COMPARING DISTANCE-BASED AND STRESS-BASED CENTRALITIES TO RANK PRIORITY LOCATIONS FOR CYCLING INVESTMENTS IN EMERGING COUNTRIES

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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 (LTS), to determine the relative importance of road segments in the network and to rank priority locations for investments in cycling projects. 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 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 (LTS), para determinação da importância relativa de segmentos viários na rede e hierarquização de projetos cicloviários prioritários. 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 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 congestion, 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, the Brazilian National Urban Mobility Policy (PNMU-Brazil) establishes that municipalities with more than 20,000 inhabitants must prepare urban mobility plans that favor collective and non-motorized transport, but since its institution by Law No. 12,587, of January 3, 2012 (Brazil, 2012), the deadline for complying with the legal requirement has been repeatedly extended due to the inability of most municipalities, with only 14% of them having prepared their plans 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 the Brazilian context (Brazilian Ministry of Regional Development, 2019). In addition, although there are several Bicycle Compatibility Indexes (BCI) or Level of Service (BLOS) models in the literature (Harkey *et al*., 1998; Landis *et al*., 1997; 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). However, decision-making regarding cycling investments in small- and medium-sized Brazilian cities can benefit from simpler methodologies for evaluating the operational quality of existing roads, such as those based on the level of cyclists' stress (Monari and Segantine, 2020).

Recently, several works in the literature 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 *et al*. (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 to propose cycling networks in two small-sized cities, prioritizing links in the network with greater centrality. Despite this, authors such as Ferenchak and Marshall (2020) emphasize the need for validation of the LTS classification through measures of the physiological stress of cyclists, and others, such as Zeile *et al.* (2016) or Rybarczyk *et al.* (2020), the need to include additional stress variables in models of this nature.

This 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 projects. 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).

To achieve this goal, the two following Research Questions must be answered:

- Are there differences between priority locations for cycling investments based on the shortest paths and the least stressful routes for cyclists?
- What are the locations with the greatest similarity and dissimilarity in terms of their relative importance to cycling when evaluated by both criteria described?

2. METHOD

This section presents the research method and is subdivided into i) Cycling routes, ii) Centrality, iii) Ranking of centralities and iv) Case study data. 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 associated with the BCI (Klobucar and Fricker, 2007), the BLOS (Lowry *et al.*, 2012) or the LTS (Monari *et al.*, 2018).

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

2.1.1. Stress factor

Tables 1 and 2 present, in this order, the criteria for the LTS classification of mixed traffic sections (original) and 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 *et al.*, 2012; Furth, 2017). Equations 3 to 6, in turn, summarize the changes proposed by Rodrigues *et al.* (2022) to the LTS classification, which follow the preliminary assessment to include 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: LTS in mixed traffic (Source: Mekuria *et al.*, 2012)

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

Table 2: LTS criteria for bike lane classification (Source: Furth, 2017)

Number of lanes per direction	Bike lane width	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

[b] Includes any marked buffer next to the bike lane.

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

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

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

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

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

Stress factors are usually assigned to network links based on Marginal Rates of Substitution (MRS) associated with the maximum detour acceptable by cyclists from their shortest paths, in which values between 15% and 25% are suggested in the literature (Furth *et al.*, 2016; Cervero *et al.*, 2019). In this research, however, we sought to standardize the intervals between the four increasing LTS classifications by adopting a maximum detour rate of 30%, that is, from LTS 1 to LTS 4, stress factors of 1.00, 1.10, 1.20 and 1.30 were respectively assigned.

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). Gravity-based centrality (or O-D centrality), in turn, can be calculated by weighting this contribution by the potential demand accumulated at each origin and by the attractiveness of each destination (McDaniel *et al.*, 2014), as presented by Equations 7 to 10.

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

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

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

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

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} is the shortest path from *i* to *j*; σ_{ij}^* is the low-stress path from *i* to *j*; M_i and M_j are, respectively, the multipliers for origin *i* and destination *j*; *O* is the set of all origins; *J* is the set of all destinations; D_{ij} is the network distance between *i* and *j*; and δ is the reachable distance threshold for bicycles, adopted in this work as 5 km (Brazilian Ministry of Cities, 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 *et al.*, 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 3) 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; y_k 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 3: Weighting factors (y_k) for age-income combinations (k) of the population (Source: 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 their respective cycling attractiveness (Equations 13 and 14) based on the weighting system presented in Table 4, adapted from the work of McNeil (2011).

