIFICADA COMERCIAL	RETAIL RATIO
1	63,78365803	112	1,755935665	-0,917662004	17	0,266525949	-0,368082644	12,88851569	8,660073954	0,67192174
2	61,11798903	235	3,845021797	-0,295735653	22	0,359959487	0,091292651	5,333277235	3,49025187	0,65442910
3	61,18396106	262	4,282167997	-0,165596097	21	0,343227206	0,009026723	2,833922419	1,625011901	0,57341439
4	85,62078623	404	4,718480381	-0,03570477	35	0,408779241	0,331319832	0,163829961	0,086318719	0,52687993
5	64,9932775	242	3,723462015	-0,331924314	21	0,32311034	-0,089879851	1,292676804	0,66713655	0,51608920
6	999,0448838	35	0,035033461	-1,429979046	73	0,07306979	-1,319229116	4,295470367	1,04047761	0,242226
7	80,12319287	176	2,196617405	-0,786469909	31	0,386904202	0,223769024	9,739051042	1,352435318	0,13886725
9	252,446829	256	1,014074928	-1,138515866	30	0,118836906	-1,094210535	0,860472306	0,62211649	0,72299420
11	37,83193557	175	4,62572156	-0,063319311	18	0,475788503	0,660777544	0,475837634	0,323537048	0,67993160
12	92,38561024	141	1,526211708	-0,986051421	9	0,097417769	-1,199519856	0,273804905	0,085384662	0,31184489
14	86,04581773	195	2,266234492	-0,765744722	33	0,383516606	0,207113573	10,75901644	6,574399027	0,61105948
15	100,2992766	197	1,964121843	-0,85568444	24	0,239283879	-0,502020994	17,24990314	3,731814305	0,21633827
16	30,54493791	301	9,854333341	1,493251955	9	0,294647841	-0,229818564	0,991710175	0,673751551	0,67938352
17	20,85858409	202	9,684262324	1,442621373	20	0,958837854	3,035737783	0,299528927	0,2469172	0,82435176
18	24,05237371	200	8,315187614	1,035044287	11	0,457335319	0,570050624	1,301565046	0,903737117	0,69434648
19	86,24164704	153	1,774084856	-0,912258943	19	0,220311191	-0,595302104	1,423840687	1,0646939	0,74776195
20	435,0560348	339	0,77920997	-1,208435772	56	0,128719051	-1,045623983	0,751404936	0,49656244	0,66084532
21	43,71284471	278	6,359686765	0,45288662	19	0,434654851	0,458539845	2,309939904	0,96479182	0,41766966
22	23,91137748	267	11,16623249	1,883807729	21	0,878243005	2,63948518	0,159621626	0,138596252	0,86827991
23	58,00441013	290	4,999619846	0,047991176	16	0,275841095	-0,322283802	0,472281373	0,323485156	0,68494159
24	18,29073739	198	10,82515132	1,782266983	11	0,601397296	1,278345681	0,070356374	0,058418093	0,83031699
25	25,05633025	306	12,21248271	2,19527913	11	0,439010817	0,479956384	0,072418759	0,062260576	0,85972994
26	24,89004703	115	4,62032072	-0,064927155	8	0,321413615	-0,098221967	3,179817555	2,054974601	0,64625550
27	21,71622554	83	3,822026983	-0,302581268	10	0,460485179	0,585537224	3,763078119	2,495782739	0,66322905
28	38,2561671	175	4,574425858	-0,078590175	12	0,313674916	-0,136270053	2,80135673	1,511351014	0,53950680
29	34,07665171	221	6,485378959	0,490305512	17	0,498875305	0,774286101	0,355342755	0,279750042	0,78726817
30	25,18561053	154	6,114602615	0,379924434	18	0,714693812	1,835379287	1,124126145	0,84072287	0,74789014
31	21,58305729	203	9,405525699	1,359640758	15	0,694989584	1,738501486	0,231014679	0,178273902	0,77169945
32	17,19287233	168	9,77149116	1,468589624	4	0,232654551	-0,534614745	0,187699358	0,123436361	0,65762803
33	28,68119889	220	7,67053012	0,843128082	13	0,453258598	0,550007021	0,716599644	0,529845012	0,73938776
34	559,9036281	614	1,096617291	-1,113942791	50	0,089301082	-1,239426352	0,201202413	0,160079561	0,79561451
35	332,8126237	268	0,805257917	-1,200681231	25	0,075117343	-1,309162119	2,433509037	1,369421315	0,5627352
36	74,69805169	182	2,436475864	-0,715063425	11	0,14725953	-0,954467871	2,790965752	1,753709127	0,62835207
37	55,39952449	210	3,79064254	-0,311923392	10	0,342963233	0,007728872	2,256749456	1,348943724	[illegible]
38	114,8314011	187	1,628474426	-0,955607545	17	0,14804313	-0,950615226	14,67415298	1,118722089	[illegible]
