Rev. Bras. Cartogr, vol. 74, n. 4, 2022 DOI: http://dx.doi.org/10.14393/rbcv74n4-65916

Revista Brasileira de Cartografia
ISSN 1808-0936 | https://doi.org/10.14393/revbrascartogr
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto

# Evaluating the Cycling Infrastructure and Spatial Interpolation of Quality Indicators: an Approach Based on the Analytic Hierarchy Process and Geostatistics

*Avaliação da Infraestrutura Cicloviária e Interpolação Espacial de Seus Indicadores de Qualidade: uma Abordagem Baseada em Análise Hierárquica e Geoestatística*

Wellington de Aquino Traldi [1], Samuel de França Marques [2], Cira Souza Pitombo [3], Pablo Brilhante de Sousa [4] and Ricardo Almeida de Melo [5]

1 University of São Paulo, Department of Transportation Engineering, São Carlos, Brazil. E-mail. traldiwellington@gmail.com
ORCID: https://orcid.org/0000-0003-2471-5732
2 University of São Paulo, Department of Transportation Engineering, São Carlos, Brazil. E-mail. samuelmarques@usp.br
ORCID: https://orcid.org/0000-0001-5602-3277
3 University of São Paulo, Department of Transportation Engineering, São Carlos, Brazil. E-mail. cirapitombo@usp.br
ORCID: https://orcid.org/0000-0001-9864-3175
4 Federal University of Paraíba, Department of Civil and Environmental Engineering, João Pessoa, Brazil. E-mail. pablo@ct.ufpb.br
ORCID: http://orcid.org/0000-0002-2526-3312
5 Federal University of Paraíba, Department of Civil and Environmental Engineering, João Pessoa, Brazil. E-mail. ricardo@ct.ufpb.br
ORCID: https://orcid.org/0000-0001-8993-5264

Recebido: 06.2022 | Aceito: 08.2022

**Abstract:** The main aims of this article are: (1) to evaluate the quality of cycling infrastructures in the city of João Pessoa (PB) using the Analytic Hierarchy Process (AHP) and (2) to extend the proposed assessment (using quality indicators) to the entire cycling network of the municipality applying geostatistical spatial interpolators. Therefore, a two-step approach was proposed. Initially, the physical and operational factors that affect the quality of cycling infrastructures were identified to formulate the hierarchy. Afterwards, five specialists in cycling infrastructures and cycle path users were asked to fill in a form, aiming to weight the criteria. Next, we used a database collected in the field from 27 sections of cycle paths. After obtaining the scores for each section, they were classified, and maps were created to locate the critical sections. Having verified if there was spatial dependence, related to the cycling quality indicator, geostatistical modeling was carried out and the quality indicator was estimated for 32 cycle path sections, not previously collected in the field. Therefore, the complete cycle network map, which was properly evaluated, can be used as a low-cost tool to support decision-making and implementation of transport policies.
**Keywords:** Urban mobility. Multi Criteria Analysis. Active travel modes. Ordinary Kriging. Urban and Cycling infrastructure.

**Resumo**: O presente artigo tem dois objetivos associados: (1) avaliar a qualidade da infraestrutura cicloviária no município de João Pessoa (PB) através de Processo de Análise Hierárquica e (2) realizar uma extensão da avaliação proposta, através de indicadores de qualidade, para toda a rede cicloviária do município, por meio de interpoladores espaciais geoestatísticos. Assim, é proposta uma abordagem de duas etapas. Incialmente, foram identificados fatores físicos e operacionais que afetam a qualidade da infraestrutura cicloviária para a elaboração da hierarquia. Posteriormente, foi aplicado um formulário a cinco especialistas em infraestrutura cicloviária e usuários de ciclovias/ciclofaixas, com o objetivo de ponderar os critérios. Após a ponderação dos critérios, que compõem a estrutura hierárquica proposta, foram utilizados dados de 27 trechos cicloviários, coletados em campo. Após a pontuação associada a cada trecho, estes foram classificados e mapas temáticos foram construídos para a localização dos trechos críticos. Observando-se a existência de dependência espacial, em relação ao indicador de qualidade cicloviária, foi possível realizar uma modelagem geoestatística e estimar o indicador de qualidade para 32 trechos não inspecionados previamente em campo. Dessa forma, o mapa da rede cicloviária completa, devidamente avaliada, pode ser utilizado como ferramenta de baixo custo de apoio à tomada de decisão e implementações de políticas de transporte.
**Palavras-chave:** Mobilidade urbana. Análise Multicritério. Modos ativos. Krigagem Ordinária. Infraestrutura urbana e cicloviária.

## 1 INTRODUCTION

In recent years, there has been a significant increase in the interest and relevance of topics associated with using active travel modes, cycling infrastructure and sustainable mobility (DIXON, 1996; MONTEIRO; CAMPOS, 2011; SILVEIRA; MAIA, 2015; CAMPOS; CARDOSO, 2016). The Urban Mobility Law, Law 12587 of 2012 (BRASIL, 2012), established the guidelines of the National Urban Mobility Policy aiming to integrate the different travel modes and improve the accessibility and mobility of people and freight in the municipality. Furthermore, article 5 of this Law establishes equity in the use of public circulation space, roads and public places; and efficiency, efficacy and effectiveness in urban mobility. Thus, more recently, more investments have been made in non-motorized travel modes in Brazilian cities, resulting in an increase in the number of cycle paths.

Recently, an extremely important factor has affected the way people travel: the COVID-19 pandemic, which was the most serious health crisis in recent decades (COSTA; PITOMBO; SOUZA, 2022; RODRIGUES DA SILVA et al., 2022). In a survey carried out with 2,200 respondents in all regions of Brazil by *NZN Intelligence*, in partnership with *Estadão Summit Mobilidade Urbana*, 45.3% of people changed their way of commuting. It was found that 10.6% of those interviewed started to ride bikes. The data also show that 83.5% of people say they did not feel safe on public transport during the pandemic. The change in habits is reflected in the production of bicycles, as the Brazilian Association of Manufacturers of Motorcycles, Mopeds, Scooters, Bicycles and Similar (Abraciclo) predicted a 12.8% increase in production in 2021. Moreover, the sector also had a reduction in import tax (ANTP, 2021).

There has been a bicycle boom in Brazilian cities related to a growing cycling infrastructure. The use of active travel modes has been increasing in the country, leading to an increase in the demand in the cycle sector and to reflections on urban planning (ANTP, 2021). In 2020, according to the National Association of Public Transport, bicycle sales increased by 50% in sales from May to June (ANTP, 2020). Thus, the bicycles are seen as an alternative travel mode, especially in large urban centers where motor vehicle traffic is greater, saving time and encouraging healthier lifestyles.

All these factors have contributed to the increase in demand for cycling infrastructures in Brazil. However, it is important to identify the different aspects that can influence the quality of cycling infrastructure to plan its use effectively and improve global mobility (BATISTA; LIMA, 2020). Therefore, considering the increase of the cycling demand, it is important to use tools that can evaluate the implemented infrastructures regarding their physical and operational quality, so that public authorities could improve infrastructures.

Implementing existing cycle paths, or even expanding the cycling network, requires data collection for several purposes, such as: (1) analyzing the potential user demand, considering a series of factors, which includes infrastructure (PROVIDELO; SANCHES, 2010; MALDONADO-HINAREJOS; SIVAKUMAR; POLAK, 2014; DE SOUSA; KAWAMOTO, 2015); (2) identifying indicators related to the urban cycling system that characterize the quality of urban cycle paths (MEDEIROS et al, 2019; FONSECA et al., 2018); and (3) measuring these indicators in the field, aiming to detect critical sections and locations that can be potentially improved.

However, measuring certain indicators in the field to assess the quality of the cycling infrastructure, and detecting critical sections according to different criteria, can be an onerous task, depending on the extent of the evaluated cycling network. Thus, spatial interpolation techniques can be helpful in the cycle path assessment process as the evaluation can be expanded for the entire network, considering a significant set of sampled segments and the existing spatial dependence.

Geostatistics consists of a set of spatial interpolators that use information collected at sampled points in space to estimate variables of interest at unsampled points. Inspired by the pioneering work of Krige (1951), the statistical formalism of this tool was introduced by Matheron´s (1963, 1971) Theory of Regionalized Variables (RVs). The RVs refer to data that can be obtained in any geographic coordinate of the spatial field in which they ocurr and that present spatial dependence, that is, points close to each other are more related than distant points (TOBLER, 1970).

