Comparing distance-based and stress-based centralities to rank priority locations for cycling infrastructure investments in small-sized cities

Comparação entre centralidades baseadas na distância e no estresse para ranquear locais prioritários para investimentos em infraestrutura cicloviária em cidades de pequeno porte

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ABSTRACT

The lack of technical guidelines to define investment priority locations is one of the barriers to cycling in emerging countries, limiting the preparation of urban mobility plans even when legally required. The objective of this paper is to propose and compare two approaches, with and without considering the cyclists' perception of stress (assessed with the LTS, or Level of Traffic Stress), to determine the relative importance of road segments in the network and to rank priority locations for investments in cycling infrastructure. A case study was conducted in the city of Bariri (Brazil), for which the overall contribution of each network link to the identified cycling routes was mapped and ranked according to both criteria. The spatial distribution of differences between homologous ranks (i.e., ranks of the same network link according to different criteria) was also mapped, and the spatial autocorrelation between these differences was assessed by the Local Moran's Index, allowing the identification of road segments of greater similarity and dissimilarity between the proposed approaches for resource allocation.

RESUMO

A carência de diretrizes técnicas que auxiliem na definição de locais com prioridade de investimentos é uma das barreiras ao ciclismo em países emergentes, limitando a preparação de planos de mobilidade urbana mesmo quando exigidos legalmente. O objetivo deste trabalho é propor e comparar duas abordagens, com e sem considerar a percepção do estresse de ciclistas (avaliada com base no LTS, ou Level of Traffic Stress), para determinação da importância relativa de segmentos viários na rede e hierarquização de infraestruturas cicloviárias prioritárias. Um estudo de caso foi conduzido na cidade de Bariri (Brasil), para a qual foram mapeadas e ranqueadas, por ambos os critérios, as contribuições gerais de cada link da rede às rotas cicláveis identificadas. A distribuição espacial das diferenças de classificações homólogas (classificações, pelos diferentes critérios, correspondentes a um mesmo link) também foi mapeada e a autocorrelação espacial entre essas diferenças foi avaliada pelo Índice de Moran Local, permitindo elencar trechos viários de maior similaridade e dissimilaridade entre as abordagens propostas para a alocação de recursos.

1. INTRODUCTION

Active transportation (i.e., walking and cycling) plays a key role in promoting sustainable urban mobility as it helps to mitigate problems arising from prioritizing motorized transport, such as traffic jams, increased space requirements, air pollution, etc. (Pucher and Buehler, 2012). However, changing the existing road system to make it bicycle- or pedestrian-friendly is a process that faces several technical, budgetary, political and cultural obstacles (Andrade et al., 2016), especially in emerging countries.

In Brazil, for example, the Brazilian National Urban Mobility Policy (or PNMU, which in Portuguese stands for *Política Nacional de Mobilidade Urbana*) establishes that cities with more than 20,000 inhabitants must prepare urban mobility plans that favor public and non-motorized transport, but since its institution by Law No. 12,587, of January 3, 2012 (Brasil, 2012), the deadline for complying with the legal requirement has been repeatedly extended due to the minority of cities subject to the preparation of the plan (14% by 2021) having done so in full (Morais and Santos, 2020; SEMOB, 2021). Specifically with regard to cycling, one of the most likely reasons for this non-compliance is the lack of technical subsidies that guide cycling planning at the network level (Guerreiro et al., 2018).

According to Rybarczyk and Wu (2010), cycling planning must be guided by both demand- and supply-based models. However, sequential demand modeling requires origin-destination surveys, which are rare in small cities, particularly of emerging countries like Brazil (Brasil, 2019). In addition, although there are several Bicycle Compatibility Indexes (BCI) or Bicycle Level of Service (BLOS) models in the literature (Harkey et al., 1998; TRB, 2010), these metrics are rarely used in cities in the Southern Hemisphere (Arellana et al., 2020) and require extensive and costly surveys for large-scale application (Callister and Lowry, 2013). In this context, recent studies have sought to rank cycling investments based on the centrality of road segments, that is, on their contribution to the routes preferred by cyclists to reach their potential travel destinations, using the bicycle Level of Traffic Stress (LTS) classification (Mekuria et al., 2012) for this purpose.

Lowry, Furth and Hadden-Loh (2016) ranked priority cycling projects in Seattle (USA) based on the centrality of road segments, to which equivalence factors were assigned according to their LTS classification, bicycle accommodation and slope. Moran et al. (2018) ranked road sections in Philadelphia (USA) prioritizing investments in cycling, which, if properly addressed, would ensure greater network connectivity by enhancing low-stress cycling routes. In Brazil, Monari and Segantine (2022) benefited from the LTS classification and the criteria presented in the Cycling Aspects of Austroads Guides (Austroads, 2014) to respectively assign stress and slope factors to the road segments of two small-sized cities, allowing to propose cycling networks that prioritize links with greater centrality in the road system (although no weighting factor for trip attractors was considered).

Although the ease of application and the small number of input variables encourage the use of the LTS classification in large-scale cycling planning (for example, at the municipal level), many questions are still raised about i) the validation of the model and ii) the non-inclusion of important cycling stressors in the evaluation process. In the first case, authors such as Wang et al. (2016) and Ferenchak and Marshall (2020) emphasize the need to validate the LTS classification through measures of the physiological stress of cyclists. In the latter case, authors such as Vieira et al. (2016), Zeile et al. (2016) and Rybarczyk et al. (2020) highlight the need to include additional stress variables in the original model, and it is to this gap in the literature that the present research aims to somehow provide contributions. Thus, the following Research Questions are formulated:

▪ Are there differences between priority locations for cycling infrastructure investments based on the shortest paths and the low-stress cycling routes?

▪ What are the locations with the greatest similarity and dissimilarity in terms of their relative importance to cycling when evaluated with and without considering cycling stress variables?

In this context, the present research aims to propose and compare two approaches to determine the relative importance (centrality) of network links and to rank priority locations (i.e., road segments) for investments in cycling infrastructure. The first approach was developed without considering the cyclists' perception of stress, that is, assuming that they choose the shortest paths to reach their travel destinations. The second approach was developed considering the LTS classification and additional stress variables not included in the original model to identify cycling routes. A case study was conducted in the city of Bariri (Brazil).

2. METHOD

This section presents the research method and case study data. The method consists of i) identifying the shortest paths and low-stress cycling routes between the origin-destination pairs of interest, in the latter case, based on the LTS classification and the subsequent assignment of stress factors to the network links; ii) estimating the homologous centralities of each link in the network, weighing their relative contributions to cycling routes by multipliers for origins (potential demand) and destinations (attractiveness of trip attractors); and iii) ranking of centralities, for each approach, aiming to check whether there is any spatial pattern in the differences between homologous indices. QGIS 3.8.2 was used for geoprocessing the spatial data.

2.1. Cycling routes

Distance or travel time are decisive factors in cyclists' route choice (Menghini et al., 2010). Identifying the shortest path between an origin-destination pair is a process that benefits from Dijkstra's (1959) algorithm (based on graph theory), which has often been applied to GIS-assisted cycling planning to identify routes that minimize the sum of impedances (a term used in technical literature that refers to the "resistance" imposed by network links to cycling) associated with the BCI (Klobucar and Fricker, 2007), the BLOS (Lowry et al., 2012) or the LTS (Monari, 2022).