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

$$M_j = \frac{a_j}{\sum_{j \in J} a_j} \tag{14}$$

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

Table 4: Weighting system for trip attractors (Source: Adapted from McNeil, 2011)

Classification	Trip attractor (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
Other	General services (post office, bank, etc.) (*14*)	5.0
	Religious organization (*15*)	5.0
	First aid station, hospital, etc. (*16*)	10.0
Total		100.0

Altogether, five classifications were proposed for trip attractors (including those related to work, which differs from the original proposal) to which equal weights were assigned, that is, 20 out of a total of 100 points. Then, each classification was subdivided to consider the relative importance between trip attractors of the same nature (for example, a supermarket is expected to attract more bicycle trips than a beauty salon, therefore it should receive a greater weight), in addition to regrouping and including different facilities not considered in the base work.

2.3. Ranking of centralities

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 in the network through Equation 15, defined as *Rank Difference* (*RD*). Finally, the Local Moran's Index was also calculated for each network 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.

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

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

where RD_e and RD_d are, respectively, the rank differences for links e and d; $R_{dist,e}$ is the distance-based rank for link e; $R_{stress,e}$ is the stress-based rank for link e; 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 36,000 inhabitants (IBGE, 2021). Figure 1 shows the case study data required for the application of the method.

Road system information was obtained from collaborative mapping (OpenStreetMap, or OSM). We increased the original network by vectorizing bike lanes and shared-used spaces that did not exist in the OSM features, totaling 2,261 links. 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.

Altimetric data were extracted from the 30-meter spatial resolution TOPODATA DEM provided by the Brazilian National Institute for Space Research (INPE-Brazil), and aggregated population data (income and age) by census tracts were obtained from the results of the 2010 Brazilian Demographic Census (IBGE-Brazil), which we transferred to a set of regular georeferenced cells also made available by the IBGE (statistical grid) 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, which we also transferred to the statistical grid through the density of points in each polygon.