Unlike classical interpolators, such as inverse distance and nearest neighbor weighting (which are characterized as deterministic), Geostatistics assumes that the variable of interest is the result of a random process. Thus, geostatistical interpolators are able to generate uncertainty measures for estimates calculated at an unsampled point (e.g., variance and confidence intervals). In addition, they ensure that the estimates obtained are unbiased and have minimal variance. Another important difference between Geostatistics and classical interpolators refers to the adoption, by Geostatistics, of well-defined spatial models to represent the spatial correlation between database points. Among other advantages, these models can identify the maximum distance within which there is spatial correlation and only points situated within this region are used for the spatial estimation at an unsampled point (WEBSTER; OLIVER, 2007). In this context, the quality indicator calculation in non-sampled cycling segments will be strongly influenced by the values of neighboring sections, normally belonging to the same cycle path, while distant segments will have little or no influence.

Geostatistics was initially created to model spatially continuous variables. However, the lack of data referring to spatially dependent variables that cannot assume a value at any point in space has led to an increasing number of geostatistical applications to spatially discrete variables. Examples of these applications can be found in various areas of study with spatially discrete variables: epidemiology, aquaculture, agriculture, forestry sciences (CARVALHO et al., 2015; GOOVAERTS, 2009; KERRY et al., 2016; STELZENMÜLLER; EHRICH; ZAUKE, 2005) and, consistently, in transport engineering. In this context, studies have been developed both in road safety (GOMES et al., 2018; MAJUMDAR; NOLAND; OCHIENG, 2004) and in travel demand variable modeling (CHICA-OLMO; RODRÍGUEZ-LÓPEZ; CHILLÓN, 2018; LINDNER et al., 2016; LINDER; PITOMBO, 2019; MARQUES; PITOMBO, 2021a, 2021b; PITOMBO et al., 2015; SELBY; KOCKELMAN, 2013; YANG et al., 2018; ZHANG; WANG, 2014). In these studies, the authors found evidence, using a semivariogram function graph, of a consistent spatial structure in the variables under analysis, corroborated by the results obtained by them.

Thus, the present article has two objectives and contributions. The first objective of this study is to evaluate the quality of the cycling infrastructure in João Pessoa (Brazil) using the Multicriteria Analysis technique. From the evaluation obtained in a set of sampled sections, the proposal is to expand the quality indicator of the cycling infrastructure for the entire cycling network of the municipality using geostatistical modeling. Thus, this study presents a two-step method, based on the Analytic Hierarchy Process (AHP) and Geostatistics.

The main contributions are as follows: (1) Hierarchy proposal and weights to evaluate the cycling infrastructure in any other city of interest; (2) Using Geostatistics to expand urban assessments, such as the quality of sidewalks, road sections, etc. for the entire network considered.

The quality of the cycling infrastructure (variable of interest in the present study) is not a continuous phenomenon, but it still poses a major problem of data collection that motivated the development of Geostatistics. A significant difference, in this case, is that the authors do not attempt to find a continuous surface of estimated values, which refers to the final objective of the traditional approach with spatially continuous variables. In the context of spatially discrete variables, the interpolator algorithms are used to calculate estimates only in the objects where the variable is likely to occur, which, in the case of the present study, is the cycling network in João Pessoa-PB (Brazil).

This article consists of 3 sections, in addition to this introduction. Section 2 describes the materials used (data, tools such as AHP and Geostatistics, and computer packages), as well as the methodological sequence followed. Section 3 presents the Multicriteria Analysis and spatial interpolation results. Finally, Section 4 draws the main conclusions and makes suggestions for future research.

## 2 MATERIALS AND METHOD

### 2.1 Data and applications used

The research was carried out in João Pessoa from August to December 2019. João Pessoa is a municipality in the northeast of Brazil located in the state of Paraíba. Its metropolitan area comprises 12 municipalities. Occupying a territorial area of approximately 2,800 km², the estimated population of the metropolitan area in 2020 was 1,290,223 inhabitants, according to the Brazilian Institute of Geography and Statistics (IBGE). According to the 2020 Master Plan for Urban Mobility of the João Pessoa Microregion, the

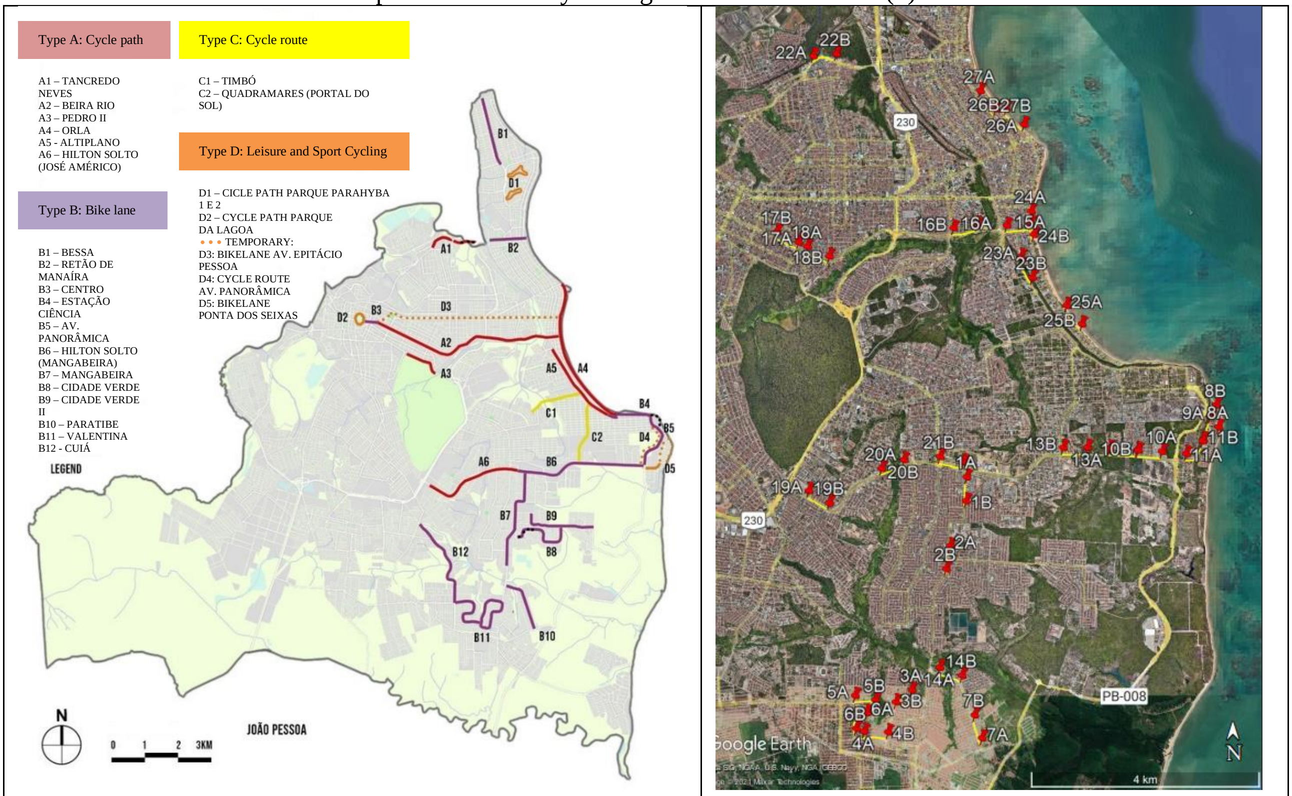
 DOI: http://dx.doi.org/10.14393/rbcv74n4-65916

cycling system in João Pessoa is currently approximately 71.5 km long, approximately 75% more than the 40.7 km it had in 2017. Figure 1a presents a map with the location and ranking of the existing cycling infrastructure in João Pessoa.

In the data collection, 27 cycling infrastructure segments (cycle paths) were selected, encompassing all regions, thus enabling us to evaluate geometric, maintenance, accessibility, traffic safety and environmental aspects (Figure 1b). The length of each of the segments was 420.00 m, totaling 11.34 km evaluated from an existing cycling network 71.5 km long. The segments were divided into 14 segments of 30.00 meters, in which 5 (five) segments were randomly selected so that 3 (three) researchers, who were previously trained, could provide scores for the criteria detailed below: slope, traffic safety, pavement width, signalization, drainage, comfort, public safety, accessibility, sinuosity, lighting, street trees (shading) and cleanliness.

In addition to the Microsoft Excel software spreadsheets to calculate the values associated with each sampled segments, the authors also used Google Earth Pro for geolocation of the sampled segments. ArcGIS10.1 and QGIS 3.16.12 (open source) software were used for geostatistical modeling and thematic map composition, respectively.