39	278,5515824	1129	4,053109267	-0,233787474	93	0,33389506	-0,036979208	1,312658728	1,192731356	[illegible]
40	126,4400106	202	1,597595564	-0,964800262	21	0,166086668	-0,861902375	1,306585809	0,844891543	[illegible]
41	82,50650839	160	1,939240953	-0,863091545	11	0,13332816	-1,022989116	0,066034907	0,051014827	[illegible]
42	36,9535335	229	6,196971664	0,404445913	21	0,460037198	0,583334681	3,643728979	1,803429124	[illegible]
43	25,65453598	175	6,821405779	0,590341566	8	0,31833693	-0,145312778	1,486191861	0,844711145	[illegible]
44	33,22306116	159	4,785832291	-0,015653932	14	0,481593187	0,689316847	0,838266297	0,536652755	[illegible]
45	35,63156463	328	9,205321277	1,300039383	14	0,392910054	0,253297396	0,134497366	0,087578954	[illegible]
46	68,34750047	495	7,242400916	0,715672909	30	0,438933389	0,479575703	0,174488778	0,127785409	[illegible]
47	9045,855802	1402	0,154988	-1,39426824	59	0,006522324	-1,646416363	0,178193642	0,114397	[illegible]
48	71,34496016	253	3,546150975	-0,38471027	25	0,350410175	0,044342508	6,306872147	3,302073999	[illegible]
51	42,21275533	246	5,827622436	0,294489692	20	0,473790442	0,650953876	[illegible]	[illegible]	[illegible]
52	46,78880287	279	5,962965156	0,33478157	26	0,555688509	1,05361388	0,348936303	0,148796747	[illegible]
53	29,66877407	212	7,145559824	0,686843065	17	0,572993005	1,138693156	0,192929645	0,042106692	0,21824894
54	75,81098385	461	6,080913036	0,369894959	42	0,554009431	1,045358523	0,167860195	0,085476091	0,50921000
55	56,75101373	401	7,065953075	0,66314393	30	0,528624918	0,92055304	0,247867805	0,167754642	0,67679076
56	1205,084521	29	0,024064702	-1,433244474	19	0,015766529	-1,600966307	0,353025981	0	[illegible]
58	105,2188085	781	7,422627296	0,769326769	49	0,465696207	0,611157763	0,123073261	0,084201029	0,68415371
59	22,13812898	247	11,15722111	1,881125018	17	0,767905906	2,097001848	0,257829371	0,19879103	0,77101778
60	23,33039848	257	11,01567126	1,838985262	15	0,642938011	1,482584747	0,509210305	0,437462337	0,85909953
61	16,11973878	160	9,925719154	1,514503697	8	0,496285958	0,76155532	0,288456871	0,248688943	0,86213561
62	24,48361939	110	4,492799788	-0,102890467	6	0,245061807	-0,473613239	2,736463969	1,619839993	0,59194639
63	18,37120453	137	7,457322667	0,779655671	4	0,217732049	-0,607982715	0,965100795	0,724813328	0,7510234
64	20,27879604	200	9,862518447	1,495688683	5	0,246562961	-0,466232663	0,114657881	0,061875092	0,53964970
65	407,8211803	670	1,642876909	-0,951319888	63	0,154479471	-0,918970315	2,844048466	1,881459941	0,66154285
66	56,61478756	355	6,270446562	0,426319581	15	0,264948446	-0,375838594	1,08809653	0,367499498	0,33774530
69	36,10209024	156	4,321079444	-0,154012058	14	0,387789181	0,228120111	0,09815972	0,057150444	0,58221890
72	342,4579491	540	1,576835934	-0,970980458	91	0,265726056	-0,372015401	0,034861133	0,022447018	0,64389812
57	783,7107766	6	0,007655886	-1,438129422	6	0,007655886	-1,640843093	3,273962615	0,684992	0,20922413
8	49,94185882	256	5,125960588	0,085603142	16	0,320372537	-0,103340534	0	0	[illegible]
10	144,974741	329	2,26936084	-0,764814	27	0,186239339	-0,762819757	0	0	[illegible]
13	79,33105426	251	3,16395644	-0,498490573	22	0,277318891	-0,31501807	0	0	[illegible]
50	312,4414442	124	0,396874366	-1,322258072	48	0,153628787	-0,923152787	0	0	[illegible]
67	547,6451303	311	0,567885996	-1,271347467	71	0,129645999	-1,041066551	0	0	[illegible]
68	6,113829496	25	4,089090155	-0,22307587	1	0,163563606	-0,874307258	0	0	[illegible]
70	562,8261706	72	0,127925821	-1,40232475	39	0,069293153	-1,337797329	0	0	[illegible]
			MÉDIA	4,838414743		MÉDIA	0,341391237			MÉDIA
			DESVIO PADRÃO	3,359057109		DESVIO PADRÃO	0,203392605			DESVIO PADRÃO