In this research, impedances were assigned to every link in the network based on the two following strategies presented by Equations 1 and 2.

$$c_{dist,e} = L_e \tag{1}$$

$$c_{stress,e} = L_e \times f_{stress,e} \tag{2}$$

where $c_{dist,e}$ and $c_{stress,e}$ are the distance-based and stress-based cycling impedances for link e, respectively; L_e is length of the link e; and $f_{stress,e}$ is the stress factor for link e.

2.1.1. Stress factor

Table 1 presents the criteria for the preliminary assessment of LTS ($LTS_{initial}$) in mixed traffic situations (original model) and for the classification of existing bike lanes (updated from 2017),

both subdivided into 4 levels of traffic stress (in which LTS1 is the least stressful and LTS4 the most) (Mekuria, Furth and Nixon, 2012; Furth, 2017). It is important to highlight that the most relevant criteria in the literature for deciding on the provision of cycling facilities (bike lanes and bike paths) are based on the joint analysis of the flow and speed of motorized traffic (Transport Scotland, 2010). Therefore, although roads segments with bike lanes do not necessarily exclude mixed traffic, in this work we opted for a more conservative approach, that is, by always considering the LTS classification of bike lanes in situations like this.

Equations 3 to 6 summarize the methodology proposed by Rodrigues, Silva and Teixeira (2022) to obtain the final LTS classification (LTS_{final}) from the preliminary assessment, which includes three other stress variables in the form of Additional Levels of Traffic Stress (ALTS): i) steep slopes, ii) existence of obstacles along the road and iii) presence of roundabouts. We only considered bus stops (Beura et al., 2018) and on-street vehicle parking rates greater than 30% (Harkey et al., 1998) as obstacles along the road.

Table 1: Preliminary assessment of LTS ($LTS_{initial}$) in mixed traffic situations and for bike lane classification [adapted from: Mekuria, Furth and Nixon, 2012; Furth, 2017].

LTS in mixed traffic situations						
Speed limit (km/h)	**Street width**					
	2-3 lanes	**4-5 lanes**		**≥ 6 lanes**		
Up to 40	1 or 2[a]	3		4		
50	2 or 3[a]	4		4		
60 or higher	4	4		4		

LTS for bike lane classification							
Number of lanes per direction	Bike lane width[b]	Prevailing speed (km/h)					
		≤ 40	50	60	65	70	≥ 80
1	≥ 1.80 m	1	2	2	3	3	3
	1.20-1.60 m	2	2	2	3	3	4
2	≥ 1.80 m	2	2	2	3	3	3
	1.20-1.60 m	2	2	2	3	3	4
3	Any width	3	3	3	4	4	4

[a]Lower value is assigned to road segments without a marked centerline or to residential streets with fewer than 3 lanes; higher value is assigned otherwise. [b]Includes any marked buffer next to the bike lane.

$$LTS_{final} = min\left\{\left(LTS_{initial} + ALTS_{sl} + ALTS_{ob} + ALTS_{rb}\right); 4\right\} \quad (3)$$

$$ALTS_{sl} = \begin{cases} 0, & \text{if } -3\% < \text{slope} < 3\% \\ 1, & \text{if slope} \leq -3\% \\ 2, & \text{if slope} \geq 3\% \end{cases} \quad (4)$$

$$ALTS_{ob} = \begin{cases} 1, & \text{if there are obstacles along the road} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$$ALTS_{rb} = \begin{cases} 1, & \text{if there is a roundabout} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where $ALTS_{sl}$, $ALTS_{ob}$ and $ALTS_{rb}$ are the Additional Levels of Traffic Stress for steep uphill or downhill slopes, existence of obstacles along the road and the presence of roundabouts, respectively.

There is a limit to how much cyclists are willing to deviate from the shortest path to ride a bicycle along road segments with better operational conditions. Authors such as Furth, Mekuria and Nixon (2016), for example, suggest that a low-stress cycling route must not be more than 25% longer than the shortest path. Other sources in the literature also point to very similar values, all of them consistently limited to 30%, although these percentages also vary between commuting and noncommuting cyclists (Winters et al., 2010; Broach, Dill and Gliebe, 2012). In this context, the application of Dijkstra's algorithm to identify routes that minimize the accumulated impedance between an origin-destination pair is based on this concept of Marginal Rate of Substitution (MRS), in which road segments with different LTS classifications must have their geometric length multiplied by different *detour* or *stress* factors (Cervero, Denman and Jin, 2019). Thus, for the four increasing final LTS classifications (LTS_{final}), the respective stress factors were considered in this research: 1.00, 1.10, 1.20 and 1.30. To facilitate comprehension, it is assumed that a cyclist would be willing to travel up to 130 meters on a link classified as LTS 1, rather than 100 meters on the same link if classified as LTS 4.

2.2. Centrality

The centrality of a given link is defined as the number of times it is used in the routes identified between all origin-destination pairs in the network (Shimbel, 1953), and the routing algorithm may be based on various criteria such as the shortest distance or travel time between O-D pairs (shortest path), or even low-stress connectivity (low-stress cycling route). In turn, gravity-based centrality (or O-D centrality) can be calculated by weighting this overall contribution by the cumulative potential demand at each origin and the attractiveness of each travel destination (McDaniel, Lowry and Dixon, 2014), as presented by Equations 7 to 10.

$$Centrality_{dist,e} = \sum_{i \in O, j \in J | D_{ij} \leq \delta} \sigma_{ij}(e) \times M_i \times M_j \tag{7}$$

$$Centrality_{stress,e} = \sum_{i \in O, j \in J | D_{ij} \leq \delta} \sigma_{ij}^*(e) \times M_i \times M_j \tag{8}$$

$$\sigma_{ij}(e) = \begin{cases} 1, & \text{if link } e \text{ is used in } \sigma_{ij} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$\sigma_{ij}^*(e) = \begin{cases} 1, & \text{if link } e \text{ is used in } \sigma_{ij}^* \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $Centrality_{dist,e}$ is the distance-based centrality for link e; $Centrality_{stress,e}$ is the stress-based centrality for link e; σ_{ij} and σ_{ij}^{*} are the sets of links the perform the shortest path and the low-stress cycling route from i to j, respectively; M_i and M_j are the multipliers for origin i and destination j, respectively; O is the set of all origins; J is the set of all destinations; D_{ij} is the network distance between i and j (sum of the geometric lengths of the links the performs the shortest path or the low-stress route); and δ is the reachable distance threshold for bicycles, adopted in this work as 5 km (Brasil, 2007).

2.2.1. Multipliers for origins

Socioeconomic attributes of the population such as age, gender, income, etc. are determining factors in bicycle use (Sener, Eluru and Bhat, 2009). In this context, instead of the total population residing in each origin, the potential to generate bicycle trips was quantified by the respective latent cycling demand, according to Equations 11 and 12. The weighting factors for each age-income combination of the population (Table 2) are based on the profile of cyclists in small-sized Brazilian cities (such as the case study) (Soares and Guth, 2018; Monari and Segantine, 2022).

$$q_i = \sum_{k=1}^{12} y_k \times p_{i,k} \tag{11}$$

$$M_i = \frac{q_i}{\sum_{i \in O} q_i} \tag{12}$$

where q_i is the latent cycling demand at origin i;   is the weighting factor for age-income combination k; and $p_{i,k}$ is the population belonging to age-income combination k at origin i.

Table 2: Weighting factors (y_k) for age-income combinations (k) of the population [adapted from: Monari and Segantine, 2022].