Figure 1 - Location and grouping map of the cycling infrastructure of João Pessoa (a). Location of the start and end points of the analyzed segments in João Pessoa (b)

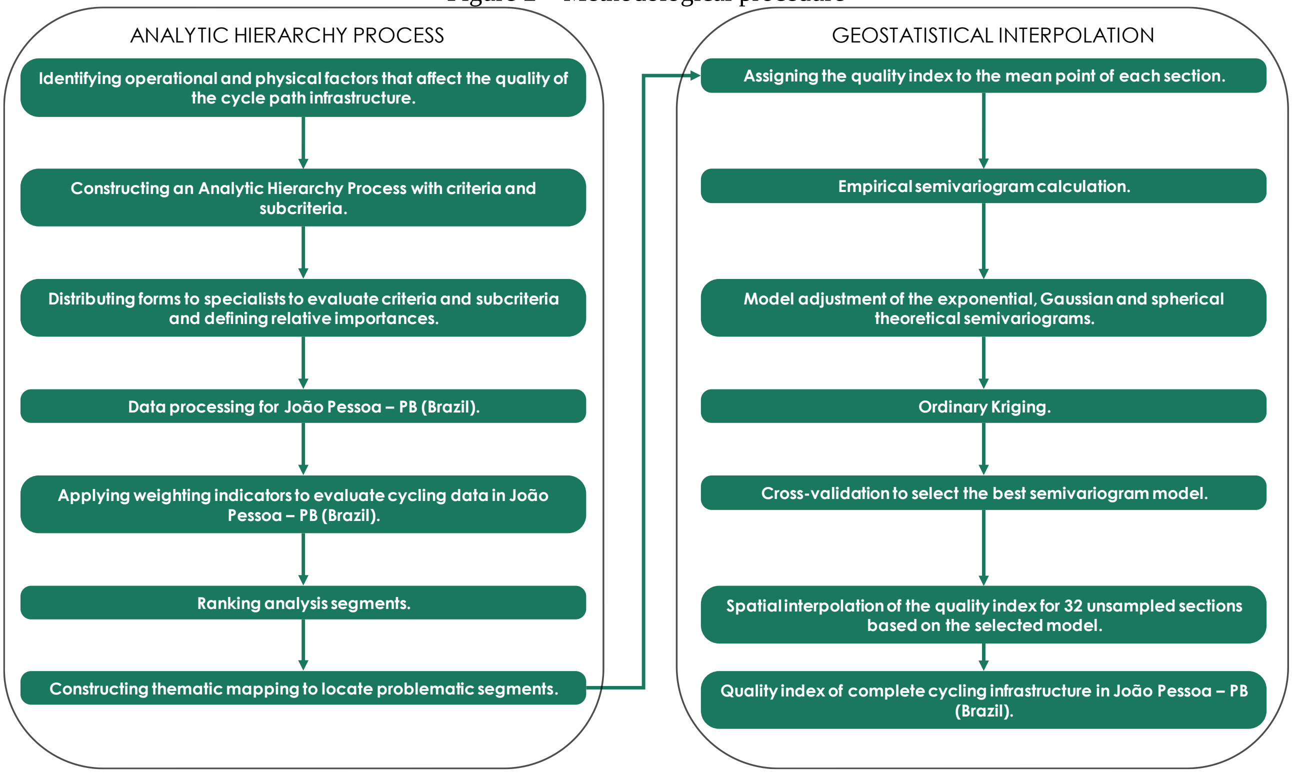



| (a) Source: Batista and Lima (2020). | (b) Source: Google Earth Pro. |
|---|---|

## 2.2 Method

The overall method of the present research follows a two-step approach, based on the Analytic Hierarchy Process and geostatistical modeling. Figure 2 illustrates the methodological procedure, described in detail in the following sections.

Figure 2 – Methodological procedure




Elaboration: The authors (2022).

### 2.2.1 THE ANALYTIC HIERARCHY PROCESS (AHP)

To construct the hierarchy, 13 criteria were used, grouped into four groups: **geometric factors** (slope, effective width and sinuosity), **conservation factors** (pavement, drainage, signalization and cleanliness), **utilization factor**s (accessibility, traffic safety and comfort) and **environmental factors** (lighting, public safety and street trees (shading)). The definition of the hierarchy was based on related literature (ANTUNES, 2015; AYACHI; DOREY; GUASTAVINO, 2015; BATISTA; LIMA, 2020; CALVEY et al., 2015; SFDPH, 2009; PROVIDELO; SANCHES, 2011).

The criterion weight was defined using the Multicriteria Decision Making (MDM) method proposed by the American mathematician Thomas Saaty in the early 1970s - the Analytic Hierarchy Process (AHP). The AHP method is based on three analytical thinking principles: hierarchy construction, priority definition, and logical consistency (COSTA, 2002; SAATY, 1991; SAATY; VARGAS, 2001; VARGAS, 1990).

Relative priorities were defined based on interviews with specialists in the field of Transport, who made pairwise comparisons between the hierarchy level criteria in light of the higher level, using the Saaty Scale, with nine different categories (SAATY, 1991). The sample of evaluators consisted of 4 men and 1 woman and the average age was 43 years, characterized as: (Evaluator 1) specialist researcher in the area of Transport and constant user of cycling infrastructure; (Evaluator 2) specialist researcher in the area of Transport, also a constant user of cycling infrastructure; (Evaluator 3) specialist researcher in the area of Sanitation and constant user of cycling infrastructure; (Evaluator 4) urban planner. This evaluator is a constant user of the cycling infrastructure; (Evaluator 5) civil engineer and doctoral student in the area of Transport.

Finally, the logical consistency of the judgments was evaluated by the Consistency Ratio (CR) proposed by Saaty to determine the inconsistency as a function of the order of the judgment matrix.

Considering the evaluators' judgments and their respective global criterion weights, a representative average weighting of such criteria can be obtained, which denote the priorities of each one compared to the main objective: the evaluation of the quality of the cycling infrastructure.

After defining the relative priorities of the criteria presented in the hierarchy, a cycle infrastructure quality indicator was calculated from the product of the weights assigned to each criterion by the measured value of the criterion, considering the 27 segments sampled for João Pessoa. Thus, a final score was obtained for each section. The final score of the segment is the sum of all analyzed portions. Then, these values were normalized.

Afterward, the descriptive measures of the set of values were calculated and four levels were adopted to classify the segments, considering the 1st quartile, 2nd quartile (median) and 3rd quartile values. Finally, according to the levels, the sections were classified as “very poor”, “poor”, “good” and “very good”. Finally, thematic maps of the sampled segments were prepared to detect the location of critical segments.

The map was prepared using a Geographic Information System (GIS) free software (QGIS 3.16.12) from the IBGE's 2019 Block Face Database for Public Areas. This database is a digital representation of the urban street design of the country's municipalities, with details of blocks, streets and squares. Based on the streets in João Pessoa and knowing the geolocation of the analyzed segments, obtained from the GIS Google Earth Pro, we proceeded by inserting the segments in the QGIS software.

### 2.2.2 GEOSTATISTICAL MODELING

The geostatistical modeling, used in this study, to extend the evaluation of the cycling quality for unsampled segments based on the sampled sections (11.34 km), comprises the following steps: (1) experimental variogram calculation and adjustment (2) Ordinary Kriging and (3) Cross-validation. These steps are briefly described below.

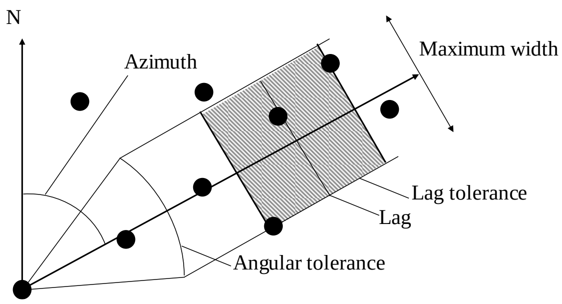
The semivariogram *γ(h)* is the main tool used for geostatistical modeling. In addition to visualizing the spatial structure of the variable of interest, it plays a fundamental role in estimating in unsampled locations. The empirical semivariogram function is given by Equation 1 (CRESSIE, 1993)

$$\gamma(h) = 1/2N(h) \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{1}$$

where $Z(x_i)$ is the value of the variable of interest at point $x_i$, $h$ expresses the distance between points in the database, and $N$ is the number of pairs of points identified at a distance $h$, known as *lag*.

The empirical semivariogram calculation process involves the search for pairs of points according to the parameters shown in Figure 3. The points inside the hatched area are those used to apply Equation 1 together with the reference point located at the origin. For the present case study, for the sake of simplicity, the omnidirectional semivariogram was used, which selects all pairs of points located at a distance *h*, regardless of the azimuth between these points. Thus, the angular tolerance is equal to 90º. Afterward, Equation 1 is applied to the pairs identified at distances 2*h*, 3*h* and so on, until the graph begins to show a certain constancy in the value of the mean semivariance.