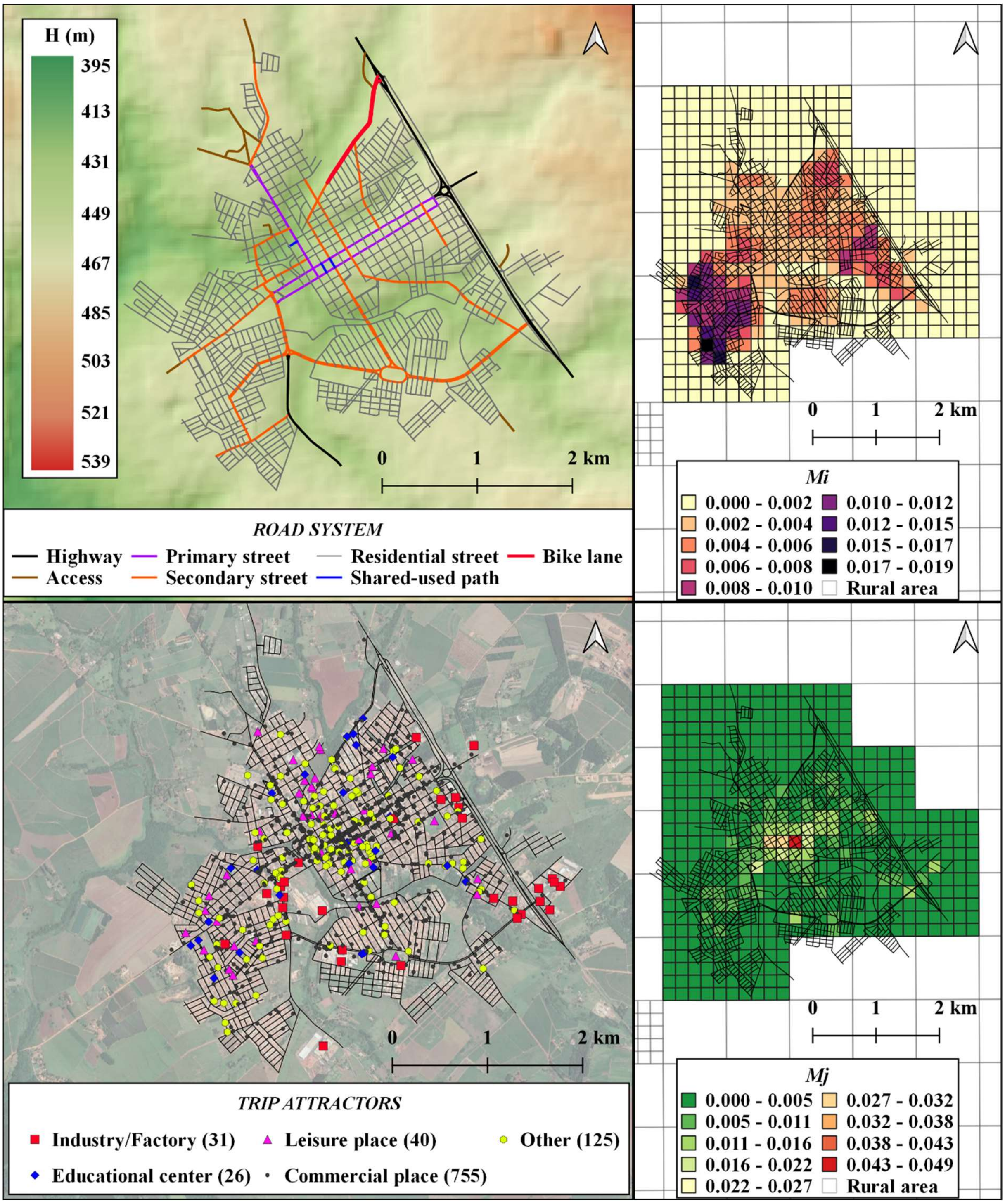

Figure 1: Case study data

3. RESULTS AND DISCUSSION

The results from the application of the method in the case study allow numerical and visual comparisons between the distance-based and stress-based centralities of each link in the network of the city of Bariri, as shown in Figure 2. Furthermore, the results also suggest a strong positive correlation between centralities for both data sets (0.83).

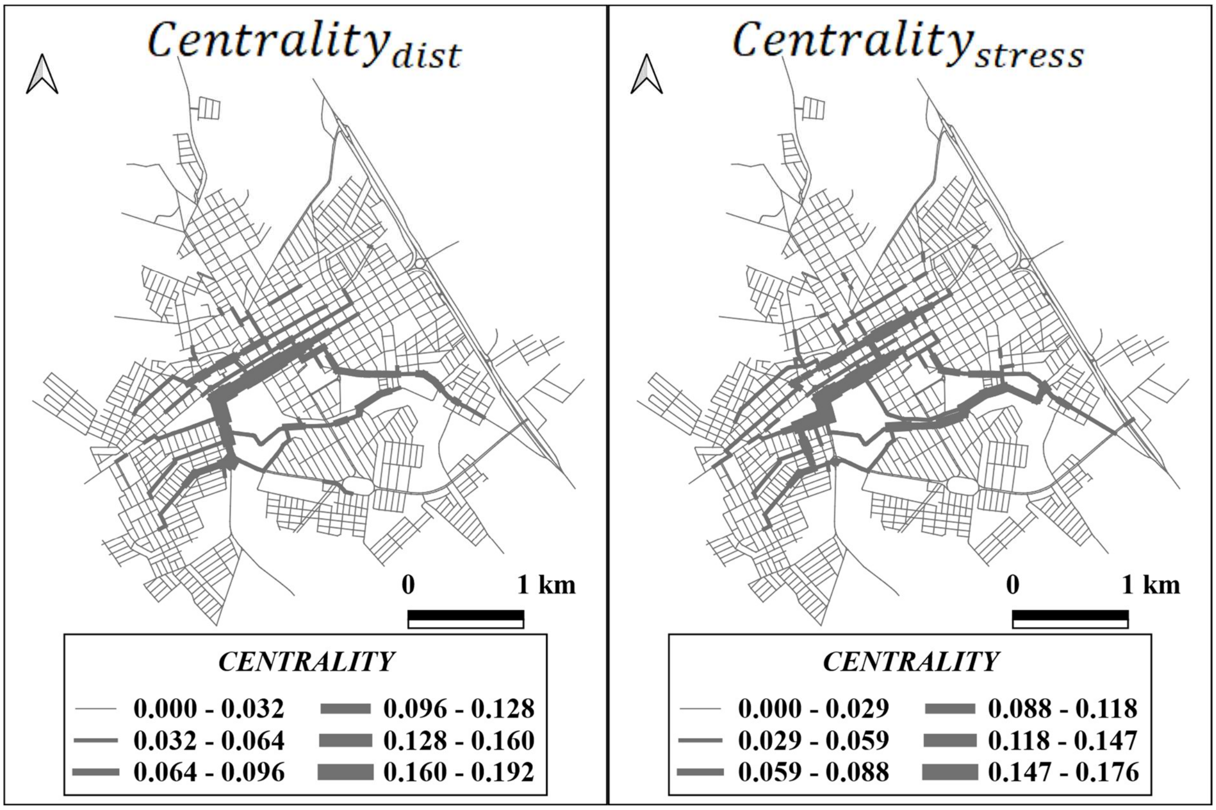

Figure 2: Distance-based and stress-based centralities of each link in the Bariri network