Income	Age			
	10-29	30-49	50-69	≥ 70
≤ 2 minimum wages	27.5 (*1*)	20.5 (*4*)	13.6 (*7*)	2.2 (*10*)
2-5 minimum wages	6.7 (*2*)	5.0 (*5*)	3.3 (*8*)	0.5 (*11*)
> 5 minimum wages	8.9 (*3*)	6.7 (*6*)	4.4 (*9*)	0.7 (*12*)

2.2.2. Multipliers for destinations

Multipliers for destinations were defined according to Equations 13 and 14, which are based on the scoring system presented in Table 3, adapted from the work of McNeil (2011). In short, the author suggests a "basket" of nonwork bicycle travel destinations, to which points are assigned based on their relative attractiveness to cycling. In the present research, however, we incorporated work-related travel destinations into the scoring criteria, since most of Brazilian cyclists ride a bike to work (Lobo, Andrade and Rodrigues, 2020). Furthermore, each destination type was assigned the same weight, that is, 20 points (out of 100), which in turn were subdivided to define the final score (y_l) for each

different subgroup l of trip attractors of the same nature. In the latter case, among other adaptations, we also considered some facilities not included in the original publication (e.g., health units), and ruled out others that rarely exist in small-sized cities in emerging countries (e.g., light rail stops).

$$a_j = \sum_{l=1}^{16} y_l \times u_{j,l} \qquad (13)$$

$$M_j = \frac{a_j}{\sum_{j \in J} a_j} \qquad (14)$$

where a_j is the cycling attractiveness of destination j; y_l is the score for trip attractor l; and $u_{j,l}$ is the number of trip attractors l at destination j.

Table 3: Scoring system for trip attractors [adapted from: McNeil, 2011].

Destination type	Subgroup of trip attractors (l)	y_l
Industry/Factory	Any industry/factory (1)	20.0
Educational center	Daycare (2)	2.5
	Preschool (3)	2.5
	Elementary school (4)	5.0
	High school (5)	5.0
	College (6)	5.0
Leisure place	Sports club (7)	10.0
	Park, square and open public space (8)	10.0
Commercial place	Trade in specific goods (9)	2.5
	Beauty salon, hairdresser, etc. (10)	2.5
	Clothing store (11)	5.0
	Restaurant, coffee shop, bar, etc. (12)	5.0
	Supermarket and grocery store (13)	5.0
	General services (post office, bank, etc.) (14)	5.0
Other	Religious organization (15)	5.0
	First aid station, hospital, etc. (16)	10.0
Total		100.0

It is also important to highlight that, in the base work, in addition to the scoring system, the author proposed for each type-l trip attractor a minimum number of units to be accessible within the reachable distance threshold for bicycles so that all of the respective points were assigned; otherwise, only a fraction of these points should be assigned (McNeil, 2011). This was not done in the present research.

2.3. Ranking of centralities

The comparison between homologous centrality measures is an important process to provide evidence to transport planners about the differences in applying different criteria to estimate the

relative importance of the same network link. Furthermore, it is extremely important to check whether there is any spatial pattern in the differences between homologous indices, guiding the choice of the most appropriate criterion for other cities with similar topographical, road and land use characteristics and, therefore, helping to more assertively allocate resources to cycling infrastructure. Authors such as Monari (2022), for example, warn about statistical differences between homologous centralities measured with and without considering cycling stress variables and about the contribution of steep slopes and other ALTS in the systematic deviation of low-stress cycling routes in relation to the corresponding shortest paths.

To assess whether the data present similar spatial patterns in the centrality of each network link, we benefited from an adaptation of the methodology proposed by Conrow et al. (2018). First, each dataset (distance-based and stress-based centralities) was ranked. Then, a single value representing this similarity or dissimilarity between homologous centralities was calculated for each link through Equation 15, defined as *Rank Difference* (*RD*). Finally, the Local Moran's Index was also calculated for each link, according to Equation 16, to identify *Local Indicators of Spatial Association* (LISA), that is, clusters of positive spatial association (High-High or Low-Low) or outliers of negative spatial association (Low-High or High-Low) of *RD* (Anselin, 1995). For this last step, we used the free software called GeoDa (Anselin, Syabri and Kho, 2006).

$$RD_e = \left(R_{dist,e} - R_{stress,e} \right)^2 \tag{15}$$

$$I_e = \frac{\left(RD_e - \overline{RD} \right)}{v} \times \sum_{d=1}^{m} w_{ed} \times \left(RD_d - \overline{RD} \right) \tag{16}$$

where RD_e and RD_d are the rank differences for links *e* and *d*, respectively; $R_{dist,e}$ and $R_{stress,e}$ are the distance-based and stress-based ranks for link *e*, respectively; I_e is the Local Moran's Index for link *e*; *m* is the number of links in the network; w_{ed} is equal to 1 when link *e* is connected to link *d*, and 0 otherwise; $\overline{RD}$ is the rank differences' mean; and *v* is the rank differences' variance.

2.4. Case study data

Bariri is a city in the State of São Paulo (Brazil) with an estimated population of approximately 32,000 inhabitants (IBGE, 2022). Figure 1 shows the case study data. Road system information was obtained from collaborative mapping (OpenStreetMap, or OSM). We refined the original network by vectorizing bike lanes and shared-used paths that did not exist in the OSM features, totaling 2,261 links (Figure 1a). Furthermore, for routing purposes only, we duplicated the two-way road segments, so that each overlapping link represented a single traffic flow direction and the up and down movements in the network could be evaluated separately. The posted speed limit (or average speed measured in the field, for places where this information was previously available), the number of traffic lanes and the existence of centerlines, obstacles and roundabouts (*dummy* variables) were assigned to each link in the network based on *in situ* visits and ground-level navigation by Google StreetView.
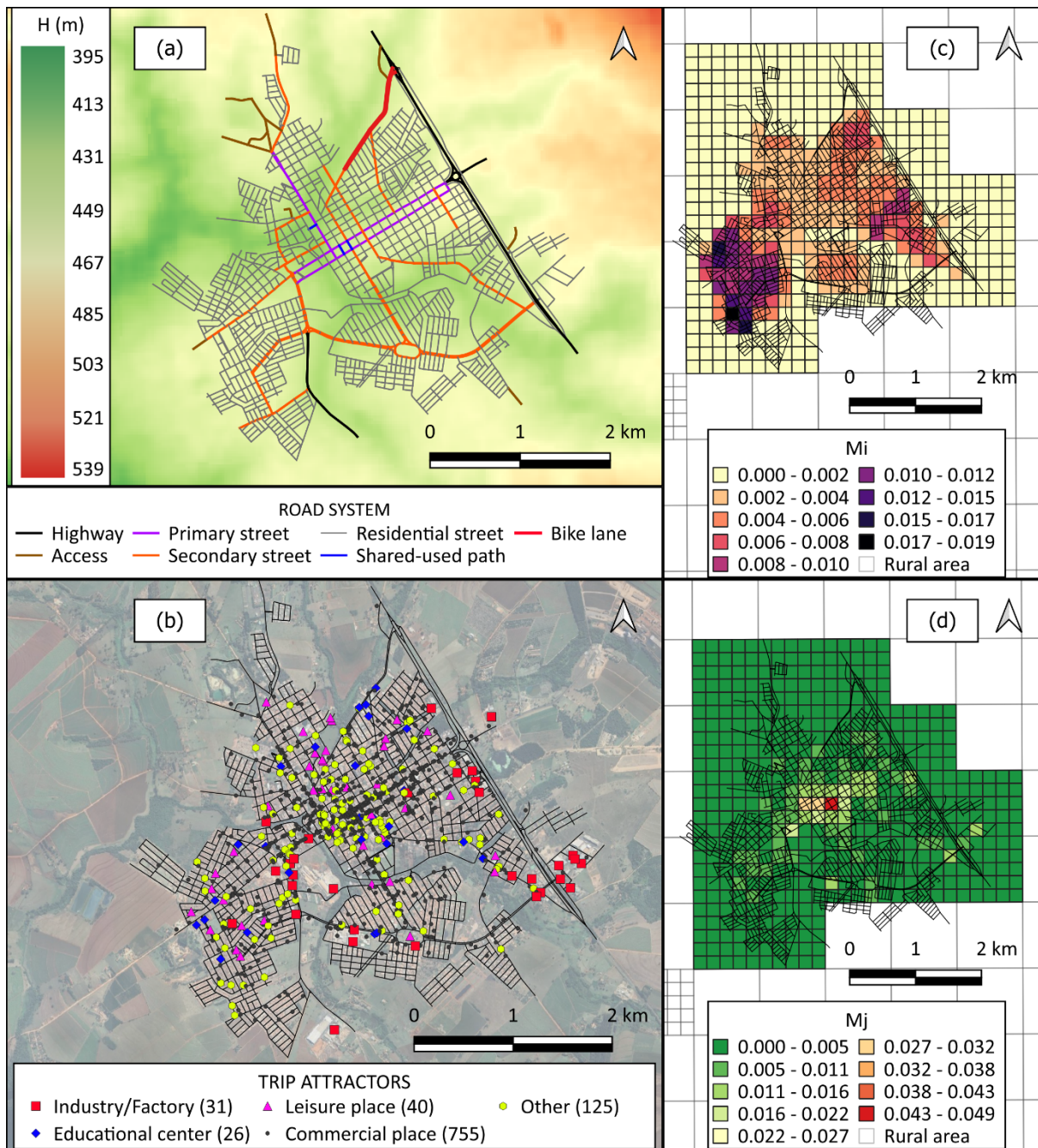
Figure 1. Case study data: (a) Road system and DEM; (b) Trip attractors; (c) Multipliers for origins; (d) Multipliers for destinations.