Figure 3 – Pair search for the empirical semivariogram calculation

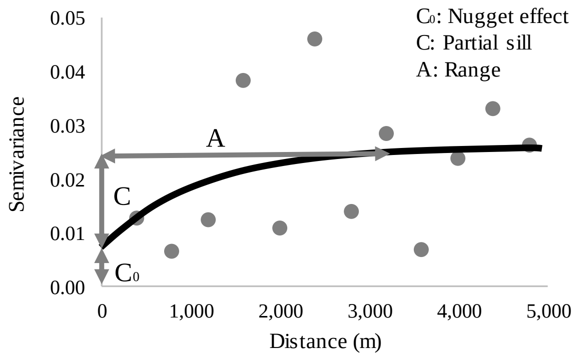



Source: Yamamoto and Landim (2015).

As Geostatistics works with data in the form of points, the cycling quality index in the 27 segments of 420 meters (variable of interest) was represented by the midpoint of each segments. The unsampled segments were also divided into segments of approximately 420 meters and the geostatistical interpolation was conducted considering the geographic coordinates of their respective midpoint.

After calculating the empirical semivariogram, a theoretical curve is calibrated to the points obtained by Equation 1. This curve is known as the theoretical semivariogram, whose equation is effectively used to calculate the optimal weights for spatial interpolation. The theoretical semivariogram (Figure 4) is characterized by three main parameters: the nugget effect ($C_0$), which corresponds to the value of the semivariance at distances that tend to zero, that is, it reflects the spatial randomness of the regionalized phenomenon and may also be caused by the sampling error; partial sill, or contribution (*C*), the portion of semivariance explained by the spatial structure of the variable of interest; and range (*a*), distance from which it is assumed that there is no more spatial dependence between the pairs of points. The range corresponds to the abscissa of the maximum semivariance (nugget effect plus partial sill), known as the sill.

Figure 4 –Theoretical semivariogram parameters




Source: Adapted from Matheron (1963).

The literature cites several theoretical semivariogram models. For the present article, the adjustment of the three most commonly used models was tested: exponential (Equation 2), Gaussian (Equation 3) and spherical (Equation 4) (CRESSIE, 1993).

$$\gamma(h) = C_0 + C[1 - \exp(-h/a)] \tag{2}$$

$$\gamma(h) = \begin{cases} C_0 + C[1.5(h/a) - 0.5(-(h/a)^2)] & se\ h < a \\ C_0 + C & se\ h \geq a \end{cases} \tag{3}$$

$$\gamma(h) = C_0 + C[1 - \exp\left((-h/a)^2\right)] \tag{4}$$

where $C_0$ is the nugget effect, *C* is the partial sill (contribution) and *a* is the range parameter. Ordinary Kriging basically consists of calculating the variable of interest at unsampled points from sampled data neighboring these points. Thus, Ordinary Kriging is a linear combination of sampled values and optimal weights (Equation 5) (CRESSIE, 1993).

$$Z^*_{x_0} = \sum_{i=1}^{n} \lambda_i\, Z(x_i) \tag{5}$$

where $Z^*_{x_0}$ is the estimated value of the Regionalized Variable *Z* at geographic position $x_0$; $\lambda_i$ is the optimal kriging weight assigned to neighbor $x_i$; and *n* is the number of neighbors. If the variable of interest shows spatial dependence, neighbors close to an unsampled point will receive greater weight than distant neighbors, because, according to the semivariogram function, the semivariance (difference) between the value of the variable at close points is smaller than at distant points. Thus, the optimal Ordinary Kriging weights are calculated from a nonlinear equation system that explicitly depend on the theoretical semivariance between the pairs of sampled points (matrix *K*) and between the sampled points and the point where the variable will be estimated (matrix *M*). The matrix operation shown in Equation 6 and Equation 7 (CRESSIE, 1993) simplifies the aforementioned equation system.

$$\begin{bmatrix} \gamma(x_1 - x_1) & \gamma(x_1 - x_2) & \dots & \gamma(x_1 - x_n) & 1 \\ \gamma(x_2 - x_1) & \gamma(x_2 - x_2) & \cdots & \gamma(x_2 - x_n) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \gamma(x_n - x_1) & \gamma(x_n - x_2) & \cdots & \gamma(x_n - x_n) & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma(x_0 - x_1) \\ \gamma(x_0 - x_2) \\ \vdots \\ \gamma(x_0 - x_n) \\ 1 \end{bmatrix} \tag{6}$$

$$[K] \cdot [\lambda] = [M] \tag{7}$$

Therefore, the optimal weight vector is obtained from Equation 8, which is applied to each unsampled point where the variable of interest is to be estimated.

$$[\lambda] = [K]^{-1} \cdot [M] \tag{8}$$

In order to compare the fit of theoretical semivariogram models to the studied phenomenon, a cross-validation procedure is carried out, which, with regard to geostatistical estimates, is based on the fictitious point test (CRESSIE, 1993). The method consists of removing the sampled points, one at a time, from the database and estimating their value based on the remaining sampled points and Equation 8. Thus, for these points, we have both the real value and the one estimated by the kriging, which are used to the calculation of goodness-of-fit measures. In the present study, the theoretical model chosen was the one that presented the lowest mean of the absolute percentage error, according to Equation 9. It is worth mentioning that, based on the cross-validation, we can obtain estimates for the points of known values, thus leading to a methodological validation.

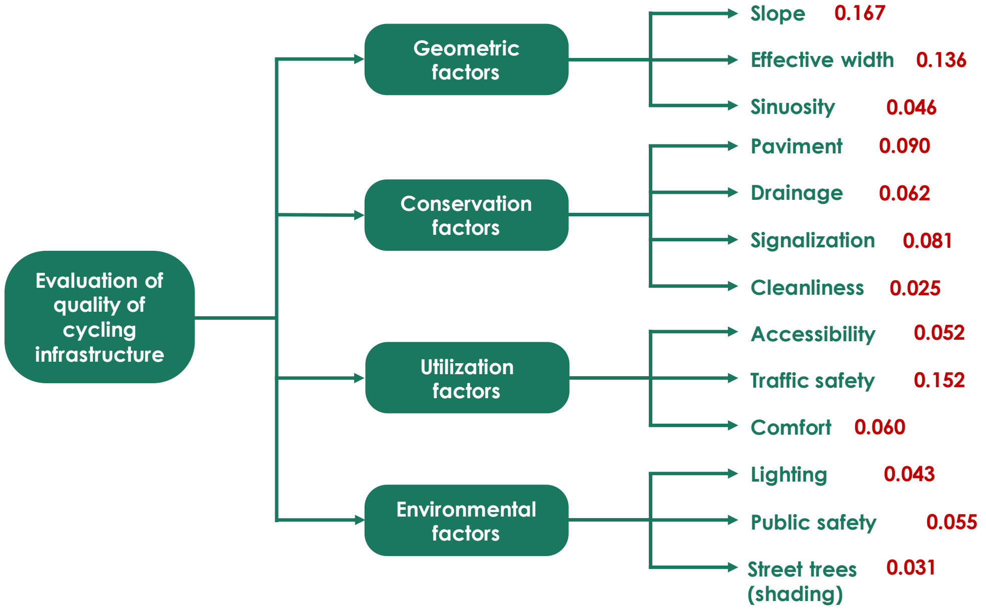
$$Error = \frac{1}{n} * \sum_{i=1}^{n} \left[ \left( \left| Z_{x_i}^{*} - Z_{x_i} \right| / Z_{x_i} \right) * 100 \right] \tag{9}$$

## 3 RESULTS

### 3.1 Results from Analytic Hierarchy Process

The average weighting criteria, obtained from the interviews conducted with the experts, is shown in Figure 5.

Figure 5 - Average weighting criteria, grouped into four main groups.




Elaboration: The authors (2022).

Having the set of final standardized scores for the segments in hand, the descriptive measures of the cycling quality indicator were determined (Table 1). Finally, the indicator was discretized considering a four-level ranking, based on quartiles. Thus, the values that limit each of the rankings are presented in Table 2.

Table 1 - Descriptive measures of the normalized final scores of the segments.

| **Descriptive measures** | **Standardized final scores** |
|---|---|
| Minimum | 0.2392 |
| Maximum | 0.9154 |
| Average | 0.5811 |
| Standard deviation | 0.1692 |
| 1st Quartile | 0.4361 |
| Median | 0.5844 |
| 3rd Quartile | 0.7305 |

Elaboration: The Authors (2022).

Table 2 - Intervals of the final scores.

| **Lower bound** | **Upper bound** | **Interval** | **Ranking** |
|---|---|---|---|
| Minimum | 1st Quartile | 0.2392 – 0.4361 | Very poor |
| 1st Quartile | Median | 0.4361 – 0.5844 | Poor |
| Median | 3rd Quartile | 0.5844 – 0.7305 | Good |
| 3rd Quartile | Maximum | 0.7305 – 0.9154 | Very good |

Elaboration: The authors (2022).