ID	ZSCORE RETAIL RATIO	AREA DE RESIDENCIAS	PROPORÇÃO ENTROPIA RESIDENCIAS	Ln(P) ENTROPIA RESIDENCIAS	ENTROPIA RESIDENCIAS	AREA DE COMERCIO	PROPORÇÃO ENTROPIA COMERCIO	Ln(P) ENTROPIA COMERCIO	ENTROPIA COMERCIO	AREA DE SEVICO	PROPORÇÃO ENTROPIA SERVICO	Ln(P) ENTROPIA SERVICO	ENTROPIA SERVICO	AREA INSTITUCIONAL	PROPORÇÃO ENTROPIA INSTITUCIONAL
1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
14	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
18	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
20	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
22	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
24	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
26	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
28	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
30	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
32	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
33	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
34	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
35	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
36	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
37	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
38	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
39	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
40	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
41	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
42	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
43	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
44	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
45	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
46	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
47	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
48	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
51	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
52	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
53	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
54	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
55	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
56	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
58	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
59	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
60	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
61	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
62	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
63	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
64	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
65	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
66	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
69	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
72	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
57	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
50	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
67	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
68	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
70	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	0,543795281														
	0,260906852														

ID	Ln(P) ENTROPIA INSTITUCIONAL	ENTROPIA INSTITUCIONAL	AREA ENTRETENIMENTO	PROPORÇÃO ENTROPIA ENTRETENIMENTO	Ln(P) ENTROPIA ENTRETENIMENTO	ENTROPIA ENTRETENIMENTO	SOMA	VALOR FINAL	ZSCORE FINAL ENTROPIA	ZSCORE FINAL DENSIDADE DE INTERSECCOES	ZSCORE DENSIDADE DE RESIDENCIAS	ZSCORE RETAIL AR	Z SCORE ENTROPIA	WALKABILITY INDEX
1	2,231099201	542,6502925	5600,427167	87,80348038	1,943511731	243,7815631	13128,37647	-13128,37647	6,762955328	-0,368082644	-0,917662004	0,491081256	6,762955328	5,600209291