Altimetric data were extracted from the 30-meter spatial resolution TOPODATA Digital Elevation Model (DEM) (INPE, 2008) (Figure 1a), and aggregated population data (income and age) by census tracts were obtained from the results of the 2010 Brazilian Demographic Census provided by the Brazilian Institute of Geography and Statistics (or IBGE (2012), which in Portuguese stands for *Instituto Brasileiro de Geografia e Estatística*). To standardize the units of analysis, we chose to transfer the census data to the statistical grid, a georeferenced vector layer also made available by IBGE (2012) that consists of a set of regular cells (200 x 200 meters in urban regions) (Figure 1c). This was done through the intersection between the two vector layers. Regarding the trip attractors,

977 potential bicycle travel destinations were georeferenced by searching for these facilities on the Google Maps platform (Figures 1b and 1d).

3. RESULTS AND DISCUSSION

Figure 2 shows the initial and final LTS classifications of each link in the network of the city of Bariri. In turn, Figures 3 and 4 summarize the following results: the upper part of Figure 3 presents the frequency distributions of the lengths of the routes identified by both criteria considered in the research (shortest paths and low-stress cycling routes); the lower part of Figure 3 shows the frequency distributions of the centralities of the road segments resulting from each of these criteria; and Figure 4 allows numerical and visual comparisons between the distance-based and stress-based centralities of each link in the network of the city of Bariri.
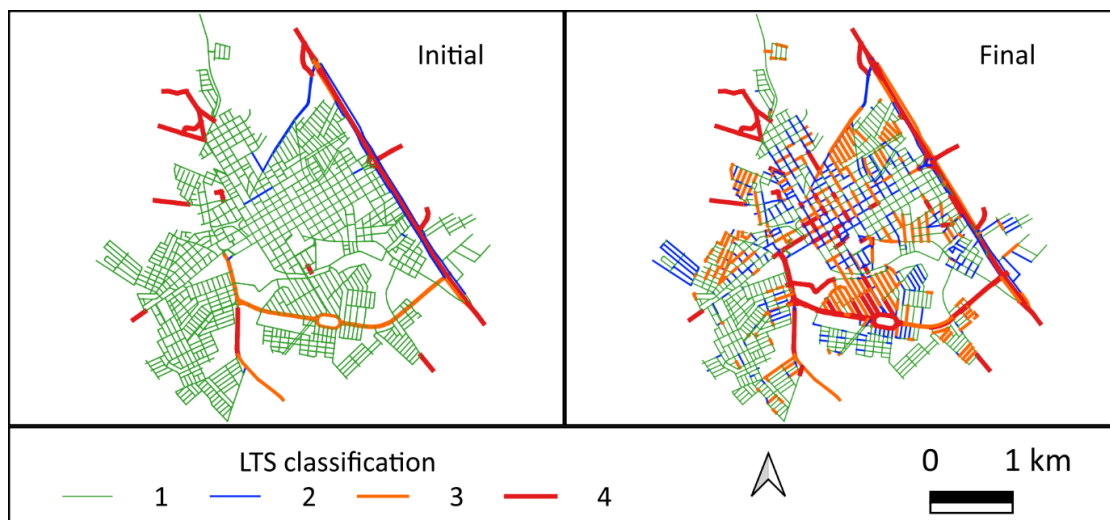

Figure 2. Initial and final LTS classifications of each link in the Bariri network.

Although most of the study area (62%) is characterized as flat terrain (EMBRAPA, 1979), there is an evident influence of terrain slopes on the LTS classification of network links located in the central region of Bariri. Many links originally classified as LTS 1 have been reclassified as LTS 2 or LTS 3 due to the influence of steep slopes (see Figure 1a). Also in the central region, where there is a large concentration of trip attractors, ALTS were considered due to the high occupancy rates of the roads by parked vehicles. In the flatter regions of the city or with a low concentration of trip attractors, such as the southwest region, the LTS 1 classification prevails.