Finally, Table 3 presents the global ranking of each segment in terms of the criteria discussed above. Thus, 6 sections were ranked as “very poor”, 7 sections were classified as “poor”, 7 sections were classified as “good” and 7 sections were ranked as “very good”.

Table 3 - Final score and ranking of segments.

| Section | Final score | Ranking | Section | Final score | Ranking | Section | Final score | Ranking |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.5008 | Poor | 10 | 0.7266 | Good | 19 | 0.7305 | Very good |
| 2 | 0.4361 | Poor | 11 | 0.5593 | Poor | 20 | 0.3495 | Very poor |
| 3 | 0.3729 | Very poor | 12 | 0.6756 | Good | 21 | 0.8086 | Very good |
| 4 | 0.4130 | Very poor | 13 | 0.4510 | Poor | 22 | 0.4905 | Poor |
| 5 | 0.3928 | Very poor | 14 | 0.2392 | Very poor | 23 | 0.6048 | Good |
| 6 | 0.4686 | Poor | 15 | 0.6892 | Good | 24 | 0.7375 | Very good |
| 7 | 0.3841 | Very poor | 16 | 0.7563 | Very good | 25 | 0.9154 | Very good |
| 8 | 0.5486 | Poor | 17 | 0.7679 | Very good | 26 | 0.6764 | Good |
| 9 | 0.5844 | Good | 18 | 0.7453 | Very good | 27 | 0.6652 | Good |

Elaboration: The authors (2022).

Considering the ranking of each segment, we proceeded by constructing a spatial identification map of the quality of these segments in João Pessoa. The results are shown in Figure 6.

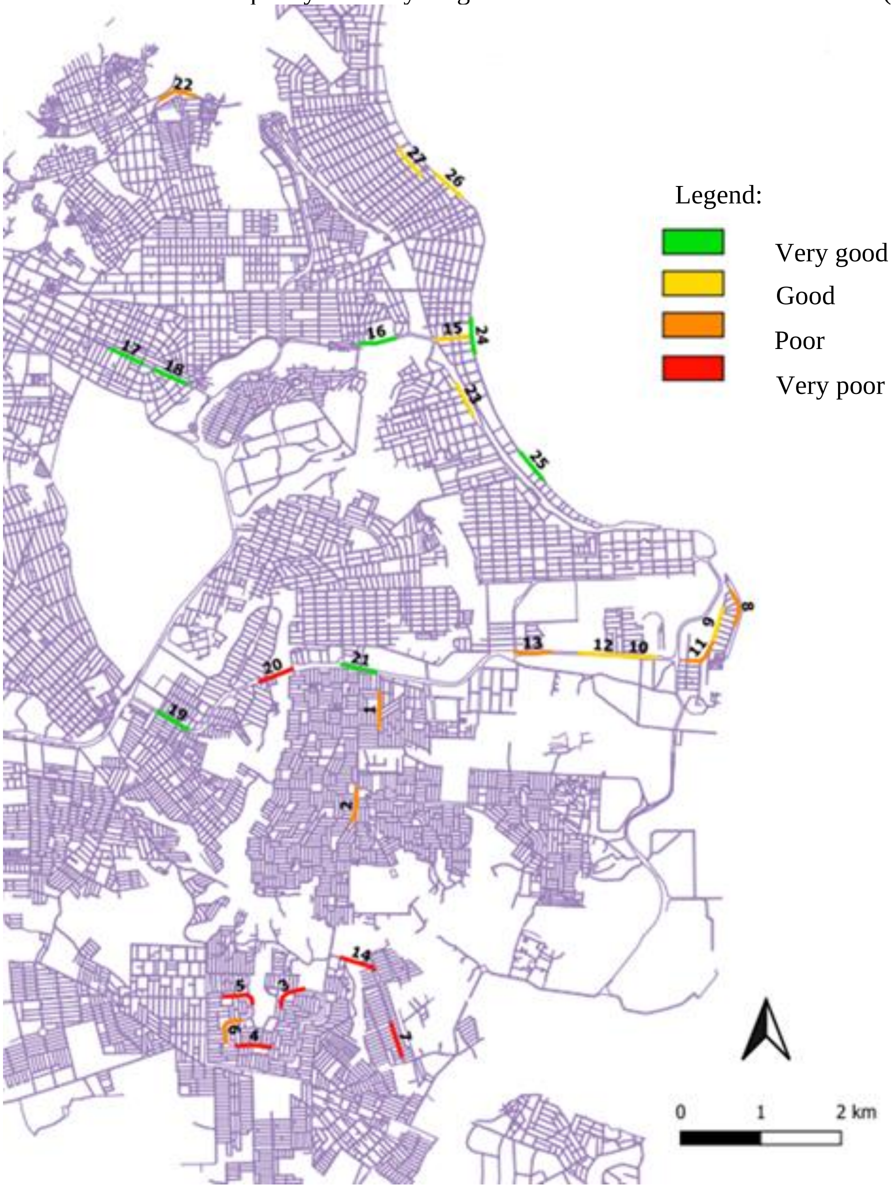
The ranking of the segments and the thematic map are tools to support government decision-making regarding maintaining the quality of cycling infrastructure in João Pessoa. Thus, it can be observed that the critical sections were 14, 20, 3, 7, 5 and 4, concentrated in the southern region of the city. Predominantly, these cycle paths are not isolated from the motorized traffic and are the segments that most need quality improvement measures, to improve user´s comfort and safety when using the infrastructure.

As an example, Figure 7 (a, b) presents critical segments 7 and 5, respectively, whose problems were visible in the photos. There is a lack of cleanliness in section 7 and, for both segments, there is a lack of horizontal signalization and the presence of road studs is irregular. In addition, for segments 5, there are cars parked in the cycle path, due to the presence of stores. If such a fact is routine, then it can directly affect the

 DOI: http://dx.doi.org/10.14393/rbcv74n4-65916

safety and feeling of cyclist comfort. It is worth mentioning that the analyses carried out for these segments are based on the figures and are only initial. They are not a substitute for a thorough field assessment to support public authorities' decision-making regarding the actions to be taken in each of the cycling infrastructure segments.

Figure 6 - Assessment of the quality of the cycling infrastructure sections in João Pessoa (Brazil).




Elaboration: The authors (2022).

Cycle path segment of section 7 (a). Cycle path segment of section 5 (b)


Segment 7 (a)


Segment 5 (b)

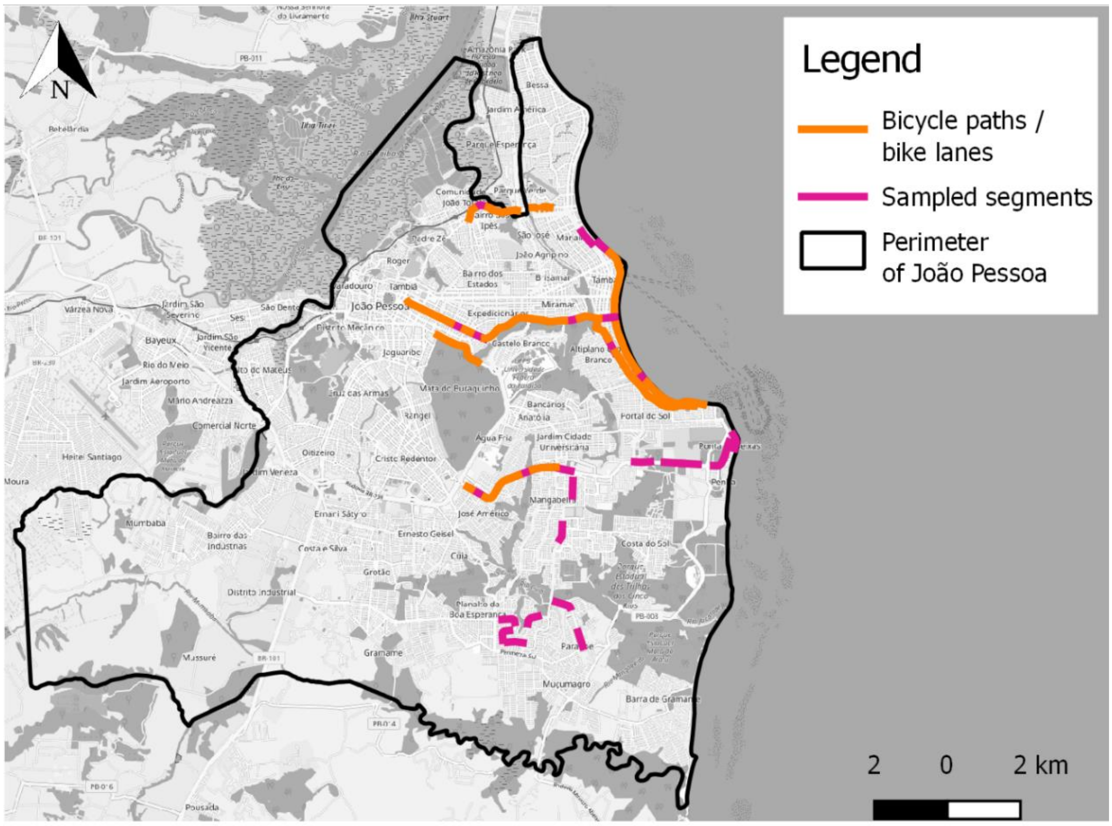
Source: Google Earth Pro.