Network links with great contribution to the identified routes are expected to receive large flows of cyclists and should be prioritized in future cycling projects and in resource allocation. 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 Sérgio Forcin Avenue (Figure 3), 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 links) 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 network links used in the shortest paths but not in the low-stress cycling 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 uphill and 6 for downhill slopes greater than 3%). The simultaneous assignment of ALTS only occurred for 1 network link, originally classified as LTS 2 and which was reclassified as LTS 4.

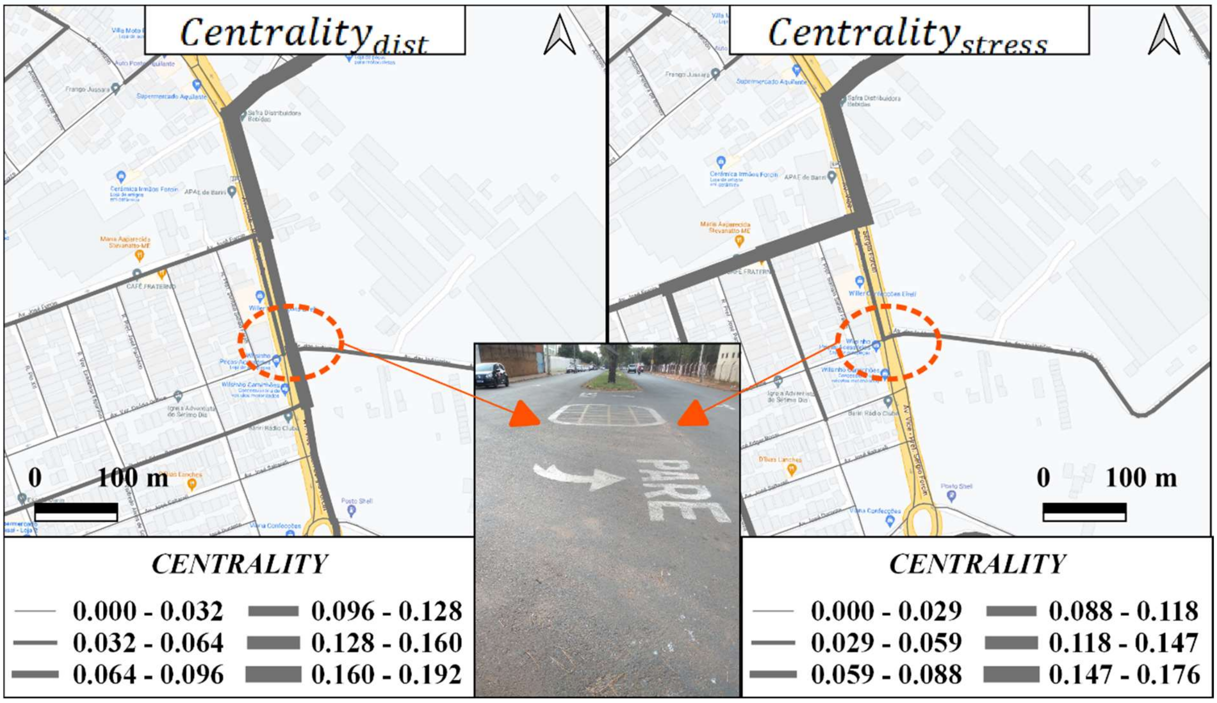

Figure 3: Distance-based and stress-based centralities of Sérgio Forcin Avenue

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 4 shows the spatial distribution and the cluster and significance maps of these rank differences.

Using the graduated symbology in five classes of equal amplitude and their graphic differentiation by both size and colors, 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 ones, 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 5%. 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 network 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). Finally, 65 outliers of negative spatial association (Low-High) contiguous to the dissimilarity localities are observed. No High-Low outliers are observed for the case study.