Some of the road segments with higher functional hierarchy previously classified as LTS 2 or LTS 3 have also become more stressful for cycling due to the presence of roundabouts. The simultaneous influence of more than one additional stressor was also observed in many cases, causing some road segments originally classified as LTS 1, in critical situations, to be reclassified as LTS 4. The authors who suggested the criteria used in the present research for the LTS reclassification highlight that, for scenarios where steep uphill slopes and roundabouts are observed simultaneously, the inclusion of both factors in the LTS reclassification is sufficient to promote a reasonable agreement between the original model and cyclists' real perceptions of stress (Rodrigues, Silva and Teixeira, 2022). As for the city's bike lanes, originally classified as LTS 2, some road sections close to roundabouts also had their classification worsened, since these cycling facilities are only partially segregated from motorized traffic.
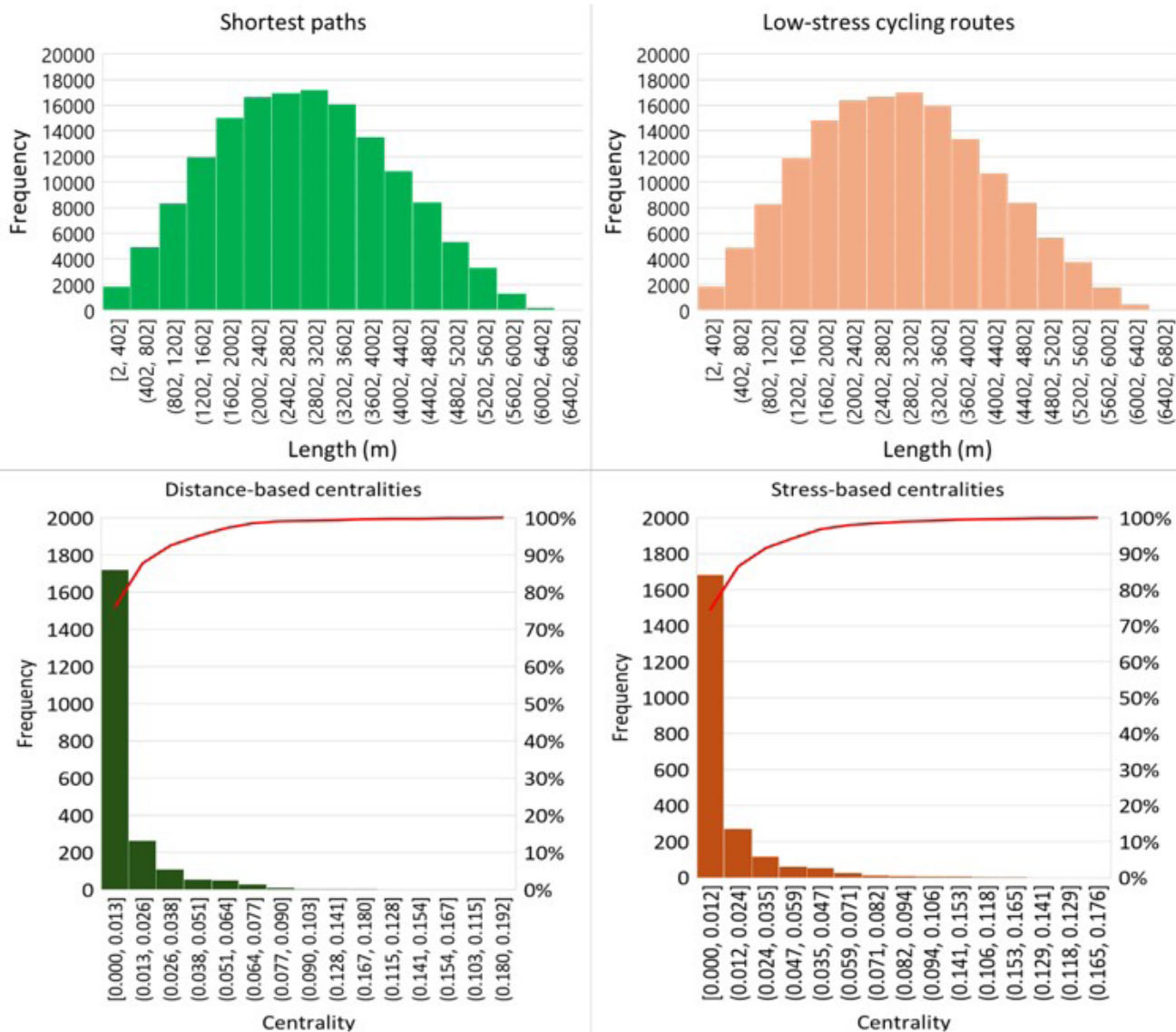
Figure 3. Frequency distributions of cycling routes' lengths and network links' centralities.

Cycling routes in Bariri were identified from each node closest to the centroid of a statistical grid cell to all those closest to the centroids of other cells. Altogether, 152,475 cycling routes were identified using each of the proposed approaches, with approximately 46% (69,297) of all homologous routes not differing from each other. As observed in the frequency distributions in Figure 3, there is good adherence between the travel distances along the shortest paths and the low-stress cycling routes in the city of Bariri. In the first case, the identified routes are on average 2,840 meters long, with maximum values around 6.4 km (greater than the reachable distance threshold for bicycles). In turn, low-stress routes are on average 2,870 meters long, with maximum values of 6.9 km, suggesting detours of the order of 500 meters due to cycling stress variables.

Regarding the frequency distributions of centralities, it is noted that, regardless of the criterion used, more than 85% of Bariri's road segments have their contribution limited to just over 1% of cycling routes. In the shortest paths, a maximum contribution of 19.2% was observed for some links. The same links were identified as the most important to the network also when considering stress variables, with maximum contributions of 17.6%. Furthermore, the results also suggest a strong positive correlation between centralities for both data sets (0.83).
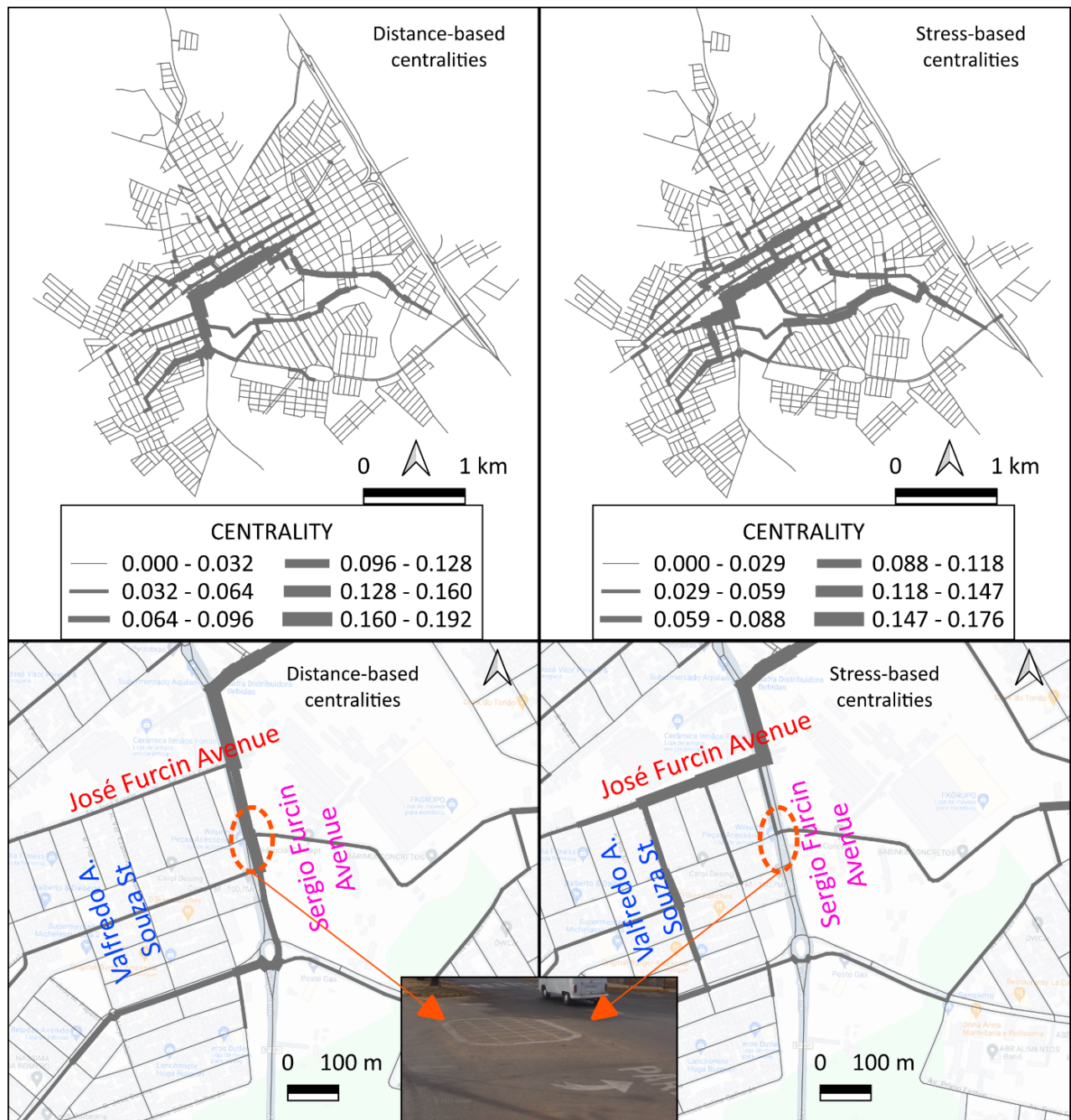
Figure 4. Distance-based and stress-based centralities of each link in the Bariri network; and, in detail, centralities of Sergio Furcin Avenue [adapted from: Google Maps, 2023].