### 3.2 Results from geostatistical modeling

In addition to the 27 sampled sections, the remaining cycling infrastructure resulted in 32 new sections of similar length. Figure 8 shows all recovered sections, highlighting the unsampled ones in orange.

There is a higher density of sampled segments in the southeast region of the city, and most of the unsampled sections are in the northeast corner. Therefore, the semivariogram aims to reproduce the same spatial structure of the points sampled in the remaining points.

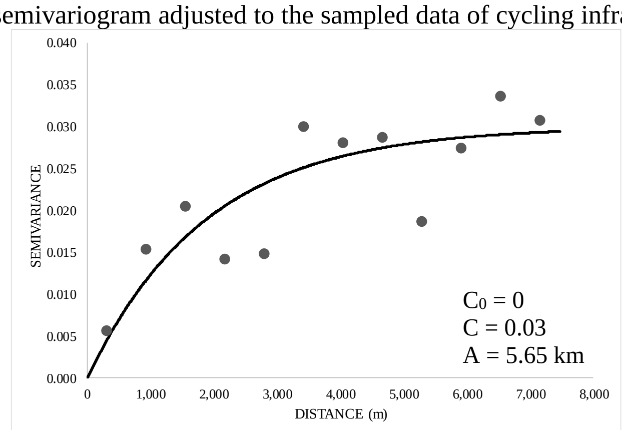
Figure 8 - Sections of cycling infrastructure in João Pessoa (Brazil)




Elaboration: The Authors (2022).

Figure 9 shows the empirical semivariogram and exponential model, which, among the three theoretical models tested, was the one that resulted in the lowest mean absolute percentage error. Although the results were similar, the error obtained when using the exponential model was slightly smaller than the others (20.99% against 21.10% for the Gaussian model and 21.40% for the spherical model). Consequently, spatial interpolation was performed based on this model.

Figure 9 - Exponential semivariogram adjusted to the sampled data of cycling infrastructure in João Pessoa

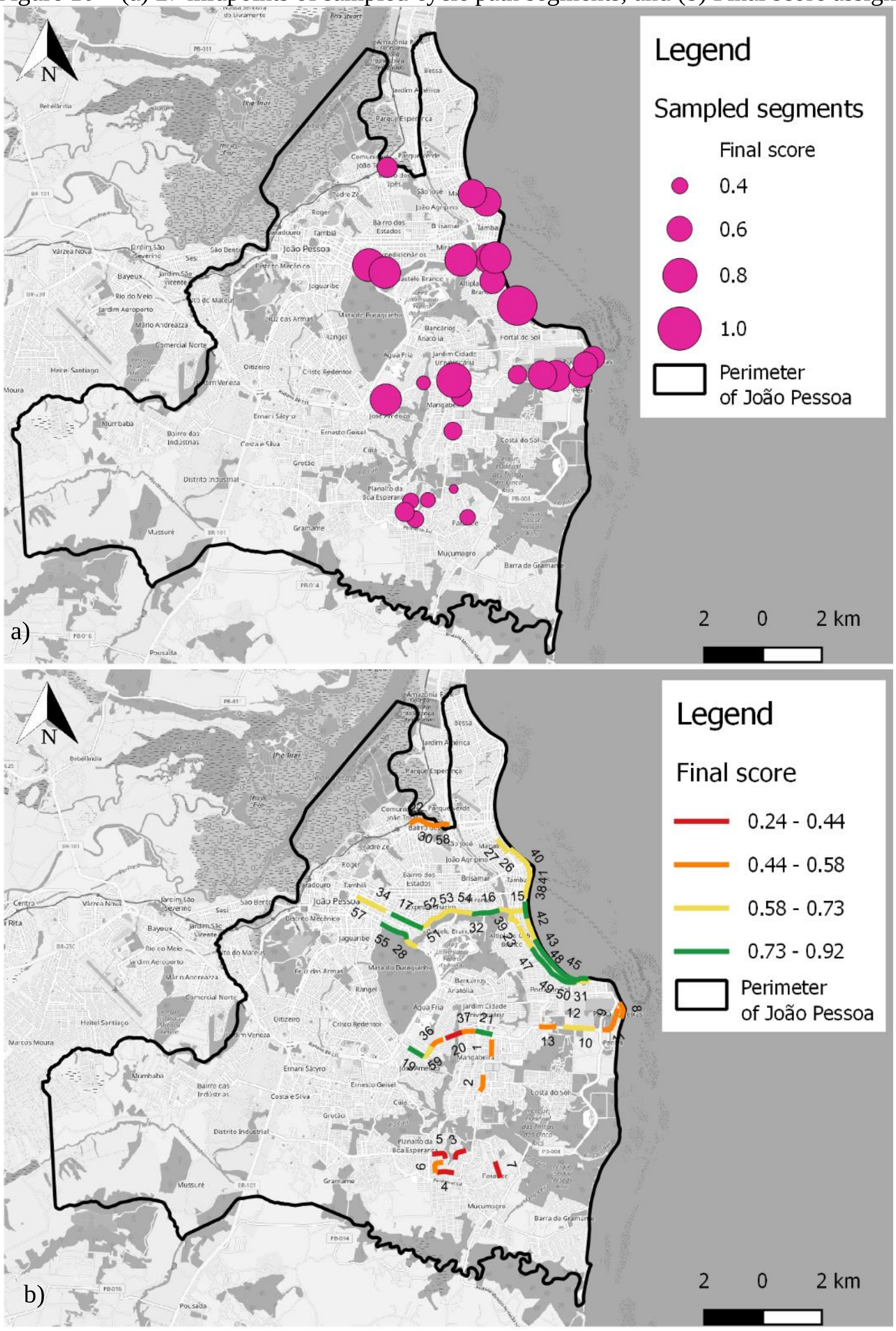



Elaboration: The Authors (2022).

The semivariogram reveals that there is, in fact, a spatial dependence for the quality indicator of the cycling infrastructure in João Pessoa, as the difference between the value of the proposed indicator is smaller at small distances and increases as a function of the distance between pairs of points, until the semivariance reaches a plateau. Based on the exponential model, cycle paths whose midpoint is located up to approximately 5.6 km are spatially dependent. Therefore, only sampled data contained within a radius of 5.6 km centered on an unsampled cycle path will participate in the estimation of the quality indicator for this cycle path segment.

The kriging equation generates a continuous surface of values interpolated from the values available in the database. In the case of the quality of cycling infrastructure in João Pessoa, the variable of interest is likely to occur only where there is a cycle path. Figure 10 exemplifies the application of kriging in the spatial estimation of the cycling infrastructure quality indicator in cycle paths that do not have this data. The real values for the sampled segments and estimated values for the other segments are shown.

Figure 10 – (a) 27 midpoints of sampled cycle path segments; and (b) Final score assigned to all recovered cycle paths.




| ID | Score | ID | Score |
|---|---|---|---|
| 1 | 0.501 | 31 | 0.724 |
| 2 | 0.436 | 32 | 0.731 |
| 3 | 0.373 | 33 | 0.714 |
| 4 | 0.413 | 34 | 0.718 |
| 5 | 0.393 | 35 | 0.732 |
| 6 | 0.469 | 36 | 0.528 |
| 7 | 0.384 | 37 | 0.527 |
| 8 | 0.549 | 38 | 0.715 |
| 9 | 0.584 | 39 | 0.678 |
| 10 | 0.727 | 40 | 0.694 |
| 11 | 0.559 | 41 | 0.701 |
| 12 | 0.676 | 42 | 0.679 |
| 13 | 0.451 | 43 | 0.800 |
| 14 | 0.239 | 44 | 0.834 |
| 15 | 0.689 | 45 | 0.770 |
| 16 | 0.756 | 46 | 0.722 |
| 17 | 0.768 | 47 | 0.819 |
| 18 | 0.745 | 48 | 0.858 |
| 19 | 0.731 | 49 | 0.803 |
| 20 | 0.350 | 50 | 0.749 |
| 21 | 0.809 | 51 | 0.729 |
| 22 | 0.491 | 52 | 0.720 |
| 23 | 0.605 | 53 | 0.712 |
| 24 | 0.737 | 54 | 0.720 |
| 25 | 0.915 | 55 | 0.737 |
| 26 | 0.676 | 56 | 0.740 |
| 27 | 0.665 | 57 | 0.683 |
| 28 | 0.723 | 58 | 0.569 |
| 29 | 0.703 | 59 | 0.626 |
| 30 | 0.536 | | |

Elaboration: The Authors (2022).