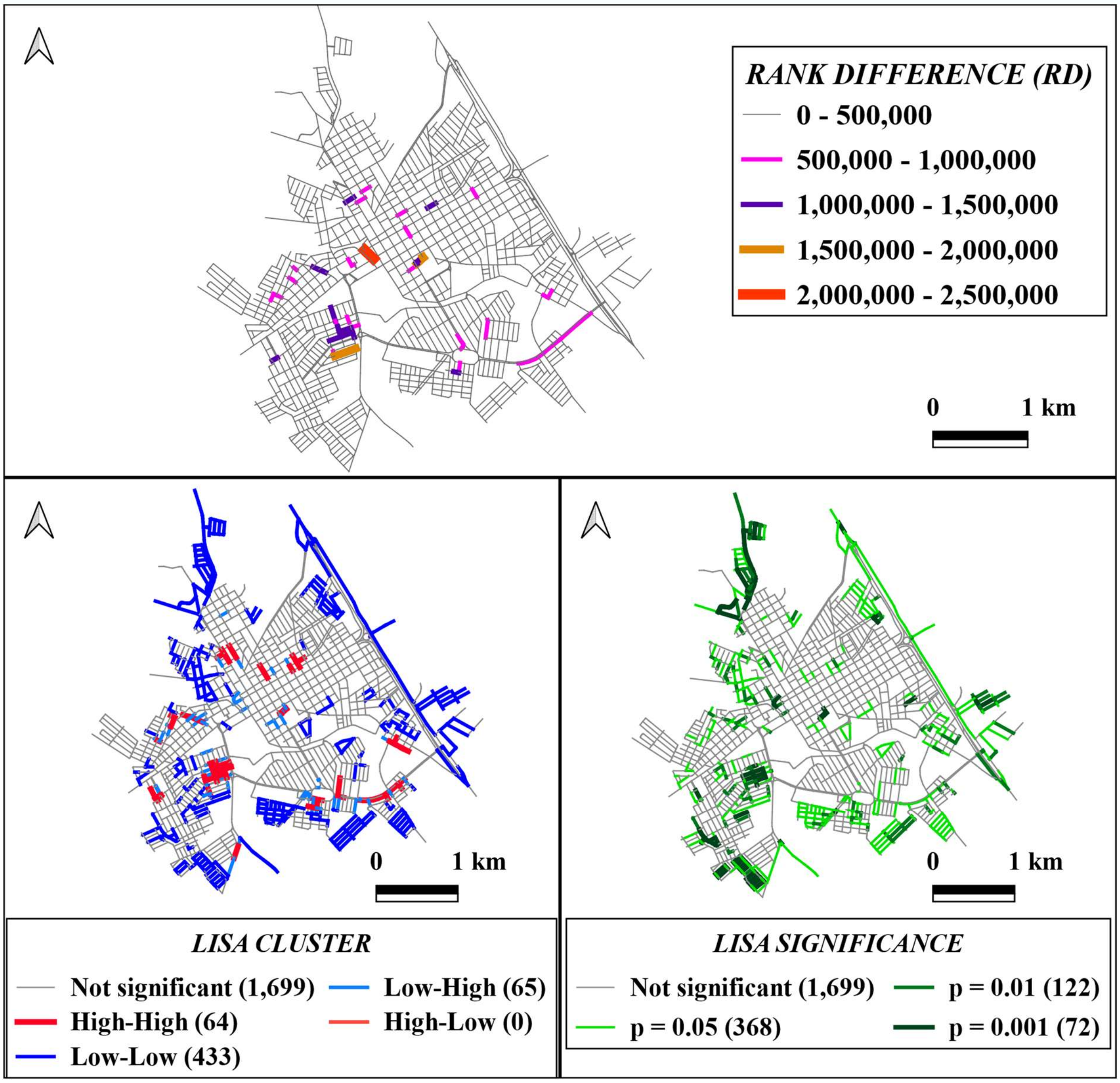

Figure 4: Spatial distribution and cluster map of the rank differences

4. CONCLUSION

This paper introduced and compared two approaches, with and without incorporating stress variables, to define priority locations for cycling investments and that can help to prepare urban mobility plans, especially in emerging countries. The output consists of mapping the centrality of each network link, from which the most relevant cycling projects can be ranked. These projects, in turn, can gradually evolve into continuous cycling networks.

The application of both approaches in a case study led to a discussion on some strengths and limitations of the research. Regarding the strengths, the method is easy to apply, and it benefits from open data and free software. As for the limitations, there is considerable agreement between homologous centralities measured with or without stress variables, which suggests that the traffic stress of this particular case study was not high enough to be considered relevant. These results, however, may not be extended to cities where there are arterial roads, or even those characterized by hilly terrain. Thus, it is suggested that future work should reproduce this research method, also for these cases.

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