Network links with great contributions to the identified routes are expected to receive large flows of cyclists and should be prioritized in future investments in cycling infrastructure. Therefore, addressing our first Research Question, the highest centrality values are observed in the city center regardless of the criterion used, which is expected due to the higher concentration of trip attractors in this region. High centrality values are also observed for both data sets in most of the city's secondary streets, which connect peripheral neighborhoods to the city center. However, the incorporation of cyclists' perception of stress in the routing algorithm reflects in large differences in centrality in some other streets of greater functional hierarchy. For example, on Sergio Furcin Avenue (see Figure 4), the high speed of motorized traffic (despite the regulated limit of 30 km/h)

and the presence of a roundabout (ALTS) cause a great number of low-stress cycling routes to detour to Valfredo Alves de Souza and José Furcin streets, resulting in increased centrality of the latter when compared to their distance-based centralities.

In total, 450 links (out of 2,261) in the Bariri network have zero distance-based centrality, and 441 have zero stress-based centrality, with 412 links in common between the two criteria having no relative importance in the network. Among the 29 links used in the shortest paths but not in the low-stress routes, only 1 has obstacles along the road (high parking rate) and 2 have roundabouts, but ALTS due to steep slopes were assigned to 14 of them (8 for up-slopes and 6 for down-slopes steeper than 3%). The simultaneous assignment of ALTS only occurred for 1 link, originally classified as LTS 2 and which was reclassified as LTS 4.

Addressing our second Research Question, all links in the network were ranked according to their centrality for both data sets (the link with the highest centrality was ranked 1st, that is, with the highest priority for cycling investments; the link with the second highest centrality was ranked as 2nd, and so on). Then, homologous rank differences were computed (*RD*), thus identifying similarities in the priority level for cycling investments and mismatches between distance-based and stress-based centralities. Figure 5 shows the spatial distribution (Figure 5a) and the cluster (Figure 5b) and significance (Figure 5c) maps of these rank differences.
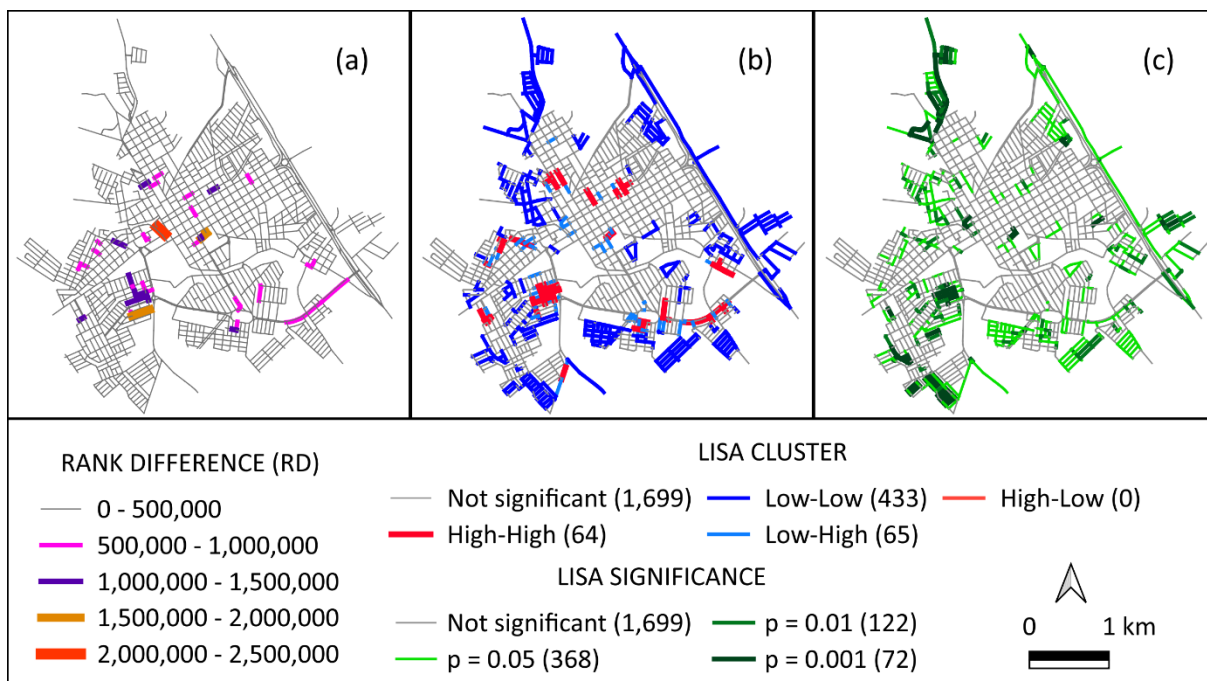

Figure 5. Rank differences: a) spatial distribution, b) cluster map and c) significance map.

Using the graduated symbology in five classes of equal amplitude and their graphic differentiation by both size and color, the 50 main links can be clearly observed in the network of the city of Bariri for which mismatches in the priority of cycling investment are expected. In 20 of these links, stress-based centralities prevail over distance-based centralities, among which 16 are classified as LTS 1, 3 as LTS 2, and only 1 as LTS 3, in the latter case, originally classified as LTS 1, but reclassified due to its slope steeper than 3%. As for the other 30 network links, in which stress-based centralities are underestimated when compared to distance-based centralities, 11 of them are classified as LTS 3 or 4 (among which 9 were assigned ALTS, mostly due to steep slopes).

The Local Moran's Index suggests 562 significant locations in terms of spatial association of rank differences. For 433 of these locations, similarity is observed in the priority level for cycling investments (Low-Low), mostly located in peripheral regions of the city of Bariri, and among which 205 have zero centrality regardless of the criterion used (distance or stress). Another 64 links, however, are characterized by dissimilarity in the priority level for cycling investments (High-High), 3 and 8 of them located, respectively, in sections of primary and secondary streets classified as LTS 3 or 4; and all others on residential streets (12 of which are also classified as highly stressful for cycling due to ALTS).

Negative spatial association (Low-High) is observed for 65 outliers, which can be understood as road segments where the same level of investment priority is observed regardless of the criterion used, close to other road segments where, on the other hand, it is observed a dissimilarity in the level of prioritization. In terms of policy-making, a Low-High outlier with high centrality has an excellent level of prioritization in cycling investments (as is the case with some outliers located in the secondary streets of Bariri), because although adjacent links decrease their relative importance when stress variables are considered, it maintains its overall contribution to the cycling routes. No High-Low outliers are observed for the case study.