## 4 CONCLUSIONS AND SUGGESTIONS FOR FUTURE STUDIES

Considering the increasing use of active modes, especially cycling, this study presented a two-step method to evaluate the quality of a cycling network, considering a relatively low cost, in terms of data collection. The method was based on the following approaches: (1) Analytic Hierarchy Process and (2) Geostatistical Modeling.

An important contribution is related to the proposed hierarchy, comprising 13 criteria, grouped under the themes of geometric factors, conservation factors, utilization factors and environmental factors. The weights found through a sample of five specialists or users of cycle paths can be used to evaluate the cycling network of other municipalities. The sampled sections (27 in this study) are the alternatives considered in the proposed hierarchy. Thus, the hierarchy application used here for other similar cities and later comparisons with the results obtained in this study are suggested.

Applying the weights to the sections sampled for João Pessoa, it can be observed that 86% of the cases classified as “very poor” are cycle paths without a clear separation from the motorized traffic. In addition, there is an apparent spatial dependence as most of the critical sections are concentrated in the south of the municipality, while the best evaluated sections are located in the north (northeast) region, which covers areas with a higher average income and a concentration of tourist attraction hubs.

Problems related to poor maintenance and conservation, as well as the expansion and integration between the cycling system and public transport, found in some segments of the cycling infrastructure, were mentioned in a diagnostic report on the reformulation of the Master Plan for João Pessoa (JOÃO PESSOA, 2021). Therefore, the study proposed here can serve as input for sectoral plans and programs to improve the cycling system and its integration with other travel modes, aiming at improving urban mobility in João Pessoa.

The existence of spatial dependence allows the use of Geostatistics in the approach aiming to extend the evaluation to unsampled sections of the cycling network of João Pessoa. Thus, geostatistical modeling constitutes the second contribution of this study, as inspections and field research require trained human resources, time and financial resources. The use of Geostatistics for spatial interpolation of indicators can be extended to other assessments of urban infrastructure, such as quality of sidewalks, diverse facilities, quality of urban roads, etc., thus, a possible spatial dependence of such variables. The authors recommend using the procedure for evaluating the quality of sidewalks, especially for those with reduced mobility, for example. It is also recommended to estimate the indicators without using all points with known values to calculate error metrics in the remaining points. Thus, a comparison can be made between the cross-validation and this new proposed validation, providing further methodological insights. A methodological improvement is also suggested based on using distances along the road network in the geostatistical modeling stages, as opposed to the Euclidean distances adopted in the present study. In this context, contiguous neighbors will have much more influence on the estimation of the indicator in an unsampled section than segments from other cycle paths, allowing a more realistic representation of the spatial variation of cycle path quality.

## Acknowledgments

The authors would like to thank the São Paulo Research Foundation (FAPESP, Brazil - grant #2019/12054-4, Brazil) and the National Council for Scientific and Technological Development (CNPq, Brazil – grant #304345/2019-9 and #422115/2016-9).

## Authors' Contribution

W. A. T.: Conceptualization, Data curation, Formal analysis, Research, Methodology, Visualization and Writing – initial draft; 2) S. F. M.: Data curation, Formal analysis, Research, Methodology, Visualization, Writing – initial draft and Writing – review and editing; C. S. P.: Conceptualization, Methodology, Supervision, Writing – initial draft and Writing – review and editing; P. B. S.: Data curation and Writing – review and editing; R. A. M.: Data curation and Writing – review and editing.

## Conflict of Interest

The authors declare no conflict of interest.

## References

ANTUNES, L. L. **Avaliação das infraestruturas cicloviárias implantadas no Corredor Universitário em Goiânia**. Goiânia, 2015. 315 f. Dissertação (Mestrado) - Universidade Federal de Goiás, Escola de Engenharia Civil e Ambiental (EECA), Programa de Pós-Graduação em Engenharia Civil - Geotecnia, Estruturas e Construção Civil.

ASSOCIAÇÃO NACIONAL DE TRANSPORTE PÚBLICOS (ANTP). **Ciclovias mais largas e sem zigue-zagues podem ser legado da pandemia**. 2020. Available at: http://www.antp.org.br/noticias/clippings/ciclovias-mais-largas-e-sem-zigue-zagues-podem-ser-legado-da-pandemia.html. Accessed on: 10 jul. 2021.

ASSOCIAÇÃO NACIONAL DE TRANSPORTE PÚBLICOS (ANTP). **Pandemia reforça necessidade de ações para mobilidade ativa**. 2021. Available at: http://www.antp.org.br/noticias/clippings/pandemia-reforca-necessidade-de-acoes-para-mobilidade-ativa-.html. Accessed on: 10 jul. 2021.

AYACHI, F. S.; DOREY, J.; GUASTAVINO, C. Identifying factors of bicycle comfort: An online survey with enthusiast cyclists. **Applied Ergonomics**, v. 46, p. 124-136, 2015. DOI. 10.1016/j.apergo.2014.07.010.

BATISTA, D. G. P.; LIMA, E. R. V. Índice de avaliação da qualidade de infraestruturas cicloviárias: um estudo em João Pessoa-PB. **Urbe. Revista Brasileira de Gestão Urbana**, v. 12. 2020. DOI. 10.1590/2175-3369.012.e20190086.

BRASIL. Lei Federal nº 12.587, de 03 de janeiro de 2012. **Política Nacional de Mobilidade Urbana**. Available at: https://www2.camara.leg.br/legin/fed/lei/2012/lei-12587-3-janeiro-2012-612248-publicacaooriginal-134894-pl.html. Accessed on: 10 jul. 2021.

DE SOUSA, P. B.; KAWAMOTO, E. Análise de fatores que influem no uso da bicicleta para fins de planejamento cicloviário. **Transportes**, v. 23, n. 4, p. 79–87. 2015. DOI. 10.14295/transportes.v23i4.928

CALVEY, J. C.; SHACKLETON, J. P.; TAYLOR, M. D.; LLEWELLYN, R. Engineering condition assessment of cycling infrastructure: cyclists' perceptions of satisfaction and comfort. **Transportation Research Part A: Policy and Practice**. 78, p. 134-143, 2015. DOI. 10.1016/j.tra.2015.04.031

CAMPOS, V. B. G.; CARDOSO, P. D. B. Metodologia para planejamento de um de sistema cicloviário. **Transportes**, v. 24, n. 4, p. 39–48, 2016. DOI: 10.14295/transportes.v24i4.1158.

CARVALHO, S. D. P. C. E.; RODRIGUEZ, L. C. E.; SILVA, L. D.; CARVALHO, L. M. T. D.; CALEGARIO, N.; LIMA, M. P. D.; SILVA, C. A.; MENDONÇA, A. R. D.; NICOLETTI, M. F. Predição do volume de árvores integrando Lidar e Geoestatística. **Scientia Forestalis/Forest Sciences**, v. 43, n. 107, p. 627–637, 2015.

CHICA-OLMO, J.; RODRÍGUEZ-LÓPEZ, C.; CHILLÓN, P. Effect of distance from home to school and spatial dependence between homes on mode of commuting to school. **Journal of Transport Geography**, v. 72, p. 1–12, 2018. DOI. 10.1016/j.jtrangeo.2018.07.013.

COSTA, H. G. **Introdução ao método de análise hierárquica: análise multicritério no auxílio à decisão**. Niterói, RJ. 2002.

COSTA, C. S.; PITOMBO, C. S.; SOUZA, F. L. U. Travel Behavior before and during the COVID-19 Pandemic in Brazil: Mobility Changes and Transport Policies for a Sustainable Transportation System in the Post-Pandemic Period. **Sustainability**, v. 14, p. 4573, 2022. DOI. 10.3390/su14084573.

CRESSIE, N. A. C. **Statistics for spatial data**. John Wiley & Sons, Inc., 1993.

DIXON, L. B. Bicycle and Pedestrian Level-of-Service Performance Measures and Standards for Congestion

Management Systems. **Transportation Research Record**, v. 1538, n. 1, p. 1–9, 1996. DOI. 10.1177/0361198196153800101.

FONSECA, N. F. D. S.; MANZATO, G. G.; TEIXEIRA I. P.; RODRIGUES DA SILVA, A. N. Um índice para a caracterização da oferta de infraestrutura cicloviária. **Anais do 32º Congresso Nacional de Pesquisa e Ensino e Pesquisa em Transporte**, ANPET, Gramado, v.1, p. 2630 – 2641, 2018.