2	1,299692118	37,01984215	3994,546	65,35794229	1,815298371	169,4916659	6084,601359	-6084,601359	3,977840256	0,091292651	-0,295735653	0,424035734	3,977840256	4,288725641
3	2,063293007	341,0011731	1172,498333	19,16349175	1,282474644	35,10956038	5198,976159	-5198,976159	3,627663249	0,009026723	-0,165596097	0,1135237	3,627663249	3,593644298
4	0	0	0	0	0	0	3577,889622	-3577,889622	2,986684161	0,331319832	-0,03570477	-0,064832901	2,986684161	3,548786153
5	1,631618238	99,80188627	246,395	3,791084394	0,578763452	3,134487274	4407,180573	-4407,180573	3,314586555	-0,089879851	-0,331924314	-0,106191428	3,314586555	2,696711111
6	0,010778569	0,015784893	1042,94	1,043937081	0,018674324	0,027849742	325,0045898	-325,0045898	1,700490467	-1,319229116	-1,429979046	-1,155847686	1,700490467	-3,523794499
7	1,850205323	187,2092091	2015,03	25,14914755	1,400523269	50,31709478	3827,226942	-3827,226942	3,085272363	0,223769024	-0,786469909	-1,552002254	3,085272363	1,194338249
9	1,130245552	21,79316557	454,24	1,799349201	0,255115455	0,655773987	785,9565423	-785,9565423	1,882751287	-1,094210535	-1,138515866	0,686831037	1,882751287	-0,757354612
11	1,164929393	24,32937521	313,646	8,290508939	0,918581192	10,87929369	4428,001405	-4428,001405	3,322819131	0,660777544	-0,063319311	0,521781343	3,322819131	5,10283625
12	0,300015251	0,855185924	979,43	10,60154279	1,025369071	15,52927725	1198,299745	-1198,299745	2,045792164	-1,199519856	-0,986051421	-0,889016079	2,045792164	-2,228315047
14	2,096702397	374,2321965	13215,99673	153,5925519	2,186370156	479,7288168	5957,329368	-5957,329368	3,927516796	0,207113573	-0,765744722	0,257809261	3,927516796	3,83380848
15	0	0	114,115	1,137744995	0,056044934	0,091092633	2204,526967	-2204,526967	2,44365532	-0,502020994	-0,85568444	-1,255072461	2,44365532	-0,671143568
16	1,071966022	18,07378045	372,945	12,20971544	1,086705542	18,95480777	6744,64925	-6744,64925	4,238823792	-0,229818564	1,493251955	0,519680642	4,238823792	5,792119262
17	2,381219867	818,3165316	246,97	11,84020924	1,073359377	18,15542802	5337,758756	-5337,758756	3,682538013	3,035737783	1,442621373	1,075312832	3,682538013	12,27194778
18	1,508365987	69,46638152	765,0216667	31,80649344	1,502515792	68,27108383	5427,176795	-5427,176795	3,717893987	0,570050624	1,035044287	0,577030478	3,717893987	6,47007
19	0,875215206	9,38063031	777,33	9,01339465	0,954888387	12,2954084	951,0280536	-951,0280536	1,948020712	-0,595302104	-0,912258943	0,781760525	1,948020712	0,626918088
20	0,006624778	-0,009320699	97,54	0,224201004	-0,649362446	-0,207982447	305,2866586	-305,2866586	1,692693979	-1,045623983	-1,208435772	0,448627714	1,692693979	-1,158362045
21	0	0	569,7383333	13,03365949	1,115066371	20,76199341	3916,422009	-3916,422009	3,120540174	0,458539845	0,45288662	-0,483412442	3,120540174	4,007094042
22	0,829944246	8,014844941	137,235	5,739318035	0,758860291	6,221915079	6285,921039	-6285,921039	4,05744224	2,63948518	1,883807729	1,243680006	4,05744224	12,46390034
23	0,893977308	10,004739	294,5283333	5,077688622	0,705666065	5,118789358	3237,753202	-3237,753202	2,852193911	-0,322283802	0,047991176	0,540983538	2,852193911	2,796601021
24	1,410263795	51,81626581	947,52	51,8032696	1,714357171	126,8704382	7651,476698	-7651,476698	4,597384187	1,278345681	1,782266983	1,098176262	4,597384187	10,03451879
25	0,604693838	3,476412808	120,475	4,808166193	0,68197947	4,68438662	7889,504037	-7889,504037	4,691500413	0,479956384	2,19527913	1,210909801	4,691500413	9,057602112
26	2,141759074	424,0642378	1652,536667	66,39347306	1,822125387	172,8246183	5004,504044	-5004,504044	3,550768798	-0,098221967	-0,064927155	0,392708064	3,550768798	3,682105772