Finally, some insights are provided to illustrate to the reader how the research method can guide the rational allocation of resources in cycling infrastructure. For example, on Sergio Forcin Avenue in Bariri, whose centralities are detailed in Figure 4, it is proposed to accommodate bike lanes, as long as it is possible to retrofit the road by narrowing traffic lanes, restricting parking, etc. (Toole, 2010) in order to ensure the minimum width of 1.20 meters required by this type of facility (GEIPOT, 2001). Therefore, due to its favorable topographical conditions, a decrease in the stress level of cyclists would be expected even if the speed of motorized traffic was 60 km/h, a value well above that compatible with the road's functional hierarchy.

4. CONCLUSION

This paper introduced and compared two approaches (with and without incorporating stress variables) to measure the overall contribution of network links to cycling routes that provide access to trip attractors. The output consists of mapping the centrality of each link in the network, from which it is possible to define priority locations for investments in cycling infrastructure by ranking those links with greater relative importance. These specific improvements, in turn, can gradually evolve into continuous cycling networks, helping transport authorities in the preparation of urban mobility plans.

Authors such as Melo and Isler (2023) argue that the application of models to measure the impact of the provision of cycling infrastructure on the accessibility of cyclists in short-term planning can guide future interventions with regard to the design of continuous and well-connected cycling networks. However, the application of these models is conditioned by data availability (O-D matrix, bicycle count data, etc.) and requires prior knowledge of the tools and techniques to be used, which is a distant reality in the case of small-sized cities (especially in emerging countries). In this context, the results of the case study suggest some strengths regarding policy implications arising from the application of the proposed method, as it is easy to apply and benefits only from open data and free software. Furthermore, while appearing to have no immediate practical effects, one-off cycling projects, such as providing isolated infrastructure in locations that would benefit from better LTS classifications, can gradually evolve to "low-stress cycling networks" (Moran et al., 2018; Monari, 2022).

As for the limitations, the case study results point to considerable agreement between homologous centralities measured with or without stress variables, which suggests that the traffic stress in the city of Bariri is not high enough to be considered relevant. Future research is encouraged to also apply the method to larger cities and cities with greater road complexity and topographical characteristics less favorable to cycling, aiming to provide a more robust body of evidence so that the approach can be validated as a tool for cycling planning. Furthermore, other stress variables must be incorporated into the method, such as pavement conditions and heavy vehicle traffic, etc., in addition to studying the impacts on centrality resulting from the use of models for traffic allocation for congested transport networks.

REFERENCES

Andrade, V.; J. Rodrigues; F. Marino et al. (2016) *Mobilidade por Bicicleta no Brasil* (1a ed.). Rio de Janeiro: PROURB/UFRJ.

Anselin, L. (1995) Local Indicators of Spatial Association - LISA, *Geographical Analysis*, v. 27, n. 2, p. 93-115. DOI: 10.1111/j.1538-4632.1995.tb00338.x.

Anselin, L.; I. Syabri and Y. Kho (2006) GeoDa: an introduction to spatial data analysis, *Geographical Analysis*, v. 38, n. 1, p. 5-22. DOI: 10.1111/j.0016-7363.2005.00671.x.

Arellana, J.; M. Saltarín; A.M. Larranaga et al. (2020) Developing an urban bikeability index for different types of cyclists as a tool to prioritize bicycle infrastructure investments, *Transportation Research Part A, Policy and Practice*, v. 139, p. 310-34. DOI: 10.1016/j.tra.2020.07.010.

Austroads (2014) *Cycling Aspects of Austroads Guides* (2nd ed.). Sydney: Austroads Ltd..

Beura, S.K.; V.L. Manusha; H. Chellapilla et al. (2018) Defining bicycle levels of service criteria using levenberg-marquardt and self-organizing map algorithm, *Transportation in Developing Economies*, v. 4, n. 2, p. 11. DOI: 10.1007/s40890-018-0066-0.

Brasil (2007) *Caderno de Referência para Elaboração de Plano de Mobilidade por Bicicleta nas Cidades*. Brasília: Brazilian Bicycle Mobility Program.

Brasil (2012) Law Nr. 12.587 of January 3, 2012. Establishes the Guidelines of the National Urban Mobility Policy. *Brazilian Union Official Diary*, Brasília.

Brasil (2019) *Pesquisa Nacional de Mobilidade Urbana 2018*. Brasília. Available at: <https://www.gov.br/cidades/pt-br/assuntos/mobilidade-urbana/Relatorio_Pemob_2018.pdf> (accessed 04/27/2024).

Broach, J.; J. Dill and J. Gliebe (2012) Where do cyclists ride? A route choice model developed with revealed preference GPS Data, *Transportation Research Part A, Policy and Practice*, v. 46, n. 10, p. 1730-40. DOI: 10.1016/j.tra.2012.07.005.

Callister, D. and M. Lowry (2013) Tools and strategies for wide-scale bicycle level-of-service analysis, *Journal of Urban Planning and Development*, v. 139, n. 4, p. 250-7. DOI: 10.1061/(ASCE)UP.1943-5444.0000159.

Cervero, R.; S. Denman and Y. Jin (2019) Network design, built and natural environments, and bicycle commuting: evidence from british cities and towns, *Transport Policy*, v. 74, p. 153-64. DOI: 10.1016/j.tranpol.2018.09.007.

Conrow, L.; E. Wentz; N. Trisalyn et al. (2018) Comparing spatial patterns of crowdsourced and conventional bicycling datasets, *Applied Geography*, v. 92, p. 21-30. DOI: 10.1016/j.apgeog.2018.01.009.

Dijkstra, E.W. (1959) A note on two problems in connexion with graphs, *Numerische Mathematik*, v. 1, n. 1, p. 269-71. http://doi.org/10.1007/BF01386390.

EMBRAPA (1979) Brazilian National Soil Survey and Conservation Service. In *Anais da 10ª Reunião Técnica de Levantamento de Solos*. Rio de Janeiro: EMBRAPA.

Ferenchak, N.N. and W.E. Marshall (2020) Validation of bicycle level of traffic stress and perceived safety for children, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2674, n. 4, p. 397-406. DOI: 10.1177/0361198120909833.

Furth, P.G. (2017) *Level of Traffic Stress Criteria for Road Segments Version 2.0*. Available at: <https://bpb-us-w2.wpmucdn.com/sites.northeastern.edu/dist/e/618/files/2014/05/LTS-Tables-v2-June-1.pdf> (accessed 04/27/2024).

Furth, P.G.; M.C. Mekuria and H. Nixon (2016) Network connectivity for low-stress bicycling, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2587, n. 1, p. 41-9. DOI: 10.3141/2587-06.

GEIPOT (2001) *Manual de Planejamento Cicloviário*. Brasília: GEIPOT.

Google Maps (2023) Bariri-SP, Brazil. Available at: <https://www.google.com.br/maps/place/Bariri> (accessed 12/22/2021).

Guerreiro, T.C.M.; J.K. Providelo; C.S. Pitombo et al. (2018) Data-Mining, GIS and multicriteria analysis in a comprehensive method for bicycle network planning and design, *International Journal of Sustainable Transportation*, v. 12, n. 3, p. 179-91. DOI: 10.1080/15568318.2017.1342156.