GOMES, M. M.; PITOMBO, C. S.; PIRDAVANI, A.; BRIJS, T. Geostatistical approach to estimate car occupant fatalities in traffic accidents. **Revista Brasileira de Cartografia**, v. 70, n. 4, p. 1231–1256, 2018. DOI. 10.14393/rbcv70n4-46140.

GOOVAERTS, P. Medical geography: A promising field of application for geostatistics. **Mathematical Geosciences**, v. 41, p. 243–264, 2009. DOI. 10.1007/s11004-008-9211-3.

JOÃO PESSOA. **P2b - Relatório do Diagnóstico Técnico: Fase II - Outubro/2021**. Prefeitura Municipal de João Pessoa, PMJP. Available at: http://pdjp.com.br/wp-content/uploads/2021/10/115_2021.10.08_P2b_DIAGNOSTICO-TECNICO.pdf. Accessed on 08/08/2022.

KERRY, R.; GOOVAERTS, P.; GIMÉNEZ, D.; OUDEMANS, P.; MUÑIZ, E. Investigating geostatistical methods to model within-field yield variability of cranberries for potential management zones. **Precision Agriculture**, v. 17, p. 247–273, 2016. DOI. 10.1007/s11119-015-9408-7.

KRIGE, D. G. A statistical approach to some basic mine valuation problems on the Witwatersrand. **Journal of the Southern African Institute of Mining and Metallurgy**, v. 52, n. 6, p. 119–139, 1951. Southern African Institute of Mining and Metallurgy.

LINDNER, A.; PITOMBO, C. S.; ROCHA, S. S.; QUINTANILHA, J. A. Estimation of transit trip production using Factorial Kriging with External Drift: an aggregated data case study. **Geo-spatial Information Science**, v. 19, n. 4, p. 245–254, 2016. DOI. 10.1080/10095020.2016.1260811.

MAJUMDAR, A.; NOLAND, R. B.; OCHIENG, W. Y. A spatial and temporal analysis of safety-belt usage and safety-belt laws. **Accident Analysis & Prevention**, v. 36, n. 4, p. 551–560, 2004. DOI. 10.1016/S0001-4575(03)00061-7.

LINDNER, A.; PITOMBO, C. S. Sequential Gaussian Simulation as a promising tool in travel demand modeling. **Journal of Geovisualization and Spatial Analysis**, v. 3 , 2019. DOI. 10.1007/s41651-019-0038-x

MALDONADO-HINAREJOS, R.; SIVAKUMAR A.; POLAK, J. W. Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach. **Transportation**, v.41, n. 6, p. 1287-1304, 2014. DOI. 10.1007/s11116-014-9551-4.

MARQUES, S. D. F.; PITOMBO, C. S. Ridership Estimation Along Bus Transit Lines Based on Kriging: Comparative Analysis Between Network and Euclidean Distances. **Journal of Geovisualization and Spatial Analysis**, v. 5, n. 1, p. 7, 2021a. DOI. 10.1007/s41651-021-00075-w.

MARQUES, S. D. F.; PITOMBO, C. S. Applying Multivariate Geostatistics for Transit Ridership Modeling at the Bus Stop Level. **Boletim de Ciências Geodésicas**, v. 27, n. 2, 2021b. DOI. 10.1590/1982-2170-2020-0069.

MATHERON, G. Principles of geostatistics. **Economic Geology**, v. 58, n. 8, p. 1246–1266, 1963. DOI. 10.2113/gsecongeo.58.8.1246.

MATHERON, G. The Theory of Regionalized Variables and Its Applications, 1971. Paris: Les Cahiers du Centre de Morphologie Mathematique in Fontainebleu.

MEDEIROS, R. S.; MELO, R. A.; SOUSA, P. B. Uso de Indicadores para Avaliação do Sistema Viário Urbano. In: 33º Congresso de Pesquisa e Ensino em Transportes, 2019, Balneário Camboriú-SC. **Anais...**Associação Nacional de Pesquisa e Ensino em Transportes, 2019. p. 178-188.

MONTEIRO, F. B.; CAMPOS, V. B. G. Métodos de avaliação da qualidade dos espaços para ciclistas. In: XXV Congresso de Pesquisa e Ensino em Transportes da ANPET, 2011, Belo Horizonte-MG.

**Anais...**Associação Nacional de Pesquisa e Ensino em Transportes, 2011. p. 1242-1253.

PITOMBO, C. S.; SALGUEIRO, A. R.; DA COSTA, A. S. G.; ISLER, C. A. A two-step method for mode choice estimation with socioeconomic and spatial information. **Spatial Statistics**, v. 11, p. 45–64, 2015. DOI. 10.1016/j.spasta.2014.12.002.

PROVIDELO, J. K.; SANCHES, S. D. P. Percepções de indivíduos acerca do uso da bicicleta como modo de transporte. **Transportes**, v. 18, n. 2, 2010. DOI. 10.14295/transportes.v18i2.424.

PROVIDELO, J. K.; SANCHES, S. P. Roadway and traffic characteristics for bicycling. **Transportation**, v. 38, n. 5, p. 765-777, 2011. DOI: http:10.1007/s11116-011-9353-x.

RODRIGUES DA SILVA, A. N.; PITOMBO, C. S.; PEDREIRA JÚNIOR, J. U.; CIRÍACO, T. G. M.; COSTA, C. S. Changes in Mobility and Challenges to the Transport Sector in Brazil due to COVID-19. Em: **TRANSPORTATION AMID PANDEMICS: PRACTICES AND POLICIES**; Amsterdam, The Netherlands: Elsevier, 2022, v. 1, p. 105-118. DOI. 10.1016/B978-0-323-99770-6.00010-7.

SAATY, T. L. **Método de análise hierárquica**. São Paulo: McGraw-Hill, Makron, 1991.

SAATY, T. L.; VARGAS, L. G. **Models, methods, concepts applications of the analytic hierarchy process** - 2001. Norwell: Kluwer Academic Publishers.

SELBY, B.; KOCKELMAN, K. M. Spatial prediction of traffic levels in unmeasured locations: Applications of universal kriging and geographically weighted regression. **Journal of Transport Geography**, v. 29, p. 24–32, 2013. DOI. 10.1016/j.jtrangeo.2012.12.009.

SFDPH. **Bicycle Environmental Quality Index (BEQI)**. Draft Report. San Francisco Department of Public Health, Environmental Health Section/Program on Health, Equity and Sustainability, San Francisco, CA United States Draft Report, 2009.

SILVEIRA, M. O.; MAIA, M. L. A. Variáveis que influenciam no uso da bicicleta e as crenças da teoria do comportamento planejado. **Transportes**, v. 23, n. 1, p. 24-36, 2015. DOI. 10.14295/transportes.v23i1.848.

STELZENMÜLLER, V.; EHRICH, S.; ZAUKE, G. P. Impact of additional small-scale survey data on the geostatistical analyses of demersal fish species in the North Sea. **Scientia Marina**, v. 69, n. 4, p. 587–602, 2005. DOI. 10.3989/scimar.2005.69n4587.

TOBLER, W. R. A Computer Movie Simulating Urban Growth in the Detroit Region. **Economic Geography**, v. 46, p. 234–240, 1970. DOI. 10.2307/143141.

VARGAS, L. G. An overview of the Analytic Hierarchy Process and its applications. **European Journal of Operations Research**, v.28, p. 2-8, 1990. DOI. 10.1016/0377-2217(90)90056-H.

WEBSTER, R.; OLIVER, M. A. **Geostatistics for environmental scientists**. 2nd. ed. John Wiley & Sons, 2007.

YAMAMOTO, J. K.; LANDIM, P. M. B. **Geoestatística: conceitos e aplicações**. Oficina de textos, 2015.

YANG, H.; YANG, J.; HAN, L. D.; LIU, X.; PU, L.; CHIN, S.; HWANG, H. A Kriging based spatiotemporal approach for traffic volume data imputation. **PloS one**, v. 13, n. 4, p. e0195957, 2018. DOI. 10.1371/journal.pone.0195957.

ZHANG, D.; WANG, X. C. Transit ridership estimation with network Kriging: A case study of Second Avenue Subway, NYC. **Journal of Transport Geography**, v. 41, p. 107–115, 2014. DOI. 10.1016/j.jtrangeo.2014.08.021.

DOI: http://dx.doi.org/10.14393/rbcv74n4-65916

## Main author's biography

Wellington de Aquino Traldi was born in Rio Claro – SP, Brasil, in 1999. He holds a bachelor's degree in Civil Engineering from the São Carlos School of Engineering, University of São Paulo (EESC/USP), with special studies in Transportation Engineering. He currently works in the area of data analysis in Logistics and Transport.