27	2,097684997	375,2556408	463,4389286	21,34067579	1,329208168	40,52314366	5239,201796	-5239,201796	3,643568502	0,585537224	-0,302581268	0,457764033	3,643568502	4,969825716
28	2,256921908	582,5596498	1163,105208	30,40307737	1,482917545	64,40750978	5370,399154	-5370,399154	3,695444056	-0,136270053	-0,078590175	-0,016436814	3,695444056	3,32787696
29	1,590499091	88,49820781	845,365	24,80774834	1,394587348	49,42367424	5310,792228	-5310,792228	3,671875424	0,774286101	0,490305512	0,933179369	3,671875424	6,643932507
30	2,095403566	372,8835333	198,795	7,893197577	0,897252974	10,11742143	4618,020327	-4618,020327	3,397952785	1,835379287	0,379924434	0,782251854	3,397952785	8,230887648
31	1,021759811	15,34654397	282,43	13,08572721	1,116797863	20,87730311	6322,856429	-6322,856429	4,072046527	1,738501486	1,359640758	0,873507821	4,072046527	9,782198078
32	0	0	0	0	0	0	6565,607382	-6565,607382	4,168030474	-0,534614745	1,468589624	0,436296544	4,168030474	5,003687153
33	1,350703718	43,26789565	343,215	11,96654998	1,077968959	18,42795632	5948,945597	-5948,945597	3,924201845	0,550007021	0,843128082	0,749664054	3,924201845	6,617008021
34	0,812555637	-0,178730813	0	0	0	0	386,0903938	-386,0903938	1,724643849	-1,239426352	-1,113942791	0,965169122	1,724643849	-0,902982524
35	0,234519974	0,574912525	745,4746667	2,239923048	0,350233099	1,120707414	483,8728771	-483,8728771	1,763307132	-1,309162119	-1,200681231	0,072592838	1,763307132	-1,9831055
36	1,680688211	115,1005303	1531,036	20,4963311	1,311676128	38,40649745	2853,274724	-2853,274724	2,700170772	-0,95446787	-0,715063425	0,324088063	2,700170772	0,400259669
37	1,621739461	96,96667545	998,202	18,0182413	1,255712399	32,32247	5607,403291	-5607,403291	3,789155707	0,007728872	-0,311923392	0,206748865	3,789155707	3,699438923
38	1,13678696	22,25194628	2285,851048	19,90614959	1,298987263	36,93976397	1656,426898	-1656,426898	2,226936055	-0,950615226	-0,955607545	-1,269662404	2,226936055	-1,899564346
39	0	0	398,9666667	1,432290074	0,156030982	0,319259467	2501,474158	-2501,474158	2,561068509	-0,036979208	-0,233787474	1,398363169	2,561068509	3,651685788
40	0	0	17,35	0,137219223	-0,862585044	-0,169090356	4364,608888	-4364,608888	3,297753672	-0,861902375	-0,964800262	0,394185823	3,297753672	1,003334483
41	0,277637453	0,751653121	0	0	0	0	1098,490432	-1098,490432	2,006327471	-1,022989116	-0,863091545	0,876742241	2,006327471	-0,026000066
42	1,982139094	271,7535218	221,915	6,005244397	0,778530687	6,67895292	5007,088961	-5007,088961	3,551790876	0,583334681	0,404445913	-0,18724981	3,551790876	4,935656343
43	1,952924176	250,3292034	399,16	15,55904189	1,19198285	26,49444442	6558,964009	-6558,964009	4,165403679	-0,145312778	0,590341566	0,094200659	4,165403679	4,559320348
44	2,328885033	709,4716449	816,8916667	24,5880913	1,390724817	48,85038397	4528,803127	-4528,803127	3,362676223	0,689316847	-0,015653932	0,369468393	3,362676223	5,095124379
45	0	0	423,385	11,88230167	1,074900574	18,2461327	5380,016954	-5380,016954	3,699246943	0,253297396	1,300039383	0,411495952	3,699246943	5,917377071
46	1,214270425	28,41108391	0	0	0	0	3957,395064	-3957,395064	3,136740957	0,479575703	0,715672909	0,722657991	3,136740957	5,534223262
47	1,088357992	-0,12685738	174,94	0,019339243	-1,713560538	-0,047341376	15,4655117	-15,4655117	1,578098434	-1,646416363	-1,39426824	0,376331845	1,578098434	-2,732670686
48	1,482527676	64,33279884	432,835	6,06679153	0,782959072	6,78578495	3739,268012	-3739,268012	3,050493322	0,044342508	-0,38471027	-0,077528309	3,050493322	2,676939758