Harkey, D.L.; D.W. Reinfurt; M. Knuiman et al. (1998) *Development of a Bicycle Compatibility Index: A Level of Service Concept*. Chapel Hill, USA: Highway Safety Research Center. DOI: http://doi.org/10.3141/1636-03.

IBGE (2012) 2010 Brazilian Demographic Census [Data set]. Available at: <https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/28971-base-de-faces-de-logradouros-dobrasil.html?=&t=acesso-ao-produto> (accessed 04/16/2022).

IBGE (2022) Population Estimates. Available at: <https://cidades.ibge.gov.br/brasil/sp/bariri/panorama> (accessed 04/16/2022)

INPE (2008) TOPODATA: banco de dados geomorfométricos do Brasil [Data set]. Available at: <http://www.dsr.inpe.br/topodata/acesso.php>(accessed 04/16/2022).

Klobucar, M.S. and J.D. Fricker (2007) Network evaluation tool to improve real and perceived bicycle safety, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2031, n. 1, p. 25-33. DOI: 10.3141/2031-04.

Lobo, Z.; V. Andrade and J. Rodrigues (2020) Available at: <http://ta.org.br/perfil/ciclista18.pdf> (accessed 03/25/2022).

Lowry, M.; D. Callister; M. Gresham et al. (2012) Assessment of cummunitywide bikeability with bicycle level of service, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2314, n. 1, p. 41-8. DOI: 10.3141/2314-06.

Lowry, M.; P. Furth and T. Hadden-Loh (2016) Prioritizing new bicycle facilities to improve low-stress network connectivity, *Transportation Research Part A, Policy and Practice*, v. 86, p. 124-40. DOI: 10.1016/j.tra.2016.02.003.

McDaniel, S.; M. Lowry and M. Dixon (2014) Using origin-destination centrality to estimate directional bicycle volumes, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2430, n. 1, p. 12-9. DOI: 10.3141/2430-02.

McNeil, N. (2011) Bikeability and the 20-Min Neighborhood: how infrastructure and destinations influence bicycle accessibility, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2247, n. 1, p. 53-63. DOI: 10.3141/2247-07.

Mekuria, M. C.; P. G. Furth and H. Nixon (2012) *Low-Stress Bicycling and Network Connectivity*. San José, CA: Mineta Transportation Institute.

Melo, L.E.A. and C.A. Isler (2023) Integrating link count data for enhanced estimation of deterrence functions: a case study of short-term bicycle network interventions, *Journal of Transport Geography*, v. 112, p. 103711. DOI: 10.1016/j.jtrangeo.2023.103711.

Menghini, G.; N. Carrasco; N. Schüssler et al. (2010) Route choice of cyclists in Zurich, *Transportation Research Part A, Policy and Practice*, v. 44, n. 9, p. 754-65. DOI: 10.1016/j.tra.2010.07.008.

Monari, M. (2022) *Nível de Estresse de Ciclistas e Geoprocessamento de Dados Abertos Combinados para a Definição de Redes Cicloviárias em Cidades de Pequeno Porte*. Thesis (Transportation Engineering), University of São Paulo, São Carlos.

Monari, M. and P.C.L. Segantine (2022) Cycling planning in small-sized brazilian cities based on open data geoprocessing, *Revista Brasileira de Cartografia*, v. 74, n. 2, p. 418-36. DOI: 10.14393/rbcv74n2-63475.

Morais, A.C.M.D. and E.M.D. Santos (2020) Avaliação das estruturas organizacionais dos organismos gestores da mobilidade diante da Política Nacional de Mobilidade Urbana, *Urbe. Revista Brasileira de Gestão Urbana*, v. 12, p. e20190232. DOI: 10.1590/2175-3369.012.e20190232.

Moran, S.K.; W. Tsay; S. Lawrence et al. (2018) Lowering bicycle stress one link at a time: where should we invest in infrastructure, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2672, n. 36, p. 33-41. DOI: 10.1177/0361198118783109.

Pucher, J. and R. Buehler (2012). *City Cycling*. Cambridge: MIT Press. DOI: 10.7551/mitpress/9434.001.0001.

Rodrigues, M.R.; A.N.R. Silva and I.P. Teixeira (2022) Assessing the applicability of the cyclists' Level of Traffic Stress (LTS) classification to a medium-sized city in a developing country, *Journal of Transport & Health*, v. 24, p. 101321. DOI: 10.1016/j.jth.2021.101321.

Rybarczyk, G. and C. Wu (2010) Bicycle facility planning using gis and multi-criteria decision analysis, *Applied Geography*, v. 30, n. 2, p. 282-93. DOI: 10.1016/j.apgeog.2009.08.005.

Rybarczyk, G.; A. Ozbil; E. Andresen et al. (2020) Physiological responses to urban design during bicycling: a naturalistic investigation, *Transportation Research Part F: Traffic Psychology and Behaviour*, v. 68, p. 79-93. DOI: 10.1016/j.trf.2019.12.001.

SEMOB (2021) Bate-Papo com a CNM Orienta os Gestores na Implementação de Planos de Mobilidade Urbana. Available at: <https://www.cnm.org.br/comunicacao/noticias/bate-papo-com-a-cnm-orienta-os-gestores-na-implementacao-de-planos-de-mobilidade-urbana>. Access: December 22, 2021.

Sener, I.N.; N. Eluru and C.R. Bhat (2009) An analysis of bicycle route choice preferences in Texas, US, *Transportation*, v. 36, n. 5, p. 511-39. DOI: 10.1007/s11116-009-9201-4.

Shimbel, A. (1953) Structural parameters of communication networks, *The Bulletin of Mathematical Biophysics*, v. 15, n. 4, p. 501-7. DOI: 10.1007/BF02476438.

Soares, A. and D. Guth (2018) *O Brasil que Pedala: A Cultura da Bicicleta nas Cidades Pequenas* (1st ed.). Rio de Janeiro: Jaguatirica.

Toole, J. (2010) Revising the AASHTO Guide for the Development of Bicycle Facilities. Available at: <https://onlinepubs.trb.org/onlinepubs/nchrp/docs/nchrp_15-37_fr.pdf> (accessed 03/25/2022).

Transport Scotland (2010) *Cycling by Design 2010*. Glasgow: Transport Scotland.

TRB (2010) *Highway Capacity Manual*. Washington, D.C.: TRB.

Vieira, P.; J. Costeira; S. Brandão et al. (2016) SMARTcycling: assessing cyclists' driving experience. In: *2016 IEEE Intelligent Vehicles Symposium*. Gothenburg, Sweden: IEEE, p. 1321-1326. DOI: 10.1109/IVS.2016.7535561.

Wang, H.; M. Palm; C. Chen et al. (2016) Does bicycle network level of traffic stress (LTS) explain bicycle travel behavior? Mixed results from an Oregon case study, *Journal of Transport Geography*, v. 57, p. 8-18. DOI: 10.1016/j.jtrangeo.2016.08.016.

Winters, M.; K. Teschke; M. Grant et al. (2010) How far out the way will we travel? Built environmental influences on route selection for bicycle and car travel, *Transportation Research Record: Journal of the Transportation Research Board*, v. 2190, n. 1, p. 1-10. DOI: 10.3141/2190-01.

Zeile, P.; B. Resch; M. Loidl et al. (2016) Urban emotions and cycling experience - enriching traffic planning for cyclists with human sensor data, *Journal for Geographic Information Science*, v. 4, n. 1, p. 204-16. DOI: 10.1553/giscience2016_01_s204.