51	1,122775346	21,27992899	167,6333333	3,971153554	0,59891668	3,397700148	5497,480277	-5497,480277	3,745692048	0,650953876	0,294489692	0,51245258	3,745692048	5,854542071
52	0	0	250,095	5,345189142	0,727963078	5,558714768	5190,577427	-5190,577427	3,624342382	1,05361388	0,33478157	-0,449837715	3,624342382	5,616513997
53	0	0	0	0	0	0	5352,201686	-5352,201686	3,688248761	1,138693156	0,686843065	-1,247749268	3,688248761	5,40472887
54	0,062606685	0,103306906	175,81	2,319057095	0,365311441	1,210254414	2328,682281	-2328,682281	2,492746444	1,045358523	0,369894959	-0,132557953	2,492746444	4,820800497
55	0,582886197	3,186925628	0	0	0	0	4304,553366	-4304,553366	3,274007664	0,92055304	0,66314393	0,509743179	3,274007664	6,288000854
56	0	0	0	0	0	0	2,591265344	-2,591265344	1,573007946	-1,600966307	-1,433244474	-2,084250669	1,573007946	-5,146419812
58	0	0	0	0	0	0	3639,873048	-3639,873048	3,011192463	0,611157763	0,769326769	0,537963774	3,011192463	5,540798532
59	0,847356846	8,517755102	481,645	21,75635531	1,337586143	41,57285625	6655,322541	-6655,322541	4,20350393	2,097001848	1,881125018	0,870895116	4,20350393	11,14952776
60	1,297968265	36,82428293	231,355	9,916461574	0,996356733	14,1147618	6289,48757	-6289,48757	4,05885245	1,482584747	1,838985262	1,208493576	4,05885245	10,07150078
61	1,56664773	82,5127467	585,1233333	36,29856173	1,559889417	80,8882033	6879,555438	-6879,555438	4,292165821	0,76155532	1,514503697	1,220130229	4,292165821	8,549910387
62	1,914106479	224,3750343	3299,841667	134,7775267	2,129617482	410,0351103	5109,979379	-5109,979379	3,592473841	-0,473613239	-0,102890467	0,184552909	3,592473841	2,726909806
63	0,55794323	2,880283279	290,8083333	15,82957355	1,199469215	27,1244088	6323,409246	-6323,409246	4,072265112	-0,607982715	0,779655671	0,794261122	4,072265112	4,430216474
64	0	0	0	0	0	0	6244,30223	-6244,30223	4,040986126	-0,466232663	1,495688683	-0,015889097	4,040986126	4,588320386
65	0,772637938	6,539069105	373,5983333	0,916083694	-0,038064847	-0,049815123	762,8004192	-762,8004192	1,873595335	-0,918970315	-0,951319888	0,451301194	1,873595335	-0,46436399
66	1,633811579	100,4420362	57,385	1,013604439	0,005868504	0,008497631	5313,60781	-5313,60781	3,672988707	-0,375838594	0,426319581	-0,789745347	3,672988707	2,557885753
69	1,150650518	23,25390614	0	0	0	0	1992,583763	-1992,583763	2,359852785	0,228120111	-0,154012058	0,1472695	2,359852785	2,809350449
72	0	0	0	0	0	0	545,1138929	-545,1138929	1,787521885	-0,372015401	-0,970980458	0,383672744	1,787521885	0,456183369
57	0	0	0	0	0	0	-0,070615598	0,070615598	1,571955435	-1,640843093	-1,438129422	-1,282339433	1,571955435	-4,430199605
8	0	0	0	0	0	0	4301,516825	-4301,516825	3,272807013	-0,103340534	0,085603142	-2,084250669	3,272807013	1,067478419
10	0	0	0	0	0	0	1401,508323	-1401,508323	2,12614102	-0,762819757	-0,764814	-2,084250669	2,12614102	-2,248563162
13	2,571169799	1368,366763	411,9	5,192165966	0,715348566	5,306012113	5173,980794	-5173,980794	3,617780059	-0,31501807	-0,498490573	-2,084250669	3,617780059	0,405002676
50	0	0	0	0	0	0	230,5895808	-230,5895808	1,663158686	-0,923152787	-1,322258072	-2,084250669	1,663158686	-3,589655628
67	1,23566415	30,37152208	508,03	0,927662773	-0,032609871	-0,043215662	1045,462526	-1045,462526	1,985360188	-1,041066551	-1,271347467	-2,084250669	1,985360188	-3,45237105
68	1,292197869	36,17669178	0	0	0	0	2302,742992	-2302,742992	2,482490026	-0,874307258	-0,22307587	-2,084250669	2,482490026	-1,573451029
70	0,516084836	-0,22466645	0	0	0	0	19,70146829	-19,70146829	1,579773335	-1,337797329	-1,40232475	-2,084250669	1,579773335	-4,582396741
								MÉDIA	-3975,669572					
								DESVIO PADRÃO	2529,078666					

Source: Organized by the author, 2017

ATTACHMENTS

ATTACH A– OD QUESTIONNAIRE

1. PESQUISADOR:

2. CÓDIGO DO QUESTIONÁRIO:

3. DATA: 4.DIA DA SEMANA:

5. ENDEREÇO:

6. RESULTADO
1-Completo com viagem
2-Completo sem viagem
3-Incompleto
5

7. SETOR CENSITÁRIO:

TELEFONE PARA CONTATO:

PERGUNTAS AO CHEFE DA FAMÍLIA:

Tipo de domicílio: 1-Particular 2-Favela ou c ortiço	Nº da Família	Total Famílias	Nº Moradores no Endereço	Nº Moradores na Residência	Tempo de Residência (0 se menos de um ano no Município)	No Município (em anos)	No Bairro (em anos)	Condição de Moradia 1-Alugada 2-Própria 3-Cedida 4-Outros 5-Não respondeu
8	9	10	11	12		13	14	15

Veículos da Família (quantidade)	Automóvel	Moto	Bicicleta
	16	17	18

Sobre seu bairro, qual é seu grau de satisfação quanto ao:

19. ACESSO AO TRANSPORTE PÚBLICO?	1 2 3 4 5
20. FACILIDADE E PRAZER EM ANDAR A PÉ?	1 2 3 4 5
21. SEGURANÇA EM ANDAR A PÉ?	1 2 3 4 5
22. FACILIDADE E PRAZER DE ANDAR DE BICICLETA?	1 2 3 4 5
23. SEGURANÇA EM ANDAR DE BICICLETA?	1 2 3 4 5
24. QUANTIDADE E INTENSIDADE TRÁFEGO?	1 2 3 4 5
25. VELOCIDADE DO TRÁFEGO?	1 2 3 4 5
26. BARULHO DE TRÁFEGO?	1 2 3 4 5
26. SER UM BOM LUGAR PARA SE VIVER?	1 2 3 4 5

Por quê? Anote as observações pertinentes.

Nº da pessoa	NOME DA PESSOA (começar pelo chefe)	Sit. Familiar	Idade	Sexo	Estuda Atual/e	Grau instruç.	Cond. Ativid.	Ocup. Princip.	Setor Ativid.	Condiç. Renda	RENDA MENSAL	Cartão Transp.	LOCAL DE ESTUDO	LOCAL DE TRABALHO
27	28	29	30	31	32	33	34	35	36	37	38	39	40	41

11.Situação Familiar
1) CHEFE
2) CÔNJUGE
3) FILHO/A
4) PARENTE AGREGADO
5) EMPREGADO RESIDENTE
6) VISITANTE NÃO RESIDENTE

11.Sexo
1) MASCULINO
2) FEMININO

11.Estuda atualmente
1) NÃO
2) CRECHE/PRÉ ESCOLA
3) 1º/2º/3º GRAUS
4) OUTROS

11.Grau de instrução
1) NÃO ALFABETIZADO
2) PRÉ ESCOLA
3) 1º GRAU INCOMPLETO
4) 1º GRAU COMPLETO
5) 2º GRAU INCOMPLETO
6) 2º GRAU COMPLETO
7) SUPERIOR INCOMPLETO
8) SUPERIOR COMPLETO

11.Condição de Atividade
1) OCUPADO
2) OCUPADO EVENTUALMENTE
3) EM LICENÇA
4) NÃO OCUPADO
5) APOSENTADO/PENSIONISTA
6) NUNCA TRABALHOU
7) DONA DE CASA
8) ESTUDANTE

11.Ocupação Principal
1) ASSALARIADO COM CARTEIRA
2) ASSALARIADO SEM CARTEIRA
3) FUNCIONÁRIO PÚBLICO
4) AUTÔNOMO
5) EMPREGADOR
6) PROFISSIONAL LIBERAL
7) TRAB. DOMÉST. COM CARTEIRA
8) TRAB. DOMÉST, SEM CARTEIRA
9) DONO DE NEGÓCIO FAMILIAR
10) TRABALHADOR FAMILIAR
11) NÃO SE APLICA

11.Setor de Atividade
1) AGRÍCOLA
2) CONSTRUÇÃO CIVIL
3) INDÚSTRIA
4) COMÉRCIO
5) SERVIÇO TRANSPORTE CARGA
6) SERVIÇO TRANSPORTE PASSAGEIROS
7) SERVIÇOS FINANCEIROS
8) SERVIÇOS PESSOAIS
9) SERVIÇOS DE ALIMENTAÇÃO
10) SERVIÇOS DE SAÚDE
11) SERVIÇOS DE EDUCAÇÃO
12) SERVIÇOS ESPECIALIZADOS
13) SERVIÇOS ADM. PÚBLICA
14) OUTROS
15) NÃO SE APLICA

11.Condição de Renda
1) TEM RENDA
2) NÃO TEM RENDA
3) NÃO RESPONDEU

11.Possui cartão transporte
1) SIM
2) NÃO

2. CÓDIGO DO QUESTIONÁRIO:

Em que lugar estava quando saiu ontem pela 1a vez? E depois de onde saiu?
ORIGEM
Endereço Bairro Cidade Referência
43

Saiu para onde?
DESTINO
Endereço Bairro Cidade Referência
44

NOME E NÚMERO DA PESSOA
42

Por que motivo saiu do endereço 1 para ir ao endereço 2?
MOTIVO

De		Para
1	Trabalho/Indústria	1
2	Trabalho/Comércio	2
3	Trabalho/Serviços	3
4	Escola/Educação	4
5	Compras	5
6	Médico/Dentista/Saúde	6
7	Recreação/Visitas	7
8	Residência	8
9	Outros	9

45 46

SERVIU PASSAGEIRO
1 Sim 1 Sim
2 Não 2 Não
47 48

Quais conduções utilizou para chegar no endereço?
MODO

ÔNIBUS	1
ÔNIBUS FRETADO	2
ÔNIBUS ESCOLAR	3
VAN	4
MOTO	5
DIRIGINDO AUTOMÓVEL	6
PASSAGEIRO DE AUTO	7
TÁXI	8
BICICLETA	9
A PÉ	10
OUTROS	11

49 50

Se a viagem FOI a pé, porquê?
A PÉ
1. TRANSPORTE PÚBLICO DEFICIENTE/RUIM/CARO
2. PEQUENA DISTÂNCIA
3. OUTROS MOTIVOS
51

Se a viagem NÃO foi a pé, porquê?
1. DISTÂNCIA EXCESSIVA
2. INSEGURANÇA
3. PERIGO ATROPELAMENTO
4. CONDIÇÕES CLIMÁTICAS
5. TOPOGRAFIA/SUBIDAS
6. OUTROS MOTIVOS
52

A que horas saiu do endereço 1?
HORA SAÍDA
53 54

A que hora chegou no endereço 1?
HORA CHEGADA
55 56

Quanto tempo levou andando?
TEMPO ANDANDO
Do endereço de origem até a 1a condução
57

Quanto tempo levou andando?
TEMPO ANDANDO
Da última condução até o endereço de destino
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I. Neighborhood satisfaction

Below are things about your neighborhood with which you may or may not be satisfied. Using the 1-5 scale below, indicate your satisfaction with each item by placing the appropriate number on the line preceding that item. Please be open and honest in your responding. The 5-point scale is as follows:

1 = strongly dissatisfied
2 = somewhat dissatisfied
3 = neither satisfied nor dissatisfied
4 = somewhat satisfied
5 = strongly satisfied

How satisfied are you with…

(example) __3_the number of pedestrian cross-walks in your neighborhood ?

a. ____the highway access from your home?
b. ____the access to public transportation in your neighborhood?
c. ____your commuting time to work/school?
d. ____the access to shopping in your neighborhood?
e. ____how many friends you have in your neighborhood?
f. ____the number of people you know in your neighborhood?
g. ____how easy and pleasant it is to walk in your neighborhood?
h. ____how easy and pleasant it is to bicycle in your neighborhood?
i. ____the quality of schools in your neighborhood?
j. ____access to entertainment in your neighborhood (restaurants, movies, clubs, etc.)?
k. ____the safety from threat of crime in your neighborhood?
l. ____the amount and speed of traffic in your neighborhood?
m. ____the noise from traffic in my neighborhood?
n. ____the number and quality of food stores in your neighborhood?
o. ____the number and quality of restaurants in your neighborhood?
p. ____your neighborhood as a good place to raise children?
q. ____your neighborhood as a good place